Level Based Persona

Simple Customer Segmentation Project

Which segment does a new future customer may belong to?

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Outline

- The purpose of the Project
- What is the concept of Persona?
- How to target personas?
- Dataset and Exploration
- Findings and Key Points
- References

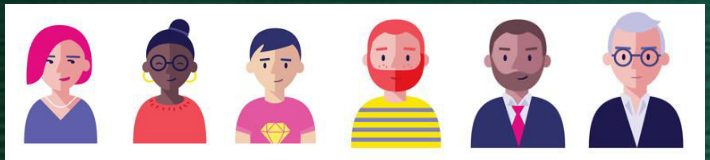
The Purpose of the Project

- Consider, investigate the concept of Persona.

- Information obtained from the dataset is aimed to use in order to make new customer definitions based on level by separating them into certain levels or categories and considering each breakout point as a persona.

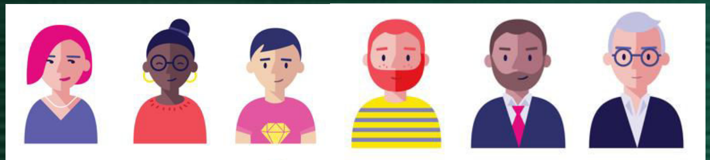
- Accordingly, when a new customer shows up, determining which segment the new future customer may belong to.

- Investigating the impact of the size of the sample with respect to the Central Limit Theorem to acquire accurate and consistent results.



What is the concept of Persona?

- Persona is a Latin origin concept widely used in Marketing, CRM and analytics.
- Persona guides the customer experience design and utilizes making the right channel investment. It develops the ability of analysts and marketer's ability to tailor communications effectively.
- Proper persona strategy → the crucial milestone of Customer engagement & better conversions
- When defining a persona, the main purpose is to get to know them as much as possible considering within a certain groups and characteristics.
- Therefore, identifying the needs and aiming at offering appropriate products or services to personas in line with their characteristics.

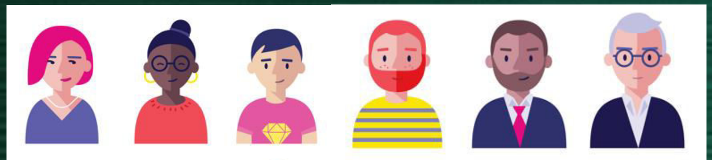


How to target personas?

- Analysing the personas' interests, purchase behaviour and channel engagement by proper segmentation

- Generating tailored and initiated strategies for targeted cross-selling, upselling, and repeated possible orders for each specific persona category.

- Utilizing market research, customer insights and web - social media analytics



Dataset and Exploration

- There are two different data tables that contain the customers' characteristics and transaction information.
- While the users.csv table represents the characteristics of the customers, the purchases.csv table contains the purchasing information of the customers.
- Each user has a unique customer number (uid). The process of combining both tables (merge) can be done with the (uid) number.

users.csv	purchases.csv
uid : Unique customer number	uid : Unique customer number
reg_date : Registration date	date : The date the customer made a purchase
device : The type of product used by the customer. (Android, iOS)	price : The amount that Customer spent
gender : The Gender of the customer	
country: Country of the customer	
age : The age of the customer	

Number of Observations : 10k *Unique Customers: 1322* *Number of Variables : 8*

Reading the Data

```
In[5]: users = pd.read_csv("Datasets/users.csv")
  ...: users.head()
  ...:
Out[5]:
        uid              reg_date device gender country  age
0  54030035  2017-06-29T00:00:00Z    and      M     USA   19
1  72574201  2018-03-05T00:00:00Z    iOS      F     TUR   22
2  64187558  2016-02-07T00:00:00Z    iOS      M     USA   16
3  92513925  2017-05-25T00:00:00Z    and      M     BRA   41
4  99231338  2017-03-26T00:00:00Z    iOS      M     FRA   59
```

```
In[7]: purchases = pd.read_csv("Datasets/purchases.csv")
  ...: purchases.head()
  ...:
Out[7]:
         date       uid  price
0  2017-07-10  41195147    499
1  2017-07-15  41195147    499
2  2017-11-12  41195147    599
3  2017-09-26  91591874    299
4  2017-12-01  91591874    599
```

```
In[6]: users.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   uid       10000 non-null  int64
 1   reg_date  10000 non-null  object
 2   device    10000 non-null  object
 3   gender    10000 non-null  object
 4   country   10000 non-null  object
 5   age       10000 non-null  int64
dtypes: int64(2), object(4)
memory usage: 468.9+ KB
```

```
In[8]: purchases.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9006 entries, 0 to 9005
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    9006 non-null   object
 1   uid     9006 non-null   int64
 2   price   9006 non-null   int64
dtypes: int64(2), object(1)
memory usage: 211.2+ KB
```

1. Step: Merging the datasets according to the "uid" variable with an inner join.

```
df = purchases.merge(users, how="inner", on="uid")
df.head()
df.shape  # (9006, 8)
```

	date	uid	price	reg_date	device	gender	country	age
0	2017-07-10	41195147	499	2017-06-26T00:00:00Z	and	M	BRA	17
1	2017-07-15	41195147	499	2017-06-26T00:00:00Z	and	M	BRA	17
2	2017-11-12	41195147	599	2017-06-26T00:00:00Z	and	M	BRA	17
3	2017-09-26	91591874	299	2017-01-05T00:00:00Z	and	M	TUR	17
4	2017-12-01	91591874	599	2017-01-05T00:00:00Z	and	M	TUR	17

2. Step: What are the total earnings in the breakdown of "country", "device", "gender", "age"?

```
df.groupby(["country", "device", "gender", "age"]).agg({"price": "sum"})
```

```
agg_df = df.groupby(["country", "device", "gender", "age"]).agg({"price": "sum"}).sort_values("price", ascending=False)
agg_df.head()
```

```
agg_df.reset_index(inplace=True)
agg_df
```

	country	device	gender	age	price
0	USA	and	M	15	61550
1	BRA	and	M	19	45392
2	DEU	iOS	F	16	41602
3	USA	and	F	17	40004
4	USA	and	M	23	39802
..	...	...	...	...	...
445	BRA	iOS	F	34	199
446	CAN	and	F	27	199
447	USA	and	F	60	199
448	BRA	iOS	M	47	199
449	DEU	and	M	26	99

[450 rows x 5 columns]

3. Step: Converting the age variable to a categorical variable and adding to the dataset as a new variable.

```
agg_df["age"].dtype  # int
agg_df["age"].value_counts()

# num to cat!
bins = [0, 19, 24, 31, 41, agg_df["age"].max()]
labels = ["0_18", "19_23", "24_30", "31_40", "41_" + str(agg_df["age"].max())]
agg_df["age_cat"] = pd.cut(agg_df["age"], bins=bins, labels=labels)
agg_df["age_cat"]
agg_df.head()
```

	country	device	gender	age	price	age_cat
0	USA	and	M	15	61550	0_18
1	BRA	and	M	19	45392	0_18
2	DEU	iOS	F	16	41602	0_18
3	USA	and	F	17	40004	0_18
4	USA	and	M	23	39802	19_23

4. Step: Considering the categorical breakdowns as customer groups and defining new level-based customers by combining these groups.

```
agg_df["customers_level_based"] = [col[0] + "_" + col[1].upper() + "_" + col[2] + "_" + col[-1] for col in agg_df.values]

# Alternative way:
for index, column in agg_df.iterrows():
    agg_df.loc[index, "customers_level_based"] = column["country"].upper() + "_" + column["device"].upper() + "_" + column["gender"].upper() + "_" + column["age_cat"].upper()

agg_df[["customers_level_based", "price"]]
```

```
In[4]: agg_df[["customers_level_based", "price"]]
Out[4]:
   customers_level_based  price
0         USA_AND_M_0_18  61550
1         BRA_AND_M_0_18  45392
2         DEU_IOS_F_0_18  41602
3         USA_AND_F_0_18  40004
4        USA_AND_M_19_23  39802
..                   ...    ...
```

✓ The variable "customers_level_based" is now our new customer definition.

For example "USA_AND_M_0_18". The USA-ANDROID-MALE-0-18 class is a single customer representing one class of customers for us.

5. Step: Segmenting the new customers according to price

```
agg_df["segment"] = pd.qcut(agg_df["price"], 4, labels=["D", "C", "B", "A"])
agg_df[["customers_level_based", "price", "segment"]].head()
```

	customers_level_based	price	segment
0	USA_AND_M_0_18	61550	A
1	BRA_AND_M_0_18	45392	A
2	DEU_IOS_F_0_18	41602	A
3	USA_AND_F_0_18	40004	A
4	USA_AND_M_19_23	39802	A

```
agg_df.groupby("segment").agg({"price": "mean"})
```

segment	price
D	1335.096491
C	3675.504505
B	7447.812500
A	20080.150442

Final Question:
What segment is a 42-year-old Turkish woman who uses IOS device in? Express the segment (group) of this person according to the final analysis?

```
new_user = "TUR_IOS_F_41_75"
agg_df[agg_df["customers_level_based"] == new_user]
```

	country	device	gender	age	price	age_cat	customers_level_based	segment
377	TUR	iOS	F	51	1596	41_75	TUR_IOS_F_41_75	D

Finding and Key Points

- It has been identified in which segment to evaluate when a new customer registered in the system.
- As a result of the analysis, a female new user between the ages of 41-75 who uses an IOS device from Turkey, belongs to segment D.
- Let's discuss the finding and its relationship with Central Limit Theorem;
  - The central limit theorem states that the arithmetic mean of a large number of independent and uniformly distributed random variables represent approximately normal distribution.
  - The principle underlying Central Limit Theorem is that a properly selected large sample is likely to resemble the population from which it is selected. The mean of the sample is distributed as a Normal Distribution for any population roughly around the mean of the population.
  - The segment turned out to be D while the number of observations is 10k. A large sample was taken, simple segmentation and rule-based classification processes have been applied and the new user was classified in D segment by its characteristics.
  - It is observed that the large samples are likely to result in a consistent mean and standard deviation according to the Central Limit theorem.
  - Consequently, taking large samples in the conclusions made is of great importance for accurate and consistent results.

References

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faafetai lava
vinaka
blagodaram
dank je
misaotra
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matondo
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dhanyavad
mauruuru
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djiere dieuf
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mamnun
chokrane
dziękuję
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taiku
sobodi
děkuji
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