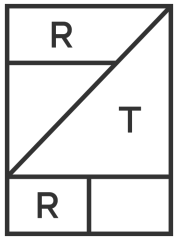
Fuss Free Fashion



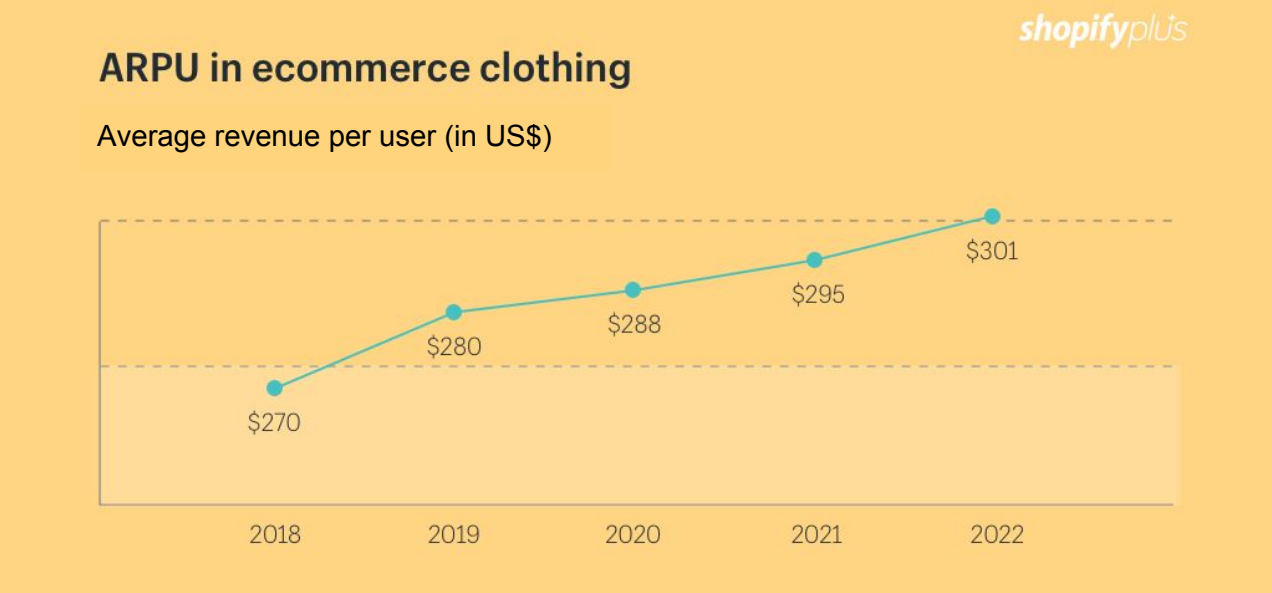
RENTTHERUNWAY
love. wear. return.

"Recommending your ideal fit so you can look your best"

Timothy Fong
GA DSI 6 Capstone Presentation

Riding the global E-commerce clothing wave

Global revenue for the E-commerce clothing market will grow by 50% to US$475bn from 2018-2022



Source: Shopify Fashion and Apparel Industry Report

Unlocking value in E-commerce clothing (Revenue)

Getting the right clothing fit **-->> higher customer satisfaction & more purchases**

BodyLabs.com - Apparel and Footwear Retail Survey 2016

STAT

If fit was not an issue,

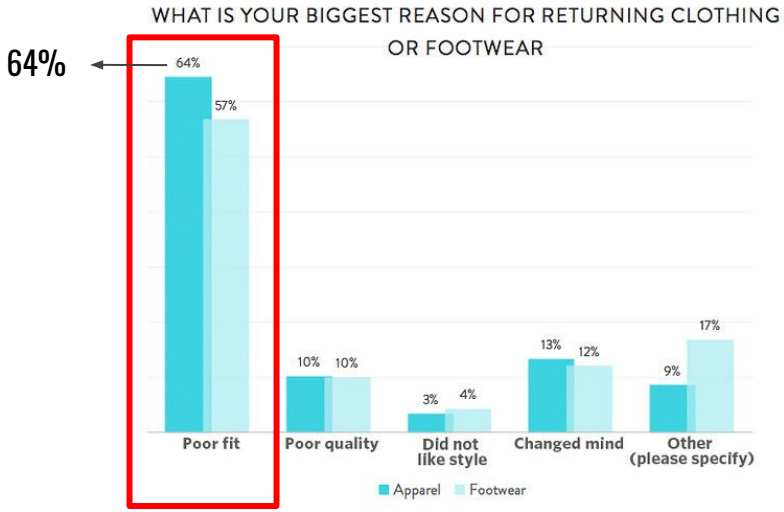
91% of women would purchase at least one more article of clothing during a single transaction, compared to only 78% for men

Survey on retail purchasing behavior from 1,130 US respondents between 6-14 April 2016

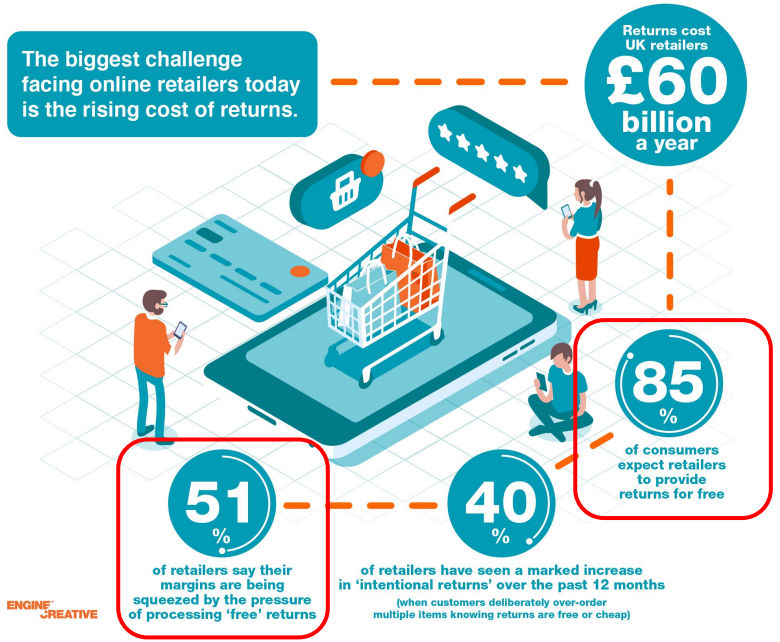
Source: SuperOffice

Unlocking value in E-commerce clothing (Costs)

Getting the right clothing fit **-->> fewer returns or exchanges for clothing**



BodyLabs.com - Apparel and Footwear Retail Survey 2016



Source: EngineCreative.co

RentTheRunway - Designer clothing & accessories rentals

Raw Dataset -->> 105,508 users, 5,850 items, 192,544 user-item interactions

User attributes:
User ID, Height, Weight, Body Type,
Bust Size, Age, Reason for renting

Item attributes:
Item ID, Size, Category, Review Date, Review
Summary, Review Text, Rating, Fit

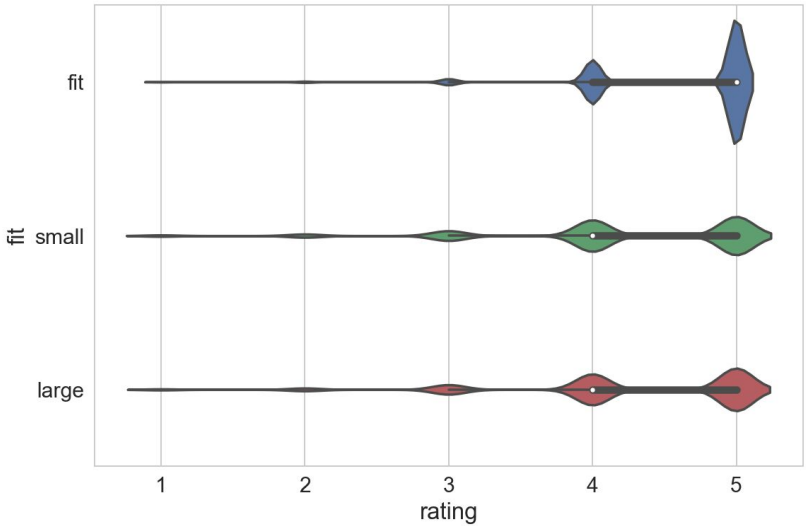
Dataset credits: **Rishabh Misra, Mengting Wan, Julian McAuley, "Decomposing fit semantics for product size recommendation in metric spaces", (RecSys, 2018)**

Exploratory Data Analysis (EDA)

User - Item-size ratings matrix is very sparse.

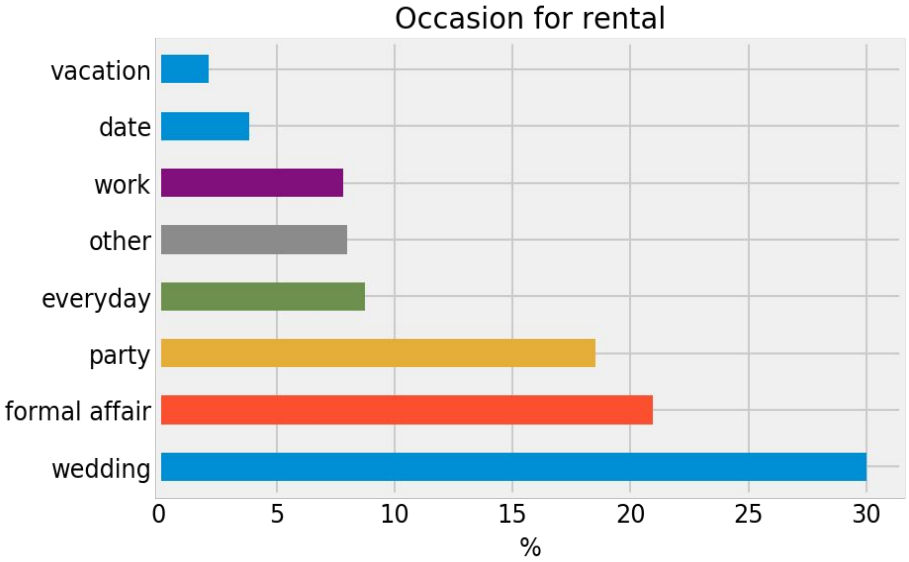
Unique classes of:	Users	Items	Item-sizes	Sparsity
At least 1 rating:	104,072	5,845	30,631	99.99%
At least 5 ratings:	5,668	4,583	10,876	99.93%
At least 10 ratings:	1,376	3,519	4,639	99.80%
At least 25 ratings:	165	1,915	1,143	99.68%

Ratings are skewed towards being more positive.

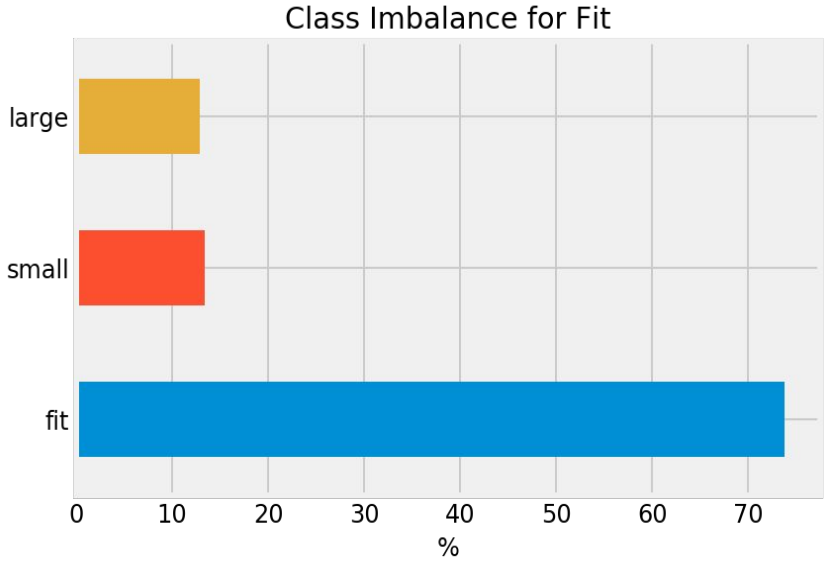


Exploratory Data Analysis (EDA)

Users generally rent for more formal occasions.

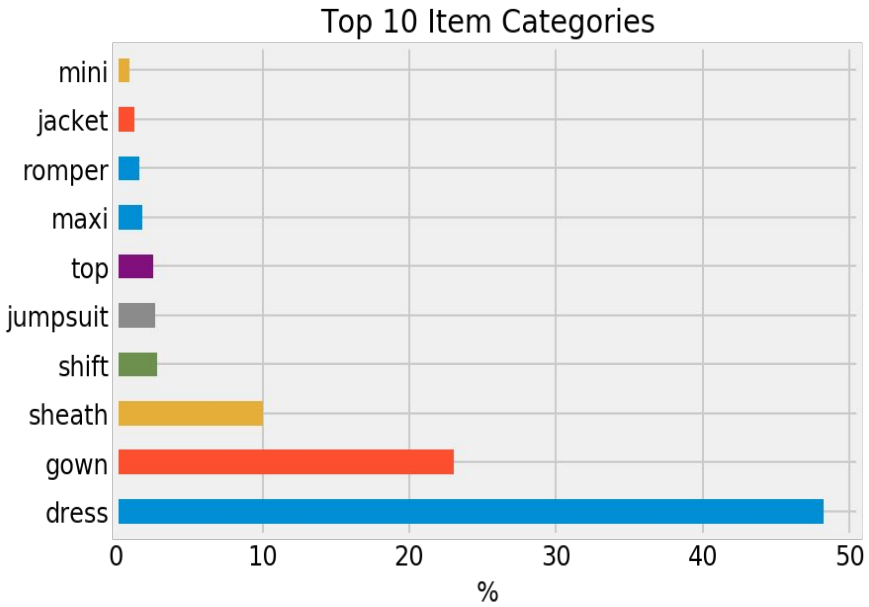


Users mainly rate their rentals as fitted.



Exploratory Data Analysis (EDA)

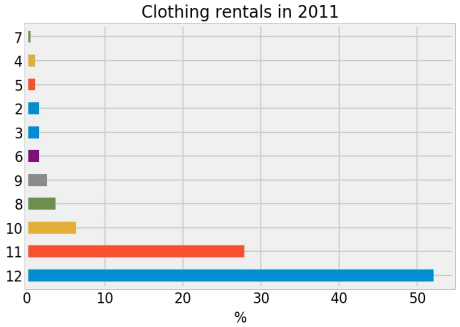
Users primarily rent dresses (48%) and gowns (23%).

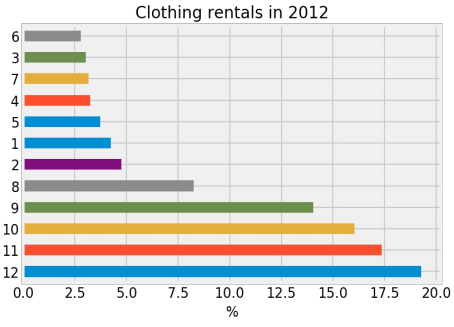


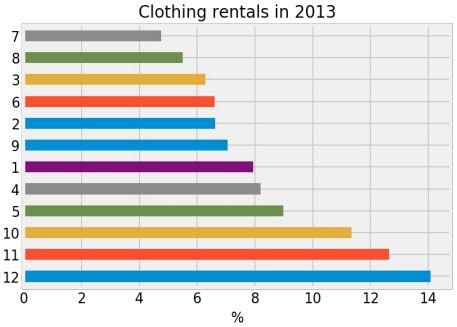
Exploratory Data Analysis (EDA)

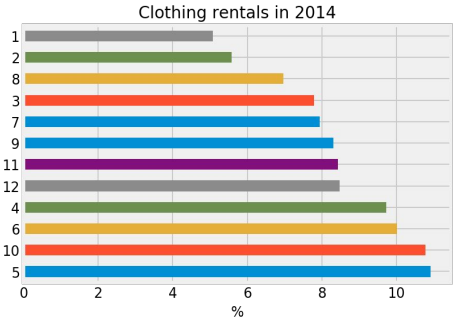
Rentals in each month have become more evenly distributed between 2011 and 2017.

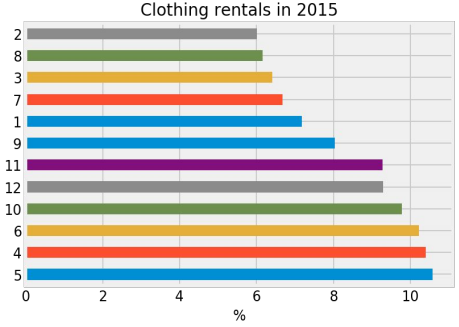
The second (months 4,5,6) and fourth quarters (months 10,11,12) have more rentals.

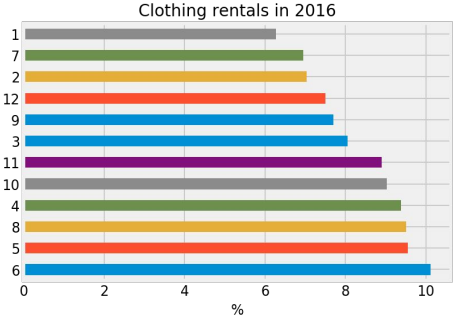


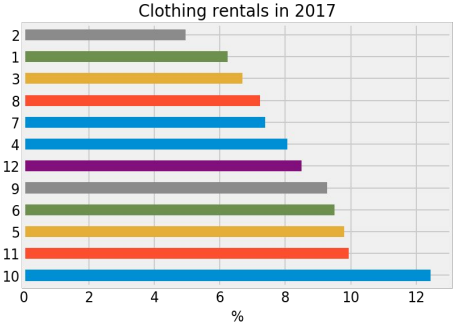












Approach - Overall

Recommender System:

- Item-based Collaborative Filtering (CF)
- Matrix Factorization (MF)
- Baseline Estimation (Base)

+

Classification Model:

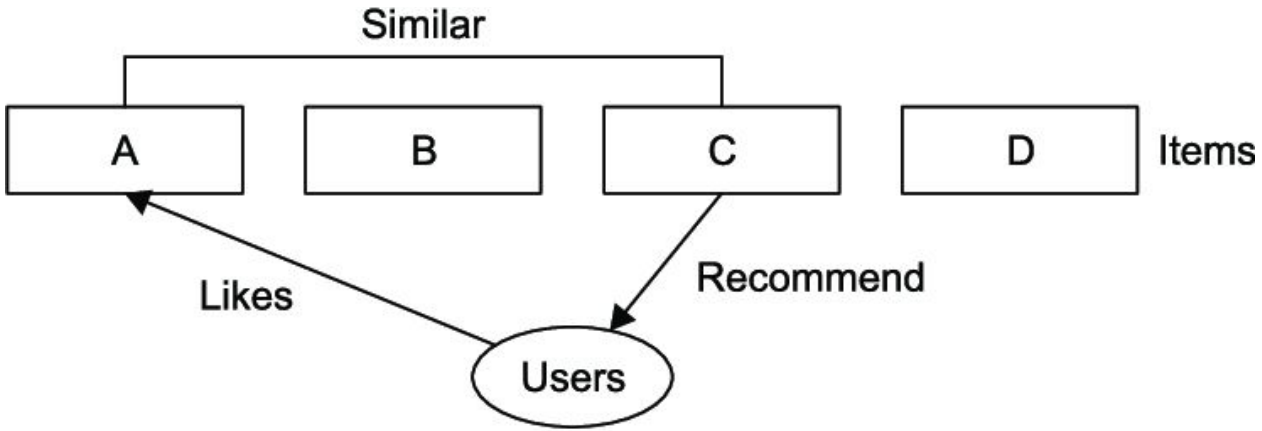
- Logistic Regression (LR)
- Large Margin Nearest Neighbor (LMNN)
- Support Vector Machine (SVM)

→

Recommend items that can fit user A

Approach - Recommender System Model

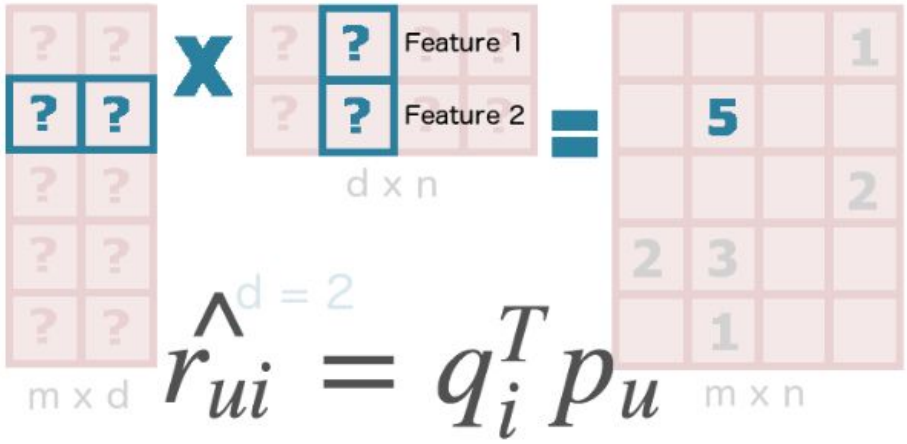
Item-based Collaborative Filtering



Approach - Recommender System Model

Matrix Factorization

m = number of users, n = number of items
choose d, the number of features



$$\hat{r}_{ui} = q_i^T p_u$$

Approach - Recommender System

Models:

- KNNWithMeans (CF)
- KNNWithZScore (CF)
- SVD (MF)
- SVDpp (MF)
- BaselineOnly

+

Recommender Metrics:

- RMSE
- Novelty
- Item coverage
- Recall @ k

→

Top N recommendations for user A

Approach - Recommender Metrics

Novelty: how many unknown/less popular items are recommended to a user? ->> higher novelty value (serendipity)

Item coverage: % of items in the train set that the model is able to recommend on a test set ->> high coverage = better

Recall @ k:

$$\text{Recall@k} = \frac{|\{\text{Recommended items that are relevant}\}|}{|\{\text{Relevant items}\}|}$$

Relevant item ->> its true rating > given threshold.
Recommended item ->> its estimated rating > the threshold, and if it is among the k highest estimated ratings.

Findings - Summary

Train-test split of 80-20

Model	RMSE (test set)	Average Recall @ k	Novelty	Item Coverage
KNNWithMeans (CF)	0.7883	0.476	99.97	0.80%
KNNWithZScore (CF)	0.8605	0.481	99.97	0.80%
SVD++ (MF)	0.7276	0.302	85.38	20.5%
SVD (MF)	0.7235	0.299	84.37	16.8%
BaselineOnly (BsO)	0.7514	0.282	71.12	0.64%

Findings - Top 10 Recommendations

Further analysis into the impact of different clothing sizing across brands is required.

User: 26196
Body type: petite; age: 44; bust size: 34c; height: 5ft 3inches
Rented between May 2014 and October 2016

Existing	3886 Dress 8	212 Gown 8	2159 Dress 8	24183 Romper 8	28976 Romper 12	15587 Gown 8	971 Sheath 8	-	-	Item ID clothing Size
SVD	14597 Dress 4	27119 Jumpsuit 8	11507 Dress 14	300 Gown 8	975 Sheath 24	27357 Blazer 8	22892 Sheath 4	17925 Sheath 14	1005 Mini 4	2171 Dress 8
BsO	27119 Jumpsuit 8	11507 Dress 14	11966 Dress 8	27357 Blazer 8	4816 Sheath 8	544 Sheath 1	17879 Dress 12	528 Dress 16	10883 Sheath 4	2171 Dress 8

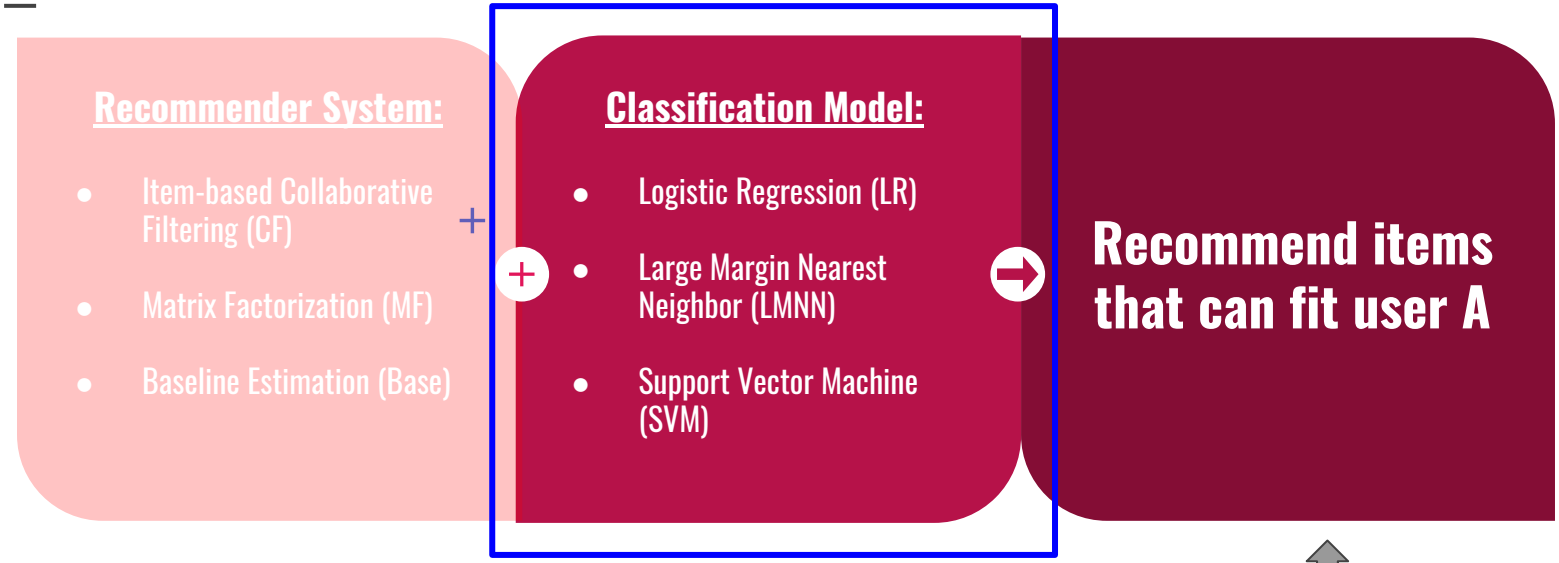
Project Limitations

1. Highly skewed ratings ->> develop more detailed rating system based on negative comments in user reviews to further segregate

2. Class imbalance in fit ->> learn fit semantics from user reviews to identify users who rate a fit but actually have negative size feedback

3. Lack of other item attributes (besides size) ->> obtain retailer's product catalog (if possible)

Next steps



Building a good classification model:
Explore using k-means clustering & weighted KNN to impute missing user attributes

Learning Fit Semantics:
Named entity recognition on user reviews

Thank You!