

How To Win Customers **With Segmentation And Personalization**

Presented by **Dinar Syahid N. U**



Hey I'm,

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I am a,

- CURRENTLY | **Data Scientist at Telkom Indonesia**
- 18 - 19 | **Data Scientist at Immobi**
- 16 - 18 | **RNO Engineer at Immobi**
- 15 - 16 | **IoT Engineer at AGIT**

Put Your Title Here



Customer Segmentation

Brief introduction about customer segmentation, types of customer segmentation, and RFM analysis.

Customer Personalization

Explanation of customer personalization with recommendation engine and types of recommendation engine.

Practice & Live Discussion

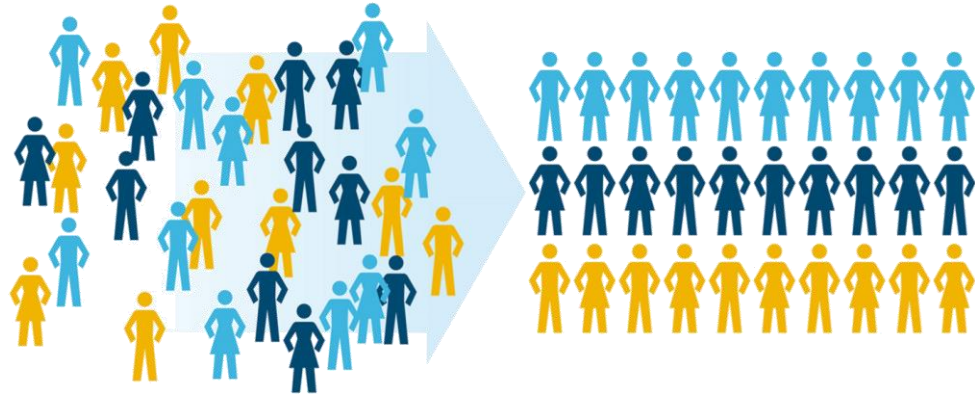
Practice session about creating RFM analysis in Microsoft Excel and Live Discussion.

Customer Segmentation

Brief introduction and
type of customer
segmentation

What is customer segmentation?

Customer segmentation is process of **grouping your customer** based on several **characteristics** to support companies or organization market their product effectively and appropriately.



Why segment customers?



Improve Product

Identify ways to improve products or new products or service



Provable

Focus on the most profitable customer



Targeted

The marketing is more effective because it is more targeted



Customer Oriented

Increase customers experience and relationship

Types of Segmentation

1



Demographic Segmentation

Age, gender, income, religion, family size

3



Geographic Segmentation

Location, population density, weather, language

2



Psychographic Segmentation

Social class, personality, lifestyle, interest, opinions

4

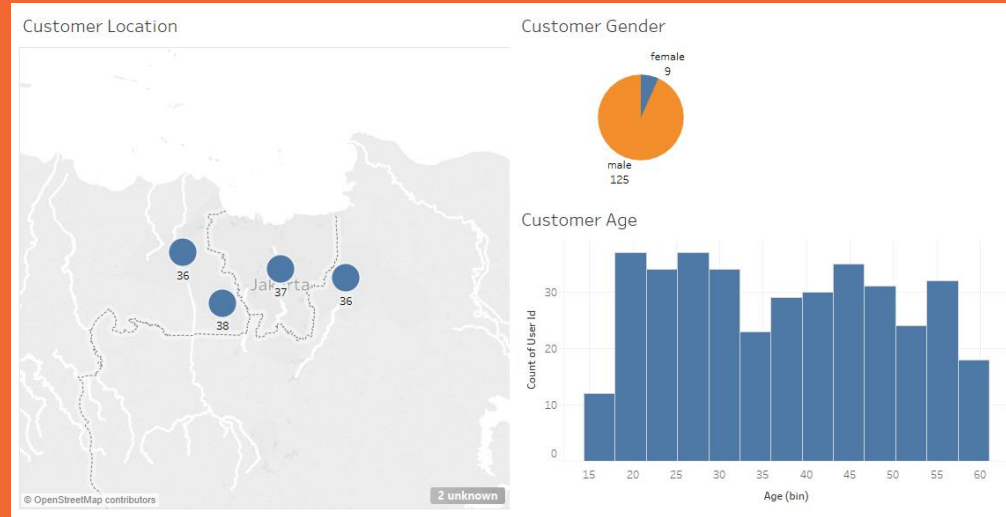


Behavioral Segmentation

Purchase, usage, benefits, special events

Demographic Analysis

Demographic analysis is a technique used to develop an understanding of the age, gender, and location of your customer and how it has changed over time.



RFM Analysis

01



RECENCY

The freshness of the customer activity, be it purchases or visits .

E.g. Time since last ordered or last engaged with product

02



FREQUENCY

The frequency of the customer transaction or visits.

E.g. Total number of transactions or average time between transactions

03



MONETARY

The intention of customer to spend or purchasing power of customer.

E.g. Total average transaction or value.

RFM Model

- Built on **historical transactions** between user and the business.
- Uses **R, F, and M variables** of customer data.
- Analysis the **entire population**.
- No need to create curated sample sets.
- Dependent on **efficient and accurate data**.
- **No** scope for **human error**.

Traditional Model

- Built on **customer understanding** and research studies commissioned by business.
- Uses **demographic and psychographic** variables.
- Analysis representative **sample sets**.
- Dependent on **skilled researchers**.
- Scope for **human error**.

RFM Analysis

What type of
business questions
that can be
solved?

RFM analysis helps marketers and data scientist find answer to the following questions:

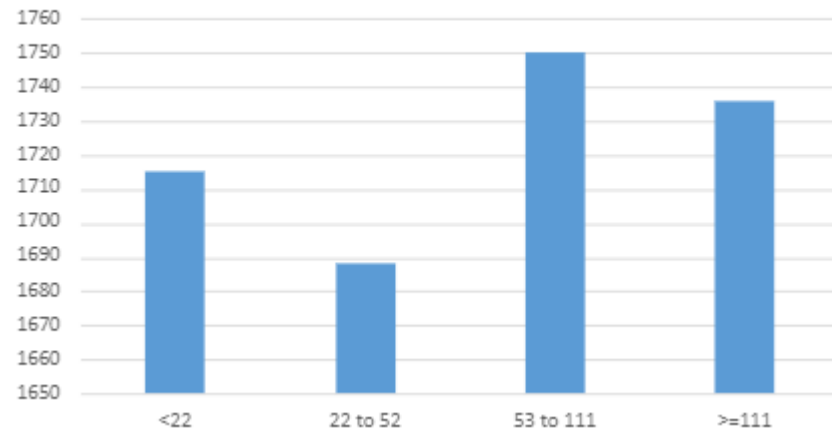
- Who are you best customers?
- Which of your customers could contribute to your churn rate?
- Who has the potential to become valuable customers?
- Which of your customers can be retrained?
- Which of your customers are most likely to respond to engagement campaigns?

Recency

Recency of the purchase

Time since the last purchase. The clients who bought recently are more likely to buy again.

Recency



customer_id	max_trans_date	recency(days)
CS1112	1/14/2015	61
CS1113	2/9/2015	35
CS1114	2/12/2015	32
CS1115	3/5/2015	11
CS1116	8/25/2014	203
CS1117	7/2/2014	257
CS1118	3/14/2015	2
CS1119	3/5/2015	11
CS1120	3/6/2015	10
CS1121	2/3/2015	41

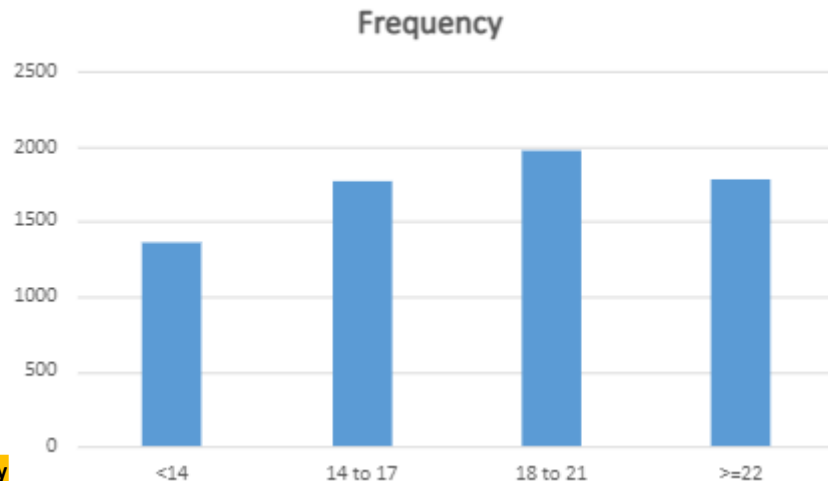
Frequency

Frequency of the purchase

The number of purchases in a given time. The probability of the sale will be higher if a person made many purchases.

customer_id frequency

CS1112	15
CS1113	20
CS1114	19
CS1115	22
CS1116	13
CS1117	17
CS1118	15
CS1119	15
CS1120	24
CS1121	26



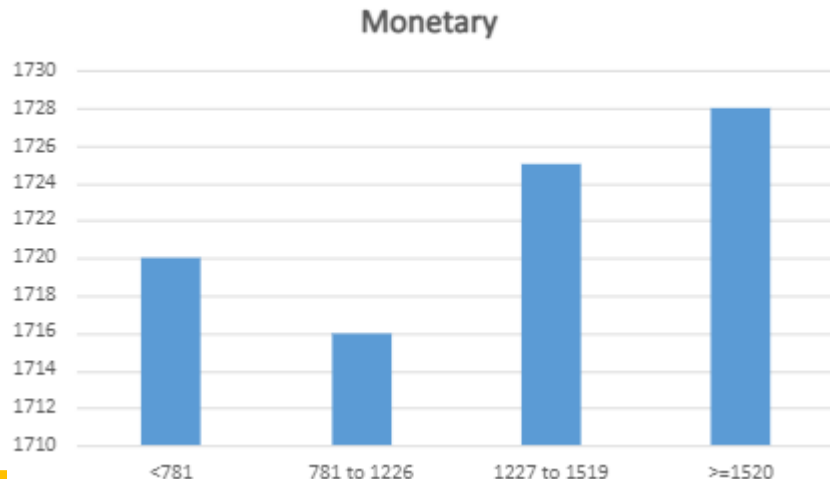
Monetary

The sum of the purchase

The sum of all the purchases in a given period. The clients who spent a big sum of money on purchases are more likely to spend it again.

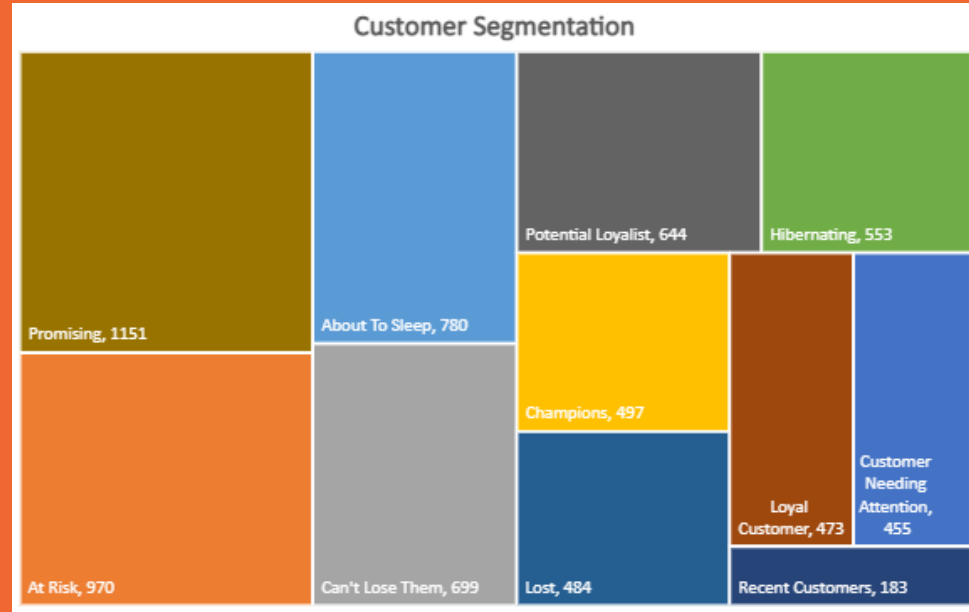
customer_id monetary

CS1112	1012
CS1113	1490
CS1114	1432
CS1115	1659
CS1116	857
CS1117	1185
CS1118	1011
CS1119	1158
CS1120	1677
CS1121	1524



Customer Segmentation

Customer segmentation result by RFM Analysis.



Customer Segment	Who They Are	Marketing Strategies
Champions	Bought recently, buy often and spend the most!	Reward them. Can be early adopters for new products. Will promote your brand.
Loyal Customers	Spend good money with us often. Responsive to promotions.	Upsell higher value products. Ask for reviews. Engage them.
Potential Loyalist	Recent customers, but spent a good amount and bought more than once.	Offer membership / loyalty program, recommend other products.
Recent Customers	Bought most recently, but not often.	Provide on-boarding support, give them early success, start building relationship.

Customer Segment	Who They Are	Marketing Strategies
Promising	Recent shoppers, but haven't spent much.	Create brand awareness, offer free trials
Customers Needing Attention	Above average recency, frequency and monetary values. May not have bought very recently though.	Make limited time offers, Recommend based on past purchases. Reactivate them.
About To Sleep	Below average recency, frequency and monetary values. Will lose them if not reactivated.	Share valuable resources, recommend popular products / renewals at discount, reconnect with them.
At Risk	Spent big money and purchased often. But long time ago. Need to bring them back!	Send personalized emails to reconnect, offer renewals, provide helpful resources.

Customer Segment	Who They Are	Marketing Strategies
Can't Lose Them	Made biggest purchases, and often. But haven't returned for a long time.	Win them back via renewals or newer products, don't lose them to competition, talk to them.
Hibernating	Last purchase was long back, low spenders and low number of orders.	Offer other relevant products and special discounts. Recreate brand value.
Lost	Lowest recency, frequency and monetary scores.	Revive interest with reach out campaign, ignore otherwise.

Fashion/Cosmetics - 01

In this business, customer purchases product every month will have a higher recency and frequency score than monetary. Accordingly, RFM score could be calculated by giving more weight to R and F scores than M.

Streaming Apps - 03

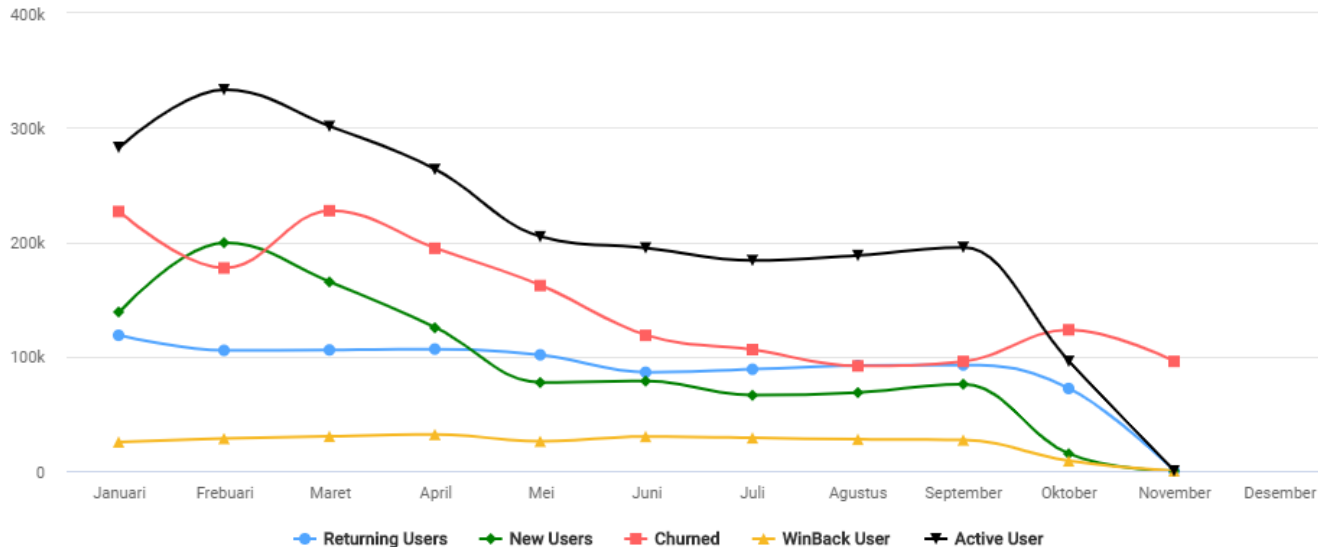
In this business, For content apps like Hotstar or Netflix, a binge watcher will have a longer session length than a mainstream consumer watching at regular intervals. For bingers, engagement and frequency could be given more importance than recency, and for mainstreamers, recency and frequency can be given higher weights than engagement to arrive at the RFE score.



02 - Consumer Durable

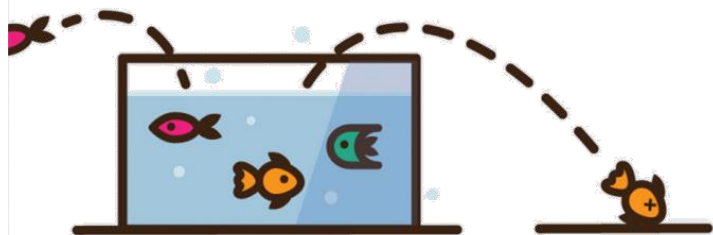
In this business, the monetary value per transaction is normally high but frequency and recency is low. For example, you can't expect a customer to purchase a refrigerator or air conditioner on a monthly basis. In this case, a marketer could give more weight to monetary and recency aspects rather than the frequency aspect.

User Status Segmentation



- **New Users** : User that first time purchase or subscribe our product.
- **Churned Users** : User that stop subscription from our product.
- **Returning Users** : User that continue their subscription from last month.
- **WinBack Users** : User that in last month stop subscription and continue subscribe in this month.
- **Active Users** : WinBack Users + Returning Users + New Users.

Segmentation based on Classification Model



Churn / Inactive User Propensity



Xsell – Upsell Propensity

Personalization with Recommendation Engine

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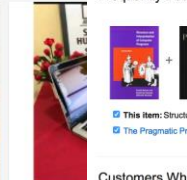
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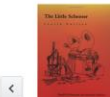


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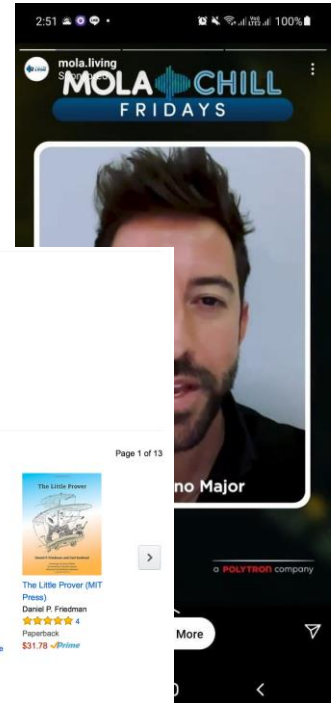
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Recommendation Engine?

*“A recommendation engine is a system that suggests products, services, information to users based on **analysis of data**”*

Goal of Recommendation Engine

Relevance

The most obvious operational goal of a recommender system is to recommend items that are relevant to the user at hand. Users are more likely to consume items they find interesting.

Novelty

Recommender systems are truly helpful when the recommended item is something that the user has not seen in the past. For example, popular movies of a preferred genre would rarely be novel to the user.



Serendipity

A related notion is that of serendipity, wherein the items recommended are somewhat unexpected, and therefore there is a modest element of lucky discovery, as opposed to obvious recommendations.

Recommendation Diversity

Recommender systems typically suggest a list of top-k items. When all these recommended items are very similar, it increases the risk that the user might not like any of these items.

Why Recommendation Engine?

Advantage of using
recommendation
engine for
personalization



The Netflix Prize

Raise of
recommendation
engine



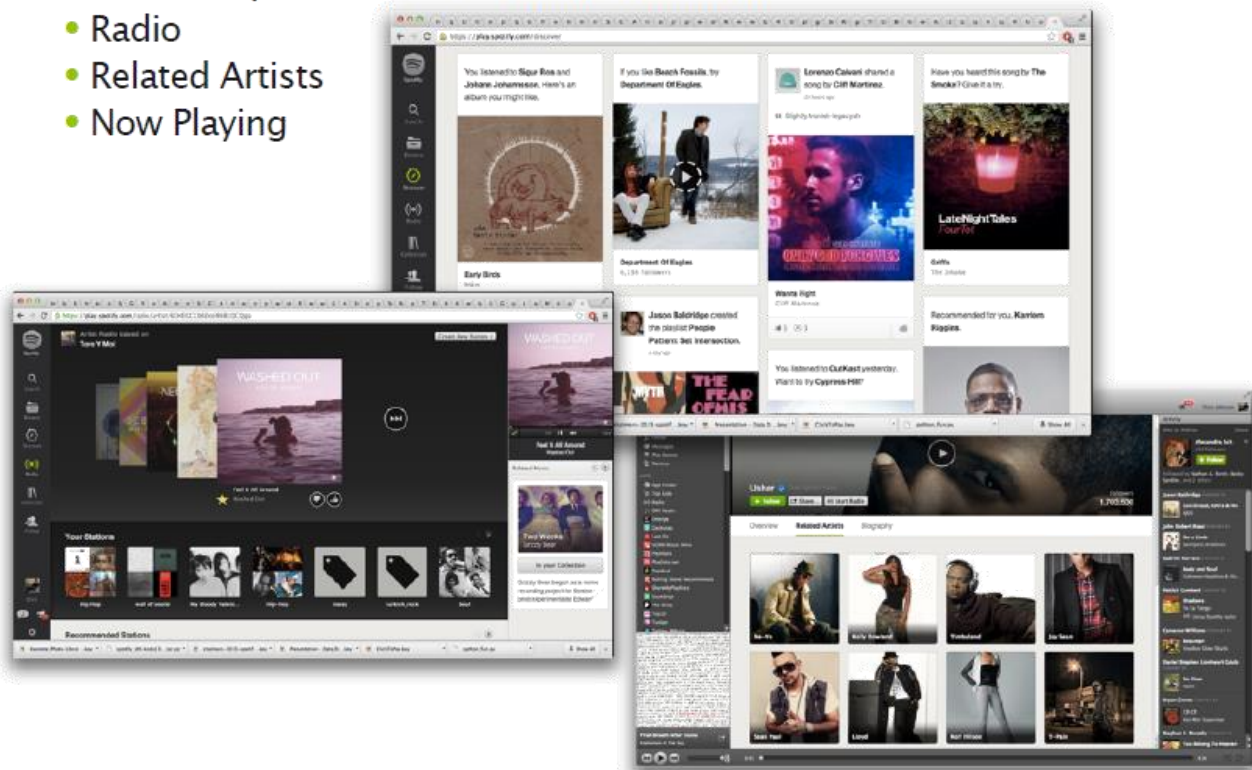
80% *of stream time achieved
through Netflix's Recommender System*

More likely
to see



Less likely

- Discover (personalized recommendations)
- Radio
- Related Artists
- Now Playing



Area of Use



Product Discovery

Marches varying individual customers taste with a huge inventory.



In E-Store

Recommendations for new products, up-sell, cross-sell suggestions and product discovery.



Loyalty Programs

Recommendations pertaining to specific program, suggestions for redemption and program upgrades.



Search

Order of search results on the store can be varied for each customer to aid product discovery.



Bills and Mailers

Whitespace can be used for cross-sell and up-sell. Usage can be analyzed to recommending plan.



Email Campaign

Effectively targeting abandoned shopping carts with personalized recommendation.

Type of Recommendation Engine

01

Personalized :

- Content –based
- Collaborative based
- Hybrid
- Knowledge Based

02

Non –Personalized :

- Popularity based
- Product association recommender
- Aggregated opinion approach

Personalized Recommendation Engine



Knowledge-Based

knowledge-based when it makes recommendations based not on a user's rating history, but on specific queries made by the user.



Content-based

A *content-based recommender* recommends based on history of similar items purchased, viewed or interacted with in the past



Collaborative

A *collaborative recommender* recommends based on usage trends of similar users.



Hybrid

A *hybrid recommender* utilizes features of both content-based and collaborative recommenders in an aim to improve quality of results



Non-Personalized Recommendation Engine

01



Popularity Based

A popularity-based recommender does not take usage history into consideration other than sheer popularity of the content.

02



Product Association

An algorithm that mines data for patterns. It's a rule-based machine learning technique which is used to uncover hidden relationships in data. This algorithm is also commonly known as market-basket analysis.

03



Aggregated Opinion Approach

This algorithm uses scores or ratings given by different customers to recommend items to all the users. This technique is most widely used by E commerce websites and restaurants.

Data Acquisition



Explicit Data

- Customer Ratings
- Feedback
- Demographics
- Physiographics
- Ephemeral Needs



Implicit Data

- Purchase History
- Click or Browse History

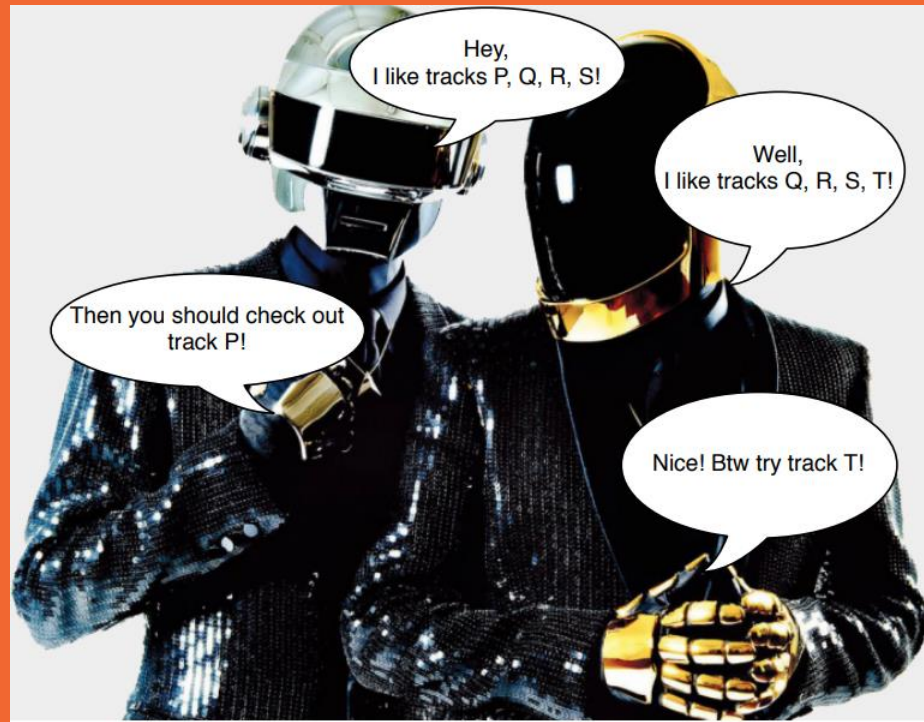


Product Information

- Product Taxonomy
- Product Attributes
- Product Description

Collaborative Filtering

Collaborative filtering is a method finds a subset of users who have similar tastes and preferences to the target user and use this subset for offering recommendation.



Basic Assumption – Collaborative Filtering

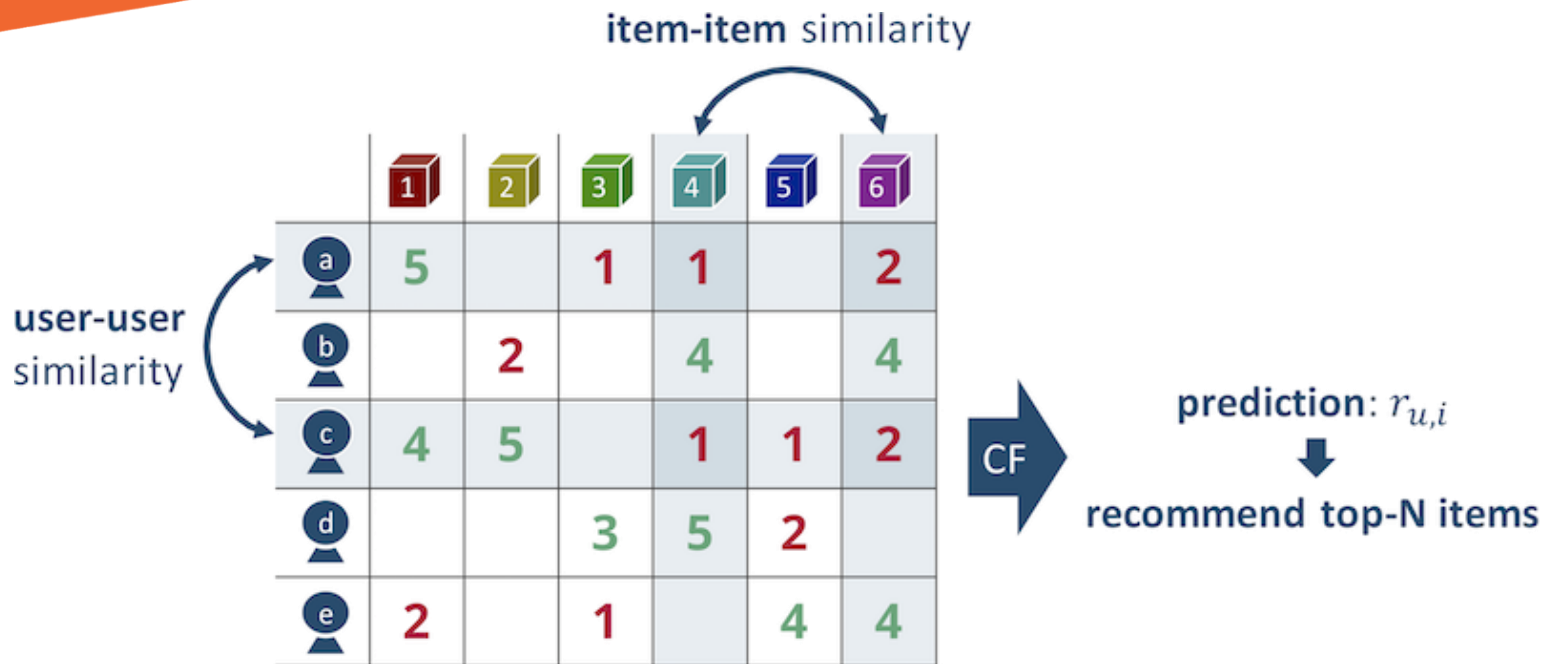
01

Users with similar interests
have common preferences

02

Sufficiently large number of
user preferences are
available

Collaborative Filtering



01

Jaccard Similarity

The Jaccard similarity is a good choice for implicit item feedback (ie binary feedback such as like/dislike or played/not played)

Cosine similarity

The cosine similarity is good for comparing the ratings of items, but does not consider the differences in mean and variance of the items

02

03

Pearson Correlation

The pearson correlation similarity also compares the ratings of items and effect of mean and variance have been removed

Collaborative Filtering Challenges

Popularity bias

Popularity bias refers to system recommends songs with the most interactions without any personalization



Item cold-start

Item cold-start problem refers to when songs added to playlist have either none or very little interactions while recommender rely on item interactions



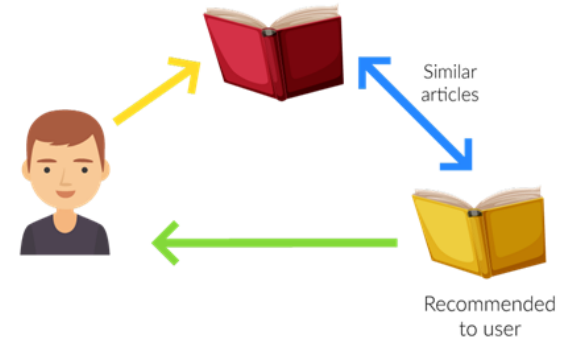
Scalability issue

Scalability issue refers to lack of the availability to scale to much larger sets of data when more and more users and song added into our database

Content Based

Recommendation are based on the content of items rather on other user's opinion.

This system will recommend items similar to those a user has liked (browsed/purchased) in the past based on product/service information.



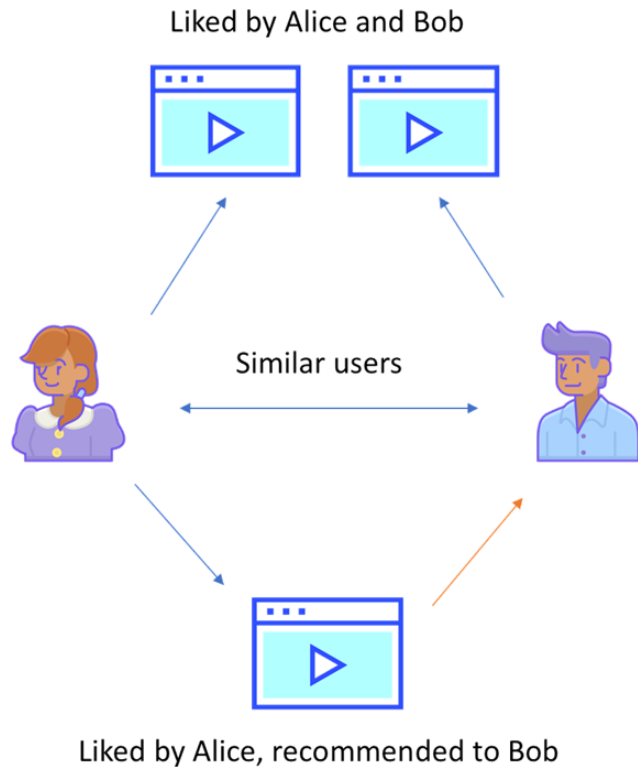
Advantages

- No need for data on other users. No cold start and sparsity.
- Able to recommend users with unique taste.
- Able to recommend new and unpopular items.
- Can provide explanation for recommendation.

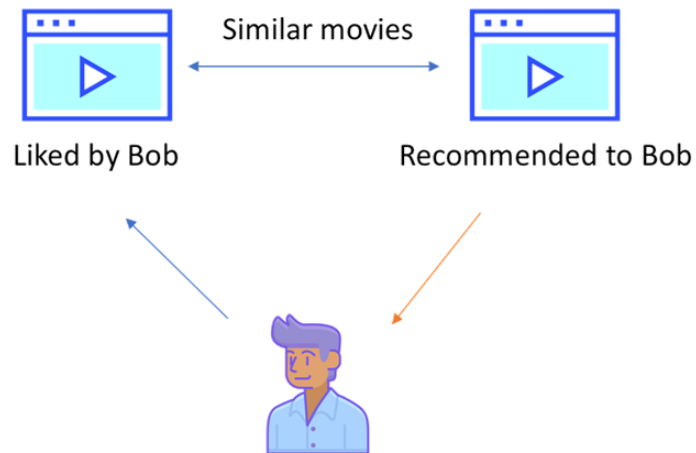
Limitations

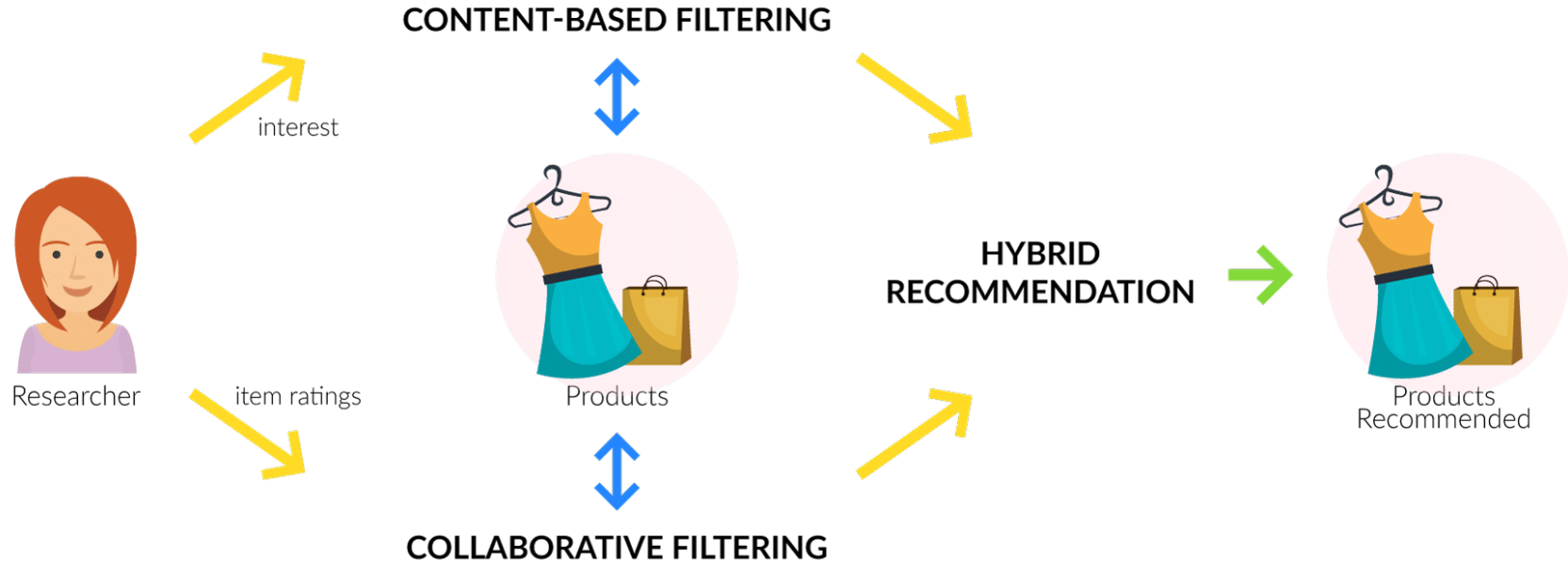
- Data should be in structured format.
- Unable to use quality judgments from other users.

Collaborative filtering

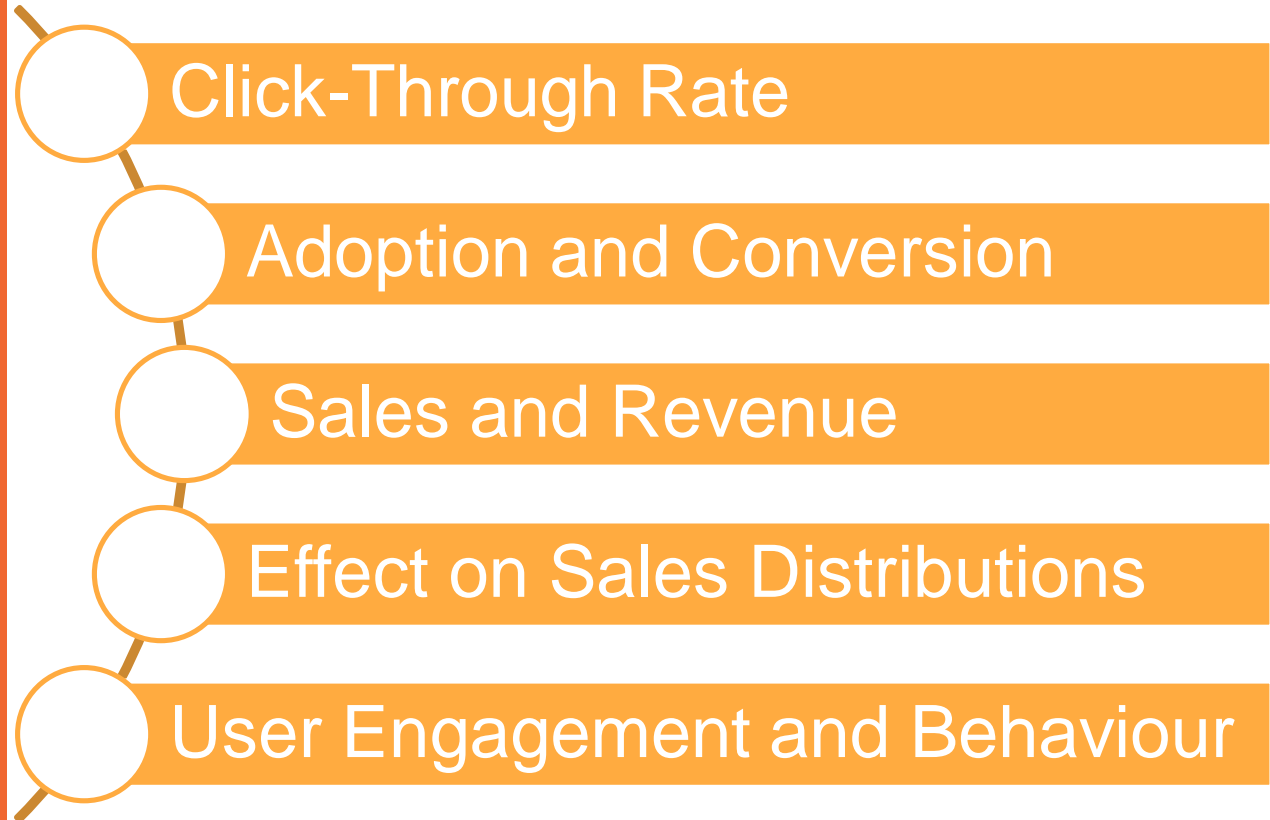


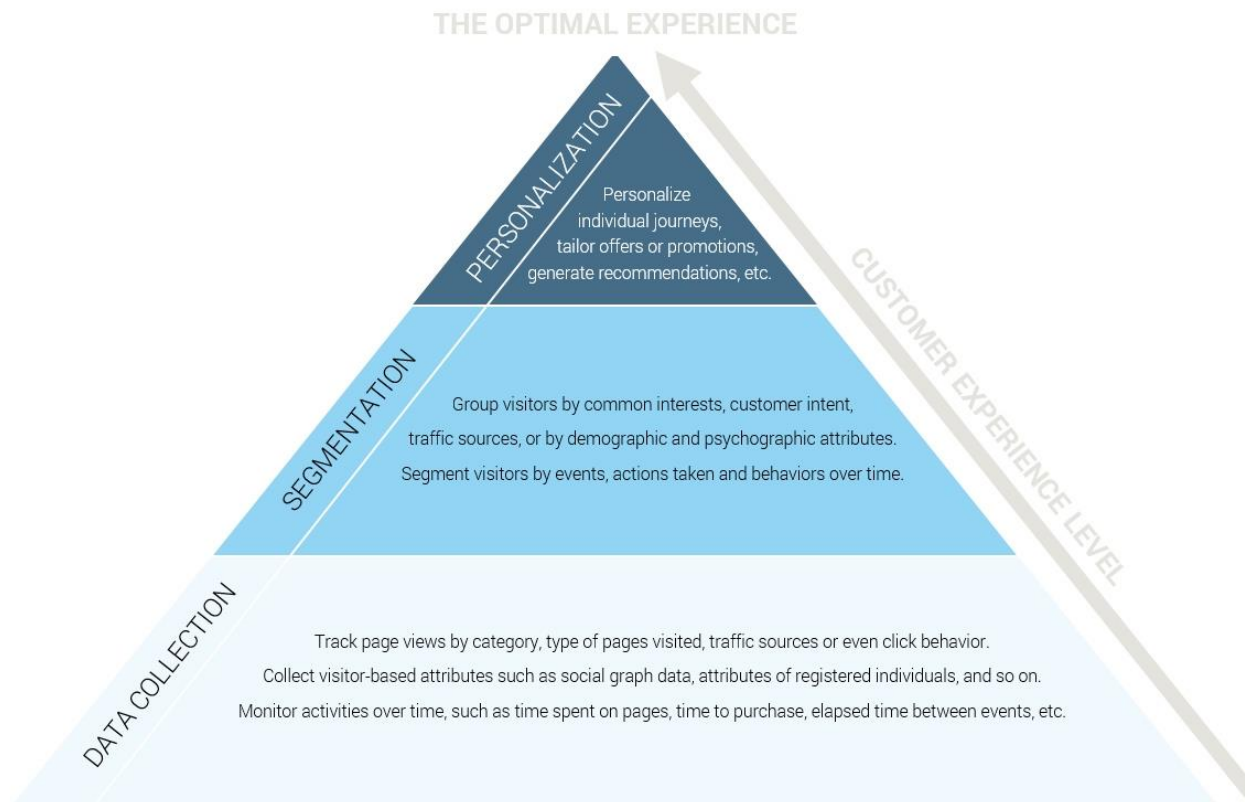
Content-based filtering





Business Value





SPEAKER SLIDE DECKS

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LIVE DISCUSSION TIME!



THANK YOU