



WHY IS POPULARITY IMPORTANT IN  
RECOMMENDATION ENGINES?





# WHAT IS POPULARITY OF RECOMMENDATION ENGINES

As our mind, popularity in recommendation system means that the rank of each features of products in the dataset when we analysis a new customer behavior based on our dataset. According to the rank, we could recommend corresponding product to our customer, so popularity is important in recommendation engines.



## RECOMMENDATIONS BY POPULARITY

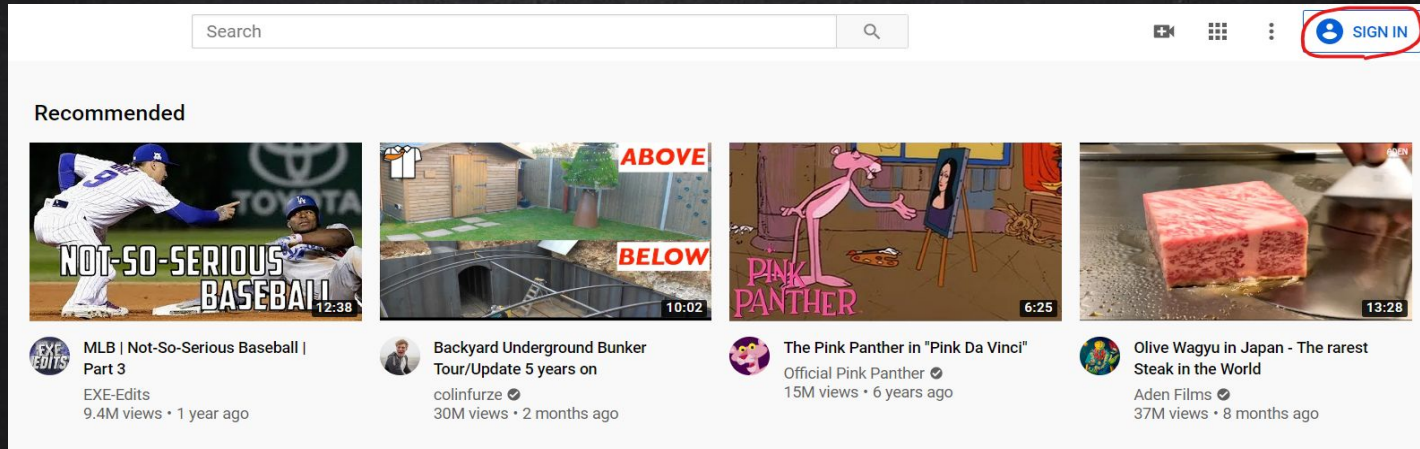
### X Pros:

- Show trend by time, location, culture...etc (Explicit data).
- Easy to apply when you have no detail data (Implicit data).
- High probability to recommend good item since it is liked by most of people.

### X Cons

- Recommendations might be same or similar for all users.

# VISITOR COLD START



- ✗ When a new user added in, and we have no historical data of new user. It's called **Visitor Cold Start**.
- ✗ Recommend the most popular items first (could be recently overall or regionally) . After users show their preference, following recommendation will be easier.
- ✗ A good first step!

# HOT PLAYLIST



## 精選排行榜



### 臺灣前 50 名

每日為你更新目前臺灣最熱播的歌曲。



### 全球前 50 名

每日為你更新目前最熱播的歌曲。



### 全球瘋傳前 50 名

每日為你更新全球最廣為轉傳討論的歌曲。



### 臺灣瘋傳前 50 名

每日為你更新在臺灣最廣為轉傳討論的歌曲。

- ✗ Sometimes user/service provider want to know the trend
- ✗ For people who have no particular preference
- ✗ Trend observing





# EVALUATION METRICS FOR RECOMMENDER SYSTEMS





## RANKING METRICS

### Precision

$$\text{Precision} = \frac{tp}{tp + fp}$$

***tp*** represents the number of items recommended to a user that he/she likes

***tp+fn*** represents the total items that a user like

### Recall

$$\text{Recall} = \frac{tp}{tp + fn}$$

***tp+fp*** represents the total items recommended to a user



## RANKING METRICS

Mean Averaged Precision  
@ K

✗ Averaged Precision  
@ K from 1 to K

Mean Averaged  
Recall @ K

✗ Averaged Recall  
@ K from 1 to K





## RANKING METRICS

### MEAN RECIPROCAL RANK (MRR)

$$\text{MRR} = \frac{1}{n} \cdot \sum_{i=1}^n \frac{1}{r(Q_i)}$$

**Larger the mean reciprocal rank, better the recommendations**



## RANKING METRICS

### Normalized Discounted Cumulative Gain(NDCG @ k)

DCG: 
$$\sum_{j=0}^{n-1} \frac{rel_{D_i}(R_i(j))}{\ln(j+1)}$$

$$rel_D(r) = \begin{cases} 1 & \text{if } r \in D, \\ 0 & \text{otherwise.} \end{cases}$$

$n: \min(\max(|R|, |D|), k)$   
 $|R|$ : length of recommended items  
 $|D|$ : length of ground truth

Ideal DCG: 
$$\sum_{j=0}^{\min(|D|, k)-1} \frac{1}{\ln(j+1)}$$

NDCG : DCG/Ideal DCG, for each user



## PREDICTION ACCURACY METRICS

RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Predicted_i - Actual_i)^2}{N}}$$