Internship Tasks for Nojoto

What would you improve about our Nojoto App as Product & Why?

1. Hold contests for artists, writers, singers, etc. so they can learn and improve.
2. Get Google ads and earn additional revenue on the App and Website
3. Host seminars, webinars, tutorials and courses for people to learn how to write, paint, sing and entertain.
4. Get guests to hold podcasts and standup shows on the app. This will also attract sponsors.
5. Keep the platform clean and for all audiences.
6. Allow creators to earn revenue through ads.

There is a data point that indicates that there are more Ola drop-offs at the Railway Station than pick-ups from the Railway Station. Why this is the case and what would you do within the product to change that?

- This might be primarily due to the fact the convenience and speed standard taxis offer over Ola.
- Ola generally takes a lot of time to book and the waiting areas at Railway Stations tend to be overcrowded and cramped.
- This can be alleviated by encouraging people to books cabs in advance.
- Also ask Ola drivers to wait at Railway Stations so customers can get cabs immediately.

How would you prioritize resources when you have two important things to do but can't do them both?

One can use the RICE framework:

- Not a hard and fast rule
- There are many reasons why you might work on a project with a lower score first. E.g. One project may be a dependency for another project
- Might want or need to work on projects "out of order" - can clearly identify when you're making these trade-offs using RICE

Reach

- **Estimate how many people each project will affect within a given period**.
- **Unit**: number of people/events per time period. E.g. "how *many customers* will this project impact over *a single quarter*?

Examples

- How many *personas* in the supply chain will this project impact *this year*?

- 500 customers reach this point in the signup funnel each month, and 30% choose this option. The reach is **500 × 30% × 3 = 450 customers per quarter**.
- Every customer who uses this feature each quarter will see this change. The reach is **2,000** customers per quarter (Assuming we have 2000 customers).
- This change will have a one-time effect on 800 existing customers, with no ongoing effect. The reach is **800 customers per quarter**.

Impact

- Estimate the **impact on an individual person**
- **Unit**: T-shirt sizing

Examples

- how much will this project increase conversion rate when a customer encounters it?
- For each customer who sees it, this will have a huge impact. The impact score is **H**.
- This will have a lesser impact on each customer. The impact score is **L**.
- This is somewhere in-between in terms of impact. The impact score is **M**.

Confidence

- Factor in **your level of confidence about your estimates**
- Be honest with yourself: **how much support do you really have for your estimates?**
- **Unit:** percentage
- **Evaluate this last**

Examples

- We have quantitative metrics for reach, user research for impact, and an engineering estimate for effort. This project gets a **100%/H** confidence score.
- I have data to support the reach and effort, but I'm unsure about the impact. This project gets an **80%/M** confidence score.
- The reach and impact may be lower than estimated, and the effort may be higher. This project gets a **50%/L** confidence score.

Effort

- **Estimate the total amount of time a project will require** from all members of your team: product, design, and engineering.
- **Unit:** "person-months" – mean amount of work performed by the average worker in one month. It is used for estimation of the total amount of uninterrupted labor required to perform a task.

Examples

- This will take about a week of planning, **1-2 weeks of design,** and **2-4 weeks of engineering time**. I'll give it an effort score of **2 person-months**.
- This project will take several weeks of planning, a significant amount of design time, and at least two months of one engineer's time. I'll give it an effort score of **4 person-months**.
- This only **requires a week** of planning, no new design, and a few weeks of engineering time. I'll give it an effort score of **1 person-month**.

How is a RICE score calculated?

- **Reach**: how many people will this impact? (Estimate within a defined time period.)
- **Impact**: how much will this impact each person? (Massive = 3x, High = 2x, Medium = 1x, Low = 0.5x, Minimal = 0.25x.)
- **Confidence**: how confident are you in your estimates? (High = 100%, Medium = 80%, Low = 50%.)
- **Effort**: how many "person-months" will this take? (Use whole numbers and minimum of half a month – don't get into the weeds of estimation.)

What should be the Success Metric of Content Creation & Content Consumption, on the Platform Level?

- Monthly recurring revenue (MRR)
- Customer Lifetime Value (CLTV or LTV)
- Customer Acquisition Cost (CAC)
- Daily Active User/Monthly Active User ratio
- Session duration
- Traffic (paid/organic)
- Bounce rate
- Retention rate
- Churn rate
- Number of sessions per user
- Number of user actions per session
- Net Promoter Score (NPS)
- Customer Satisfaction Score (CSAT)

References

1. https://www.intercom.com/blog/rice-simple-prioritization-for-product-managers/
2. https://www.altexsoft.com/blog/business/15-key-product-management-metrics-and-kpis/
3. https://medium.com/@henryfeng/know-users-behaviors-better-with-cohort-analysis-in-python-6c0dfc373963

Nojoto-Tasks-Programming

May 19, 2020

1 Programming Tasks for Nojoto

1.1 Recommendation Engine

[1]:
```
# importing libraries

import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
data = pd.read_excel('data/RecommendationEngineData.xlsx', sheet_name =␣
↪'Recommendation EnginDataSet')
```

[3]:
```
data.head(5)
```

[3]:
```
   POST_ID             POST_STRING_UNIQUE_ID          CREATED_AT  \
0  5251588  ec7e9ef3246874618d617623ee07451c 2020-04-22 19:51:00
1  5539448  e38e34aa65c0c7c2ed42426fe92e6419 2020-05-10 18:00:00
2  5503440  01e4dc698aba6a4561739c58906838cc 2020-05-08 07:33:00
3  5538585  87d93e56b144f5ba7557663b2fb6218c 2020-05-10 15:18:00
4  5540220  4b20839183de924a7bc8e4bcdc9c20a2 2020-05-10 17:11:00

      Creator_Name                                            Caption  Length  \
0      Nojoto News  Know who loved your story | Tag Nojotians #Noj…      51
1      Nojoto News  Details for Day 1 (Monday) :- \nExpress Karo N…     168
2  Anand Mohan Jha  Anshh only 4 youðŸ˜¨, sorry #Nojoto #story #Poe…       0
3  Anand Mohan Jha  #krishna_flute à¤®à¤¾à¤  à¤¤à¥< à¤®à¤¾à¤  à¤¹à…       0
4    Bhawna Mishra  #SuperMom #chitthi #letter #originalmess #message     116

   Watch_Views  Total_Watch_time  Average_Watch_time  10_Sec_Watch_Time  …  \
0        61196            732610                12.0             584192  …
1         2751             33002                12.0              25716  …
2         7086            126534                17.9             110171  …
3         1119             19908                17.8              17109  …
4         1075             15966                14.9              13091  …
```

```
   Execution_Reach  Spammy_Views  Love  Comment  Share  Report_Abuse  \
0          1000000         28445  1720      108     35             0
1            50000          1037   130       10      4             0
2            50000          2606   337      113      9             0
3            10000           447   114       34      2             0
4            10000           376   143       49      1             0

   Repost_Count  Creation_type ContentType LANGUAGE_NAME
0            73       Uploaded       Video       English
1            17       Uploaded       Video       English
2            21       Uploaded       Video       English
3            12        Created       Video       English
4            13        Created       Video       English

[5 rows x 21 columns]
```

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
POST_ID                  1000 non-null int64
POST_STRING_UNIQUE_ID    1000 non-null object
CREATED_AT               1000 non-null datetime64[ns]
Creator_Name             1000 non-null object
Caption                  996 non-null object
Length                   1000 non-null int64
Watch_Views              1000 non-null int64
Total_Watch_time         1000 non-null int64
Average_Watch_time       1000 non-null float64
10_Sec_Watch_Time        1000 non-null int64
10_Sec_Views             1000 non-null int64
Execution_Reach          1000 non-null int64
Spammy_Views             1000 non-null int64
Love                     1000 non-null int64
Comment                  1000 non-null int64
Share                    1000 non-null int64
Report_Abuse             1000 non-null int64
Repost_Count             1000 non-null int64
Creation_type            1000 non-null object
ContentType              1000 non-null object
LANGUAGE_NAME            1000 non-null object
dtypes: datetime64[ns](1), float64(1), int64(13), object(6)
memory usage: 164.2+ KB
```

1.1.1 What should be the Top 10 Content pieces for a new user & Why?

[5]:
```
from sklearn import preprocessing

scaler = preprocessing.MinMaxScaler()
```

Scaling all the metrics The `MinMaxScaler` will scale the metrics in the range of 0 - 1. We can then add and subtract the metrics to obtain a score.

[6]:
```
data['scaled_Watch_Views'] = scaler.fit_transform(data[['Watch_Views']])
data['scaled_Average_Watch_time'] = scaler.
 ↪fit_transform(data[['Average_Watch_time']])
data['scaled_10_Sec_Views'] = scaler.fit_transform(data[['10_Sec_Views']])
data['scaled_Execution_Reach'] = scaler.fit_transform(data[['Execution_Reach']])
data['scaled_Spammy_Views'] = scaler.fit_transform(data[['Spammy_Views']])
data['scaled_Love'] = scaler.fit_transform(data[['Love']])
data['scaled_Comment'] = scaler.fit_transform(data[['Comment']])
data['scaled_Share'] = scaler.fit_transform(data[['Share']])
data['scaled_Repost_Count'] = scaler.fit_transform(data[['Repost_Count']])
data['scaled_Report_Abuse'] = scaler.fit_transform(data[['Report_Abuse']])
```

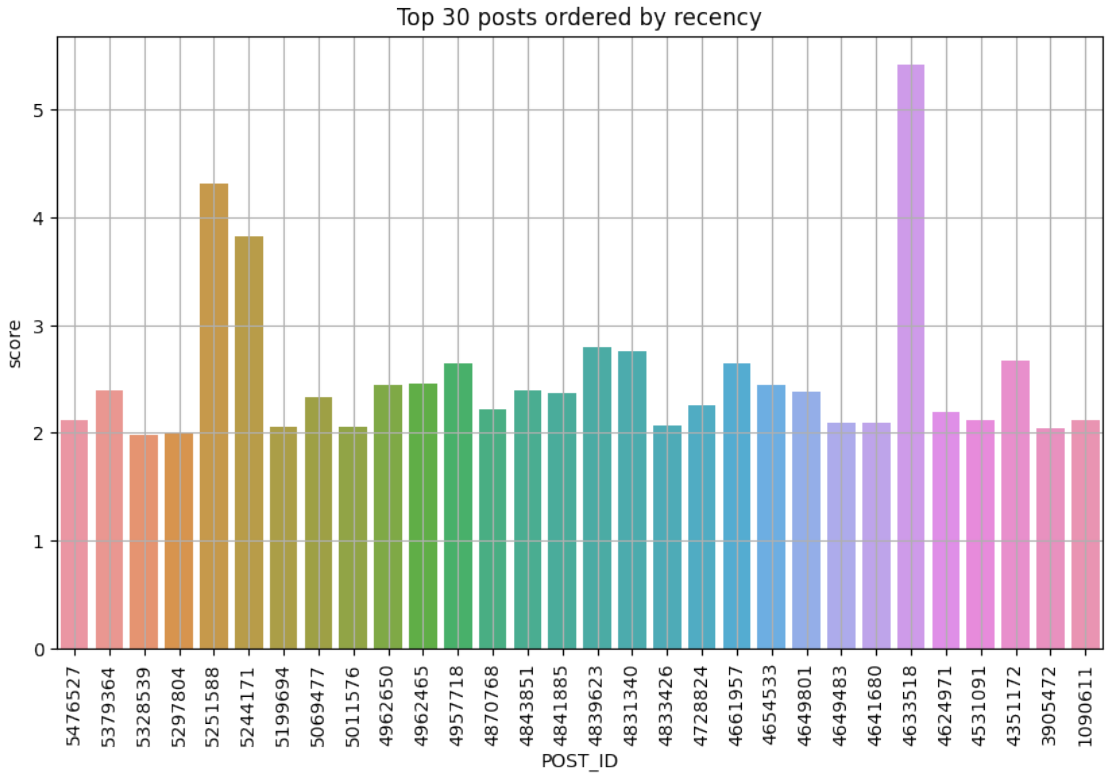
[7]:
```
data['score'] = data['scaled_Watch_Views'] + data['scaled_Average_Watch_time']␣
 ↪+ data['scaled_10_Sec_Views'] +\
data['scaled_Execution_Reach'] - data['scaled_Spammy_Views'] +␣
 ↪data['scaled_Love'] + data['scaled_Comment'] +\
data['scaled_Share'] + data['scaled_Repost_Count'] - data['scaled_Report_Abuse']
```

Getting the top 10 scores and then sorting them by receny.

[8]:
```
top_30 = data.sort_values('score', ascending = False).head(30)
```

[9]:
```
plt.figure(figsize=(10, 6), dpi = 100)
sns.barplot(x = 'POST_ID', y = 'score', data = top_30,
            order = top_30.sort_values(by = 'CREATED_AT', ascending =␣
 ↪False)['POST_ID'])
plt.grid()
plt.title("Top 30 posts ordered by recency")
plt.xticks(rotation=90)
```

[9]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29]),
 <a list of 30 Text major ticklabel objects>)
```



Taking a look at top 10 post IDs by receny. Since these posts are the most recent ones and have the highest scores, we can present them to a new user.

[10]:
```
top_10 = data[data.POST_ID.isin(top_30.sort_values(by = 'CREATED_AT', ascending␣
↪= False).head(10)['POST_ID']\
                                .to_list())]
```

[11]:
```
top_10.reset_index(drop = True, inplace = True)
top_10.iloc[:,0:18]
```

[11]:

	POST_ID	POST_STRING_UNIQUE_ID	CREATED_AT
0	5251588	ec7e9ef3246874618d617623ee07451c	2020-04-22 19:51:00
1	5476527	be65e3d72d5e21b5d2b324adf5d08730	2020-05-06 11:15:00
2	5379364	6e44130461633f7b43456469c6355703	2020-04-30 14:00:00
3	5199694	0c49aa0598481823a3d81fff5adfaba2	2020-04-19 20:07:00
4	5244171	fb6d818f7bf2bd153c69897b8f299ce0	2020-04-22 12:19:00
5	5297804	74a1d289f818f4ee6c48178f5b6a54e7	2020-04-25 15:28:00
6	5328539	875b097e3bc79fd2bcbc60dc8fcaaf24	2020-04-27 13:27:00
7	5069477	679715d4c44fed79150d3ff2e7e601a9	2020-04-12 20:00:00
8	4962650	066ca277b6748b1f230d954463ca6155	2020-04-06 17:39:00
9	5011576	092b940d8c01ec06a79efe7dfa1cbd4e	2020-04-09 14:01:00

	Creator_Name	Caption	Length	Watch_Views	Total_Watch_time	Average_Watch_time	10_Sec_Watch_Time	10_Sec_Views	Execution_Reach	Spammy_Views	Love	Comment	Share	Report_Abuse
0	Nojoto News	Know who loved your story | Tag Nojotians #Noj…	51	61196	732610	12.0	584192	21149	1000000	28445	1720	108	35	0
1	à¤•à¤µà¤¿ à¤°à¤¾à¤¹à¥ à¤² à¤ªà¤¾à¤²	Old Man - Lost Smile\n#StoryOnline \n#nojotofi…	187	1901	40310	21.2	35967	776	10000	668	336	209	8	0
2	Nojoto News	à¤…à¤à¥€ à¤¤à¥< à¤¬à¤¸ à¤œà¤¼à¤¿à¤¨à¥ à¤¦à¤-à…	67	10808	138849	12.8	111024	3418	50000	3444	716	115	107	0
3	Sourabh shresth	https://instagram.com/sourabh_shresth?igshid=1…	0	12512	267545	21.4	239129	5140	50000	3696	950	123	16	0
4	à¤•à¤µà¤¿ à¤°à¤¾à¤¹à¥ à¤² à¤ªà¤¾à¤²	#MessageForModi\ncomedy -only for fun \nà¤¨à¤¿…	236	19197	483765	25.2	436495	8274	50000	4965	1052	283	58	0
5	à¤•à¤µà¤¿ à¤°à¤¾à¤¹à¥ à¤² à¤ªà¤¾à¤²	" à¤†à¤^à¤¨à¥‡ à¤¸à¥‡ à¤¦à¥ à¤µà¤¦à¤¿à¤¯à¤ à¤µ"\n…	0	6353	118239	18.6	103216	2465	25000	2045	504	183	6	0
6	Bhawna Mishra	#lovebeat #PoetryOnline #shadi	154	3057	77706	25.4	71139	1400	10000	714	485	128	21	0
7	Nojoto News	Details for Day 1 (Monday):-\nExpress Karo Na\…	128	24508	440849	18.0	383910	10203	80000	8419	917	66	25	0
8	Nalini	#poetryonline #kinnar #nojotohindi #hindipoetr…	137	16897	244298	14.5	197238	6810	50000	3646	1183	163	35	0
9	Swati shikha laxmi	â¤ #nojotovideo #hindipoetry	0	9798	190784	19.5	164774	4033	25000	2159	867	104	40	0

```
   Repost_Count
0            73
1            51
2            42
3            17
4            65
5            42
6            33
7            41
8            30
9            24
```

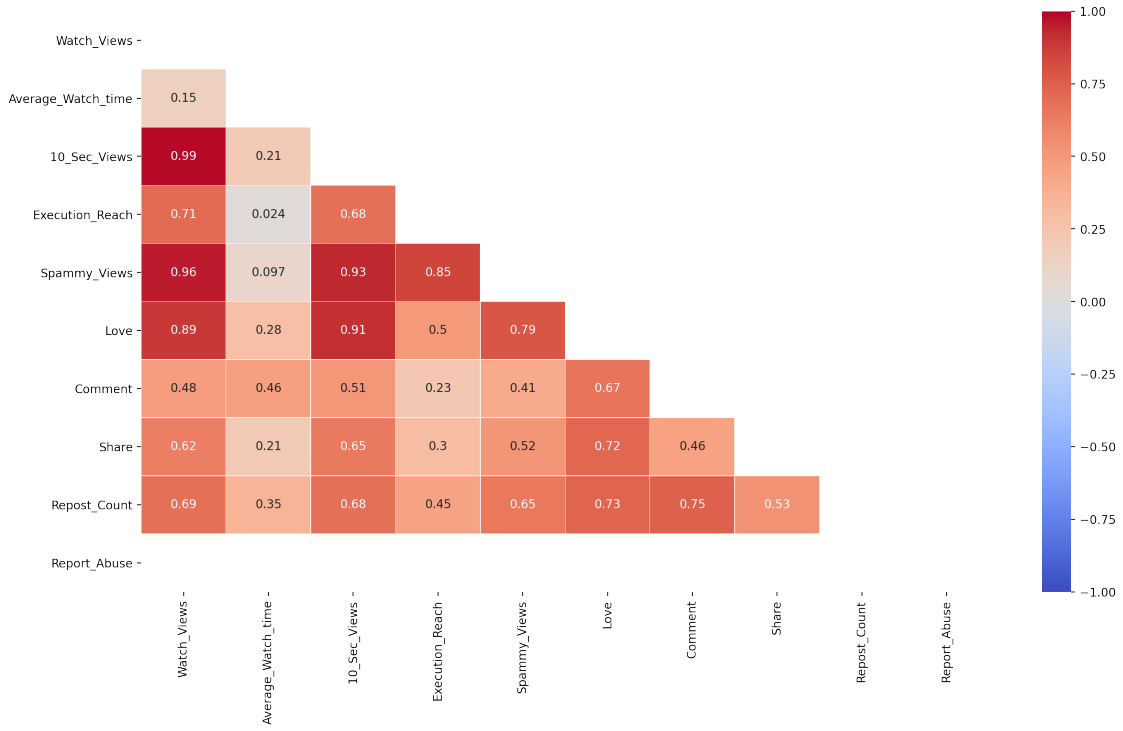
1.1.2 Which are the Recommendation Engine Variables that should be used to improve the current algorithm which can serve the content better

The following metrics are important towards the contribution of a better recommendation engine: 1. Watch_Views 2. Average_Watch_time 3. 10_Sec_Views 4. Execution_Reach 5. Love 6. Comment 7. Share 8. Repost_Count

Whereas the following can be reduced to decrease the importance of a video: 1. Spammy_Views 2. Report_Abuse

The correlation among these variables can also be obtained:

[12]:
```
plt.figure(figsize=(16, 9), dpi = 200)

corr_plot = data[['Watch_Views', 'Average_Watch_time', '10_Sec_Views',
                  'Execution_Reach', 'Spammy_Views', 'Love', 'Comment',
                  'Share', 'Repost_Count', 'Report_Abuse']].corr()
mask = np.zeros_like(corr_plot, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(corr_plot,
            square=False,
            linewidth=.1,
            vmin=-1,
            vmax=1,
            cmap='coolwarm',
            annot=True,
            mask = mask)
plt.show()
```



As shown in the correlation plot above, a lot of these variables are highly correlation with watch views. Thus stating that they're important as metrics in a recommendation system.

1.1.3 Is there any other insights that you can pick up, apart from those asked above

1. Watch views seems to be very poorly correlated with watch time and highly correlated with spammy views - suggesting that a lot of videos might be spam.
2. Views with a more 'Love' tend to be 'Shared' and 'Reposted' more often.
3. Metrics such as spammy views and report abuse can be used to detect anomalies and misbehaving users.

1.2 Cohort Analysis

[13]:
```
df = pd.read_excel('data/Online_Retail.xlsx')
df.head(5)
```

[13]:

	InvoiceNo	StockCode	Description	Quantity	\
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	
1	536365	71053	WHITE METAL LANTERN	6	
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	

	InvoiceDate	UnitPrice	CustomerID	Country

```
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
```

[14]:
```
df.isna().sum()
```

[14]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

[15]:
```
df1 = df.dropna(subset=['CustomerID'])
```

[16]:
```
def get_month(x):
    return dt.datetime(x.year, x.month, 1)
df1['InvoiceMonth'] = df1['InvoiceDate'].apply(get_month)
df1['CohortMonth'] = df1.groupby('CustomerID')['InvoiceMonth'].transform('min')
```

```
/Users/jacob1.ext/Codes/covid-19/.venv/lib/python3.7/site-
packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
/Users/jacob1.ext/Codes/covid-19/.venv/lib/python3.7/site-
packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

[17]:
```
def get_date(df, column):
    year = df[column].dt.year
    month = df[column].dt.month
    day = df[column].dt.day
```

```
    return year, month, day
invoice_year, invoice_month, _ = get_date(df1, 'InvoiceMonth')
cohort_year, cohort_month, _ = get_date(df1, 'CohortMonth')
year_diff = invoice_year - cohort_year
month_diff = invoice_month - cohort_month
df1['CohortIndex'] = year_diff * 12 + month_diff + 1
```

```
/Users/jacob1.ext/Codes/covid-19/.venv/lib/python3.7/site-
packages/ipykernel_launcher.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  # Remove the CWD from sys.path while we load stuff.
```

1.2.1 Create 1st Cohort: User number & Retention Rate

[18]:
```
cohort_data = df1.groupby(['CohortMonth', 'CohortIndex'])['CustomerID'].
↪apply(pd.Series.nunique).reset_index()
cohort_count = cohort_data.pivot_table(index = 'CohortMonth',
                                       columns = 'CohortIndex',
                                       values = 'CustomerID')
cohort_count
```

[18]:

CohortIndex	1	2	3	4	5	6	7	8	9
CohortMonth									
2010-12-01	948.0	362.0	317.0	367.0	341.0	376.0	360.0	336.0	336.0
2011-01-01	421.0	101.0	119.0	102.0	138.0	126.0	110.0	108.0	131.0
2011-02-01	380.0	94.0	73.0	106.0	102.0	94.0	97.0	107.0	98.0
2011-03-01	440.0	84.0	112.0	96.0	102.0	78.0	116.0	105.0	127.0
2011-04-01	299.0	68.0	66.0	63.0	62.0	71.0	69.0	78.0	25.0
2011-05-01	279.0	66.0	48.0	48.0	60.0	68.0	74.0	29.0	NaN
2011-06-01	235.0	49.0	44.0	64.0	58.0	79.0	24.0	NaN	NaN
2011-07-01	191.0	40.0	39.0	44.0	52.0	22.0	NaN	NaN	NaN
2011-08-01	167.0	42.0	42.0	42.0	23.0	NaN	NaN	NaN	NaN
2011-09-01	298.0	89.0	97.0	36.0	NaN	NaN	NaN	NaN	NaN
2011-10-01	352.0	93.0	46.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	321.0	43.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

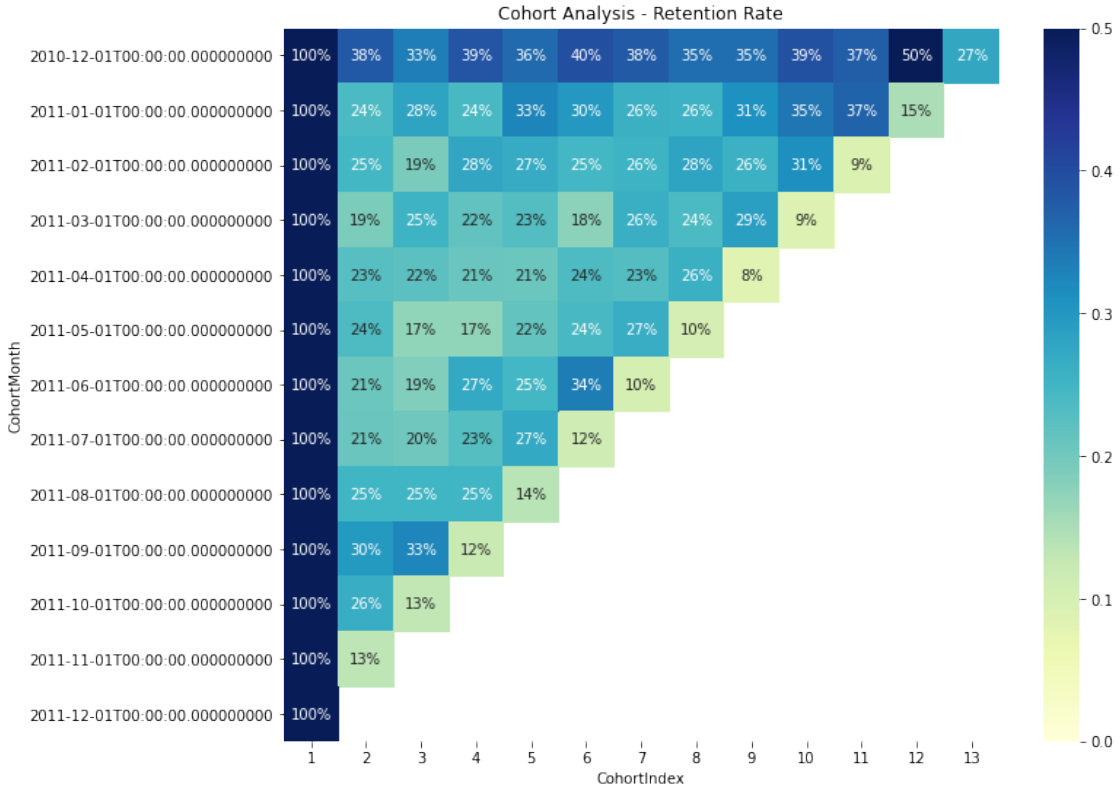
CohortIndex	10	11	12	13
CohortMonth				
2010-12-01	374.0	354.0	474.0	260.0
2011-01-01	146.0	155.0	63.0	NaN
2011-02-01	119.0	35.0	NaN	NaN
2011-03-01	39.0	NaN	NaN	NaN

```
2011-04-01     NaN    NaN    NaN    NaN
2011-05-01     NaN    NaN    NaN    NaN
2011-06-01     NaN    NaN    NaN    NaN
2011-07-01     NaN    NaN    NaN    NaN
2011-08-01     NaN    NaN    NaN    NaN
2011-09-01     NaN    NaN    NaN    NaN
2011-10-01     NaN    NaN    NaN    NaN
2011-11-01     NaN    NaN    NaN    NaN
2011-12-01     NaN    NaN    NaN    NaN
```

[19]:
```
# as percentages

cohort_size = cohort_count.iloc[:,0]
retention = cohort_count.divide(cohort_size, axis = 0)
retention.round(3) * 100
```

[19]:
```
CohortIndex      1     2     3     4     5     6     7     8     9     10  \
CohortMonth
2010-12-01   100.0  38.2  33.4  38.7  36.0  39.7  38.0  35.4  35.4  39.5
2011-01-01   100.0  24.0  28.3  24.2  32.8  29.9  26.1  25.7  31.1  34.7
2011-02-01   100.0  24.7  19.2  27.9  26.8  24.7  25.5  28.2  25.8  31.3
2011-03-01   100.0  19.1  25.5  21.8  23.2  17.7  26.4  23.9  28.9   8.9
2011-04-01   100.0  22.7  22.1  21.1  20.7  23.7  23.1  26.1   8.4   NaN
2011-05-01   100.0  23.7  17.2  17.2  21.5  24.4  26.5  10.4   NaN   NaN
2011-06-01   100.0  20.9  18.7  27.2  24.7  33.6  10.2   NaN   NaN   NaN
2011-07-01   100.0  20.9  20.4  23.0  27.2  11.5   NaN   NaN   NaN   NaN
2011-08-01   100.0  25.1  25.1  25.1  13.8   NaN   NaN   NaN   NaN   NaN
2011-09-01   100.0  29.9  32.6  12.1   NaN   NaN   NaN   NaN   NaN   NaN
2011-10-01   100.0  26.4  13.1   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2011-11-01   100.0  13.4   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2011-12-01   100.0   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN

CohortIndex    11    12    13
CohortMonth
2010-12-01   37.3  50.0  27.4
2011-01-01   36.8  15.0   NaN
2011-02-01    9.2   NaN   NaN
2011-03-01    NaN   NaN   NaN
2011-04-01    NaN   NaN   NaN
2011-05-01    NaN   NaN   NaN
2011-06-01    NaN   NaN   NaN
2011-07-01    NaN   NaN   NaN
2011-08-01    NaN   NaN   NaN
2011-09-01    NaN   NaN   NaN
2011-10-01    NaN   NaN   NaN
2011-11-01    NaN   NaN   NaN
2011-12-01    NaN   NaN   NaN
```

[20]:
```
plt.figure(figsize = (11,9))
plt.title('Cohort Analysis - Retention Rate')
sns.heatmap(data = retention,
            annot = True,
            fmt = '.0%',
            vmin = 0.0,
            vmax = 0.5,
            cmap = "YlGnBu")
plt.show()
```



1.2.2 Create the 2nd Cohort: Average Quantity Sold

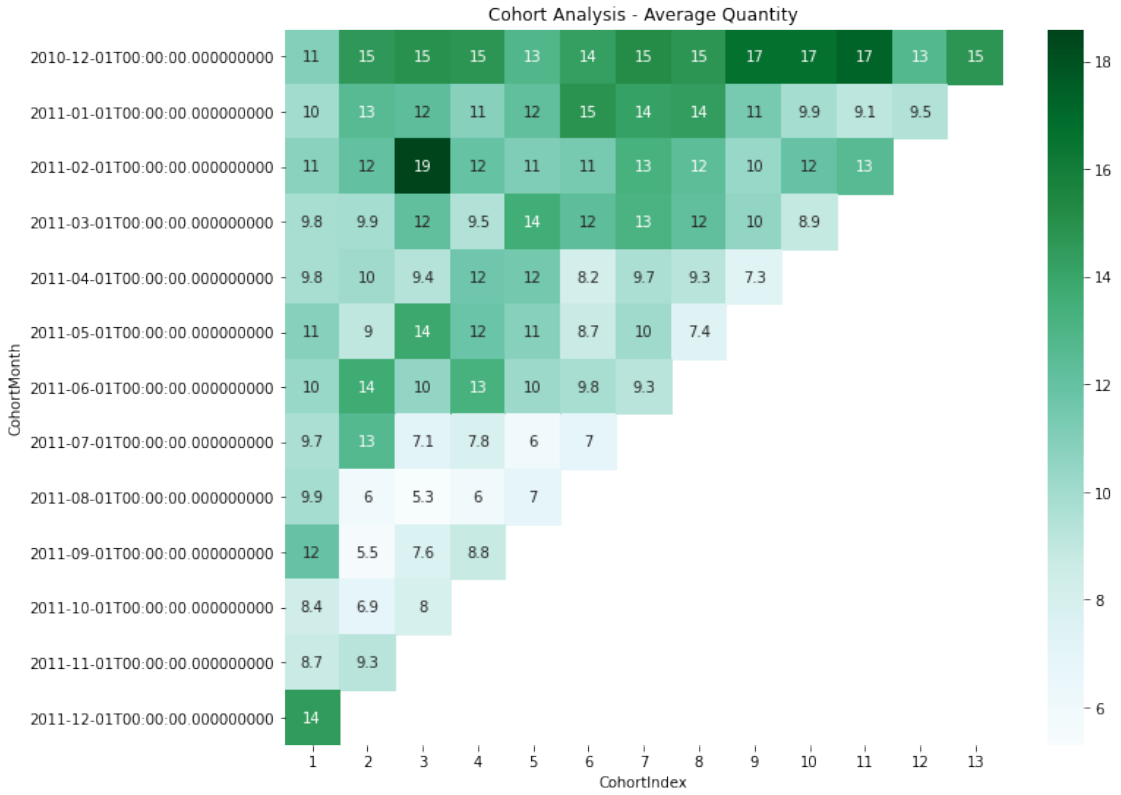
[21]:
```
cohort_data2 = df1.groupby(['CohortMonth', 'CohortIndex'])['Quantity'].mean().
↪reset_index()
average_quantity  = cohort_data2.pivot_table(index = 'CohortMonth',
                                             columns = 'CohortIndex',
                                           values = 'Quantity').round(1)
average_quantity
```

[21]:
```
CohortIndex     1     2     3     4     5     6     7     8     9     10    11  \
CohortMonth
```

2010-12-01	11.0	14.6	15.0	14.8	12.9	14.3	15.2	14.8	16.7	16.7	17.3
2011-01-01	10.0	12.6	12.3	10.9	12.2	14.9	14.2	14.4	11.4	9.9	9.1
2011-02-01	10.8	12.1	18.6	12.0	11.1	11.4	13.3	12.4	10.3	11.9	12.6
2011-03-01	9.8	9.9	12.2	9.5	13.6	12.3	13.2	12.2	10.5	8.9	NaN
2011-04-01	9.8	10.1	9.4	11.6	11.5	8.2	9.7	9.3	7.3	NaN	NaN
2011-05-01	10.9	9.0	13.9	11.8	10.9	8.7	10.1	7.4	NaN	NaN	NaN
2011-06-01	10.3	13.7	10.5	13.3	10.2	9.8	9.3	NaN	NaN	NaN	NaN
2011-07-01	9.7	12.7	7.1	7.8	6.0	7.0	NaN	NaN	NaN	NaN	NaN
2011-08-01	9.9	6.0	5.3	6.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	11.9	5.5	7.6	8.8	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	8.4	6.9	8.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	8.7	9.3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	14.5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

CohortIndex	12	13
CohortMonth		
2010-12-01	12.8	14.8
2011-01-01	9.5	NaN
2011-02-01	NaN	NaN
2011-03-01	NaN	NaN
2011-04-01	NaN	NaN
2011-05-01	NaN	NaN
2011-06-01	NaN	NaN
2011-07-01	NaN	NaN
2011-08-01	NaN	NaN
2011-09-01	NaN	NaN
2011-10-01	NaN	NaN
2011-11-01	NaN	NaN
2011-12-01	NaN	NaN

[22]:
```
plt.figure(figsize = (11,9))
plt.title('Cohort Analysis - Average Quantity')
sns.heatmap(data = average_quantity,
            annot = True,
            cmap = "BuGn")
plt.show()
```



1.2.3 Create the 3rd Cohort: Average Sales

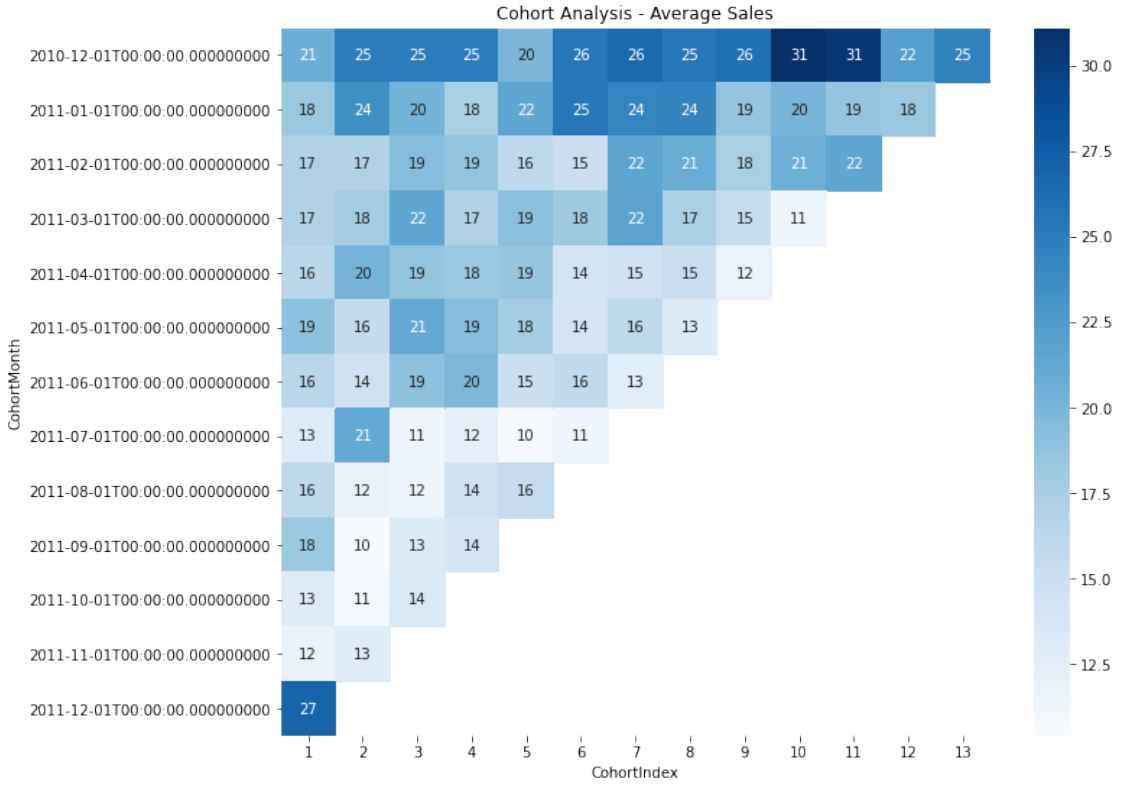
[23]:
```
df1['TotalSale'] = df1['Quantity'] * df1['UnitPrice']
cohort_data3 = df1.groupby(['CohortMonth', 'CohortIndex'])['TotalSale'].mean().
 ↪reset_index()
average_sales  = cohort_data3.pivot_table(index = 'CohortMonth',
                                          columns = 'CohortIndex',
                                      values = 'TotalSale').round(1)
average_sales
```

```
/Users/jacob1.ext/Codes/covid-19/.venv/lib/python3.7/site-
packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

[23]:
```
CohortIndex     1      2      3      4      5      6      7      8      9      10     11  \
CohortMonth
```

```
2010-12-01   20.7  25.0  25.1  25.0  19.9  25.5  26.5  25.4  26.0  31.1  30.6
2011-01-01   18.4  23.5  20.3  17.5  21.5  25.4  24.4  24.5  18.7  20.1  18.7
2011-02-01   17.0  17.0  19.3  18.8  16.1  15.1  21.6  20.9  17.5  20.6  21.5
2011-03-01   17.0  17.9  21.5  17.0  19.2  18.1  21.7  17.3  15.4  11.4   NaN
2011-04-01   16.4  20.2  18.8  18.4  18.6  14.2  14.6  15.3  11.8   NaN   NaN
2011-05-01   19.0  15.7  21.2  19.4  17.8  14.1  16.1  13.3   NaN   NaN   NaN
2011-06-01   16.4  14.5  19.0  19.8  15.0  15.9  12.7   NaN   NaN   NaN   NaN
2011-07-01   13.1  21.2  11.4  12.4  10.5  11.4   NaN   NaN   NaN   NaN   NaN
2011-08-01   16.1  11.9  11.5  14.4  15.6   NaN   NaN   NaN   NaN   NaN   NaN
2011-09-01   18.4  10.4  13.2  14.0   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2011-10-01   13.0  10.8  13.5   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2011-11-01   11.9  12.9   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2011-12-01   26.9   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN

CohortIndex    12    13
CohortMonth
2010-12-01   22.2  24.7
2011-01-01   18.4   NaN
2011-02-01    NaN   NaN
2011-03-01    NaN   NaN
2011-04-01    NaN   NaN
2011-05-01    NaN   NaN
2011-06-01    NaN   NaN
2011-07-01    NaN   NaN
2011-08-01    NaN   NaN
2011-09-01    NaN   NaN
2011-10-01    NaN   NaN
2011-11-01    NaN   NaN
2011-12-01    NaN   NaN
```

[24]:
```
plt.figure(figsize = (11,9))
plt.title('Cohort Analysis - Average Sales')
sns.heatmap(data = average_sales,
            annot = True,
            cmap = "Blues")
plt.show()
```


Cohort Analysis - Average Sales
CohortMonth
2010-12-01T00:00:00.000000000
2011-01-01T00:00:00.000000000
2011-02-01T00:00:00.000000000
2011-03-01T00:00:00.000000000
2011-04-01T00:00:00.000000000
2011-05-01T00:00:00.000000000
2011-06-01T00:00:00.000000000
2011-07-01T00:00:00.000000000
2011-08-01T00:00:00.000000000
2011-09-01T00:00:00.000000000
2011-10-01T00:00:00.000000000
2011-11-01T00:00:00.000000000
2011-12-01T00:00:00.000000000
21 25 25 25 20 26 26 25 26 31 31 22 25
18 24 20 18 22 25 24 24 19 20 19 18
17 17 19 19 16 15 22 21 18 21 22
17 18 22 17 19 18 22 17 15 11
16 20 19 18 19 14 15 15 12
19 16 21 19 18 14 16 13
16 14 19 20 15 16 13
13 21 11 12 10 11
16 12 12 14 16
18 10 13 14
13 11 14
12 13
27
1 2 3 4 5 6 7 8 9 10 11 12 13
CohortIndex
30.0
27.5
25.0
22.5
20.0
17.5
15.0
12.5