# VOD RECOMMENDATION FOR OTT VIDEO PLATFORMS

INTRO PRO
SOFTWARE SERVICES AND PRODUCTS

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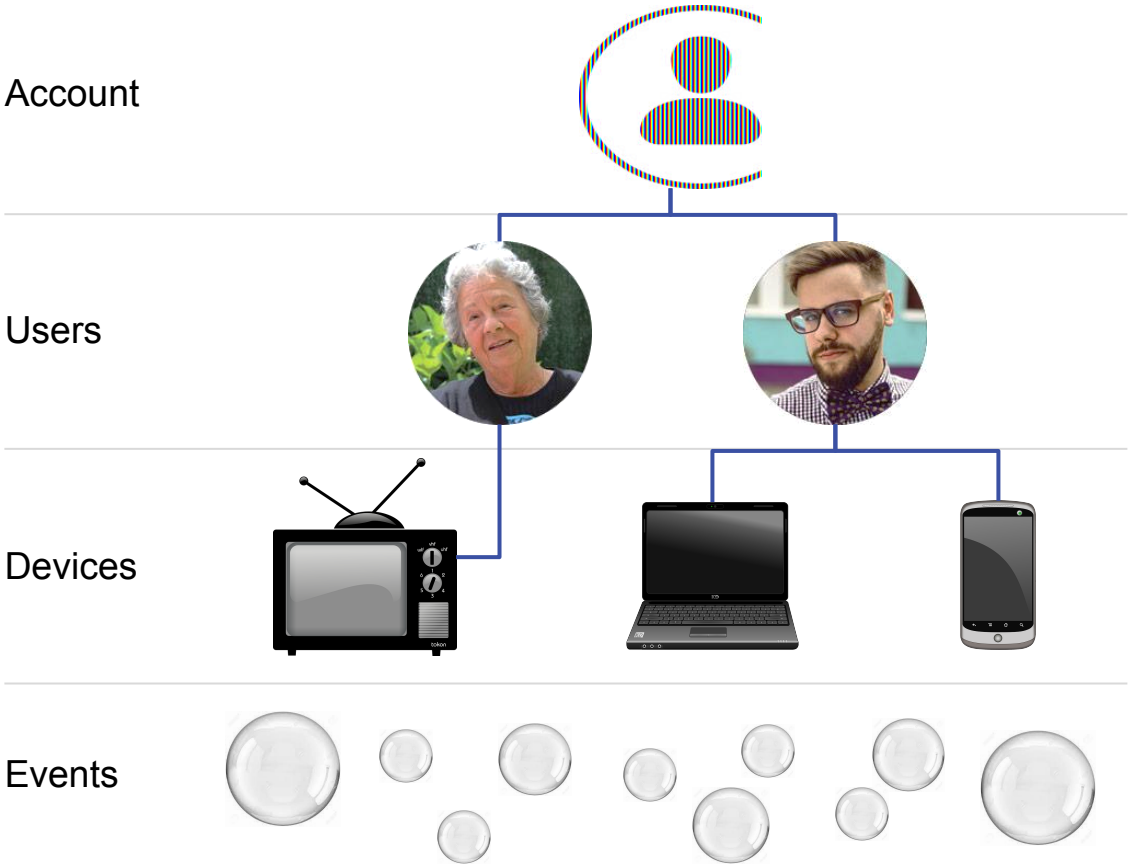
**Software Development House** from Kyiv **for Media Entertainment** and **Telecommunication industries** in embedded and backend planes

# Building Video Recommendation system

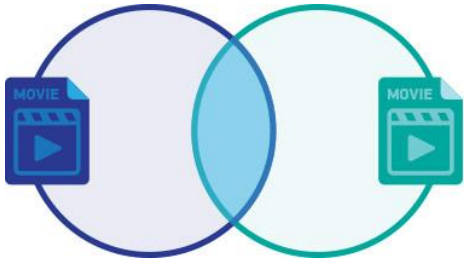



**1 000 000**
events/day/user

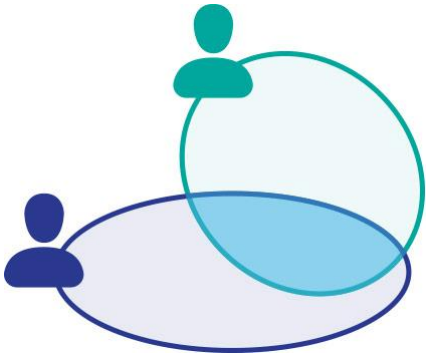
**10 000+**
users

**20 000+**
movies

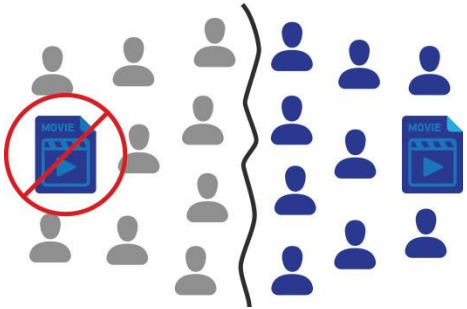
# Implemented for constructing recommender systems



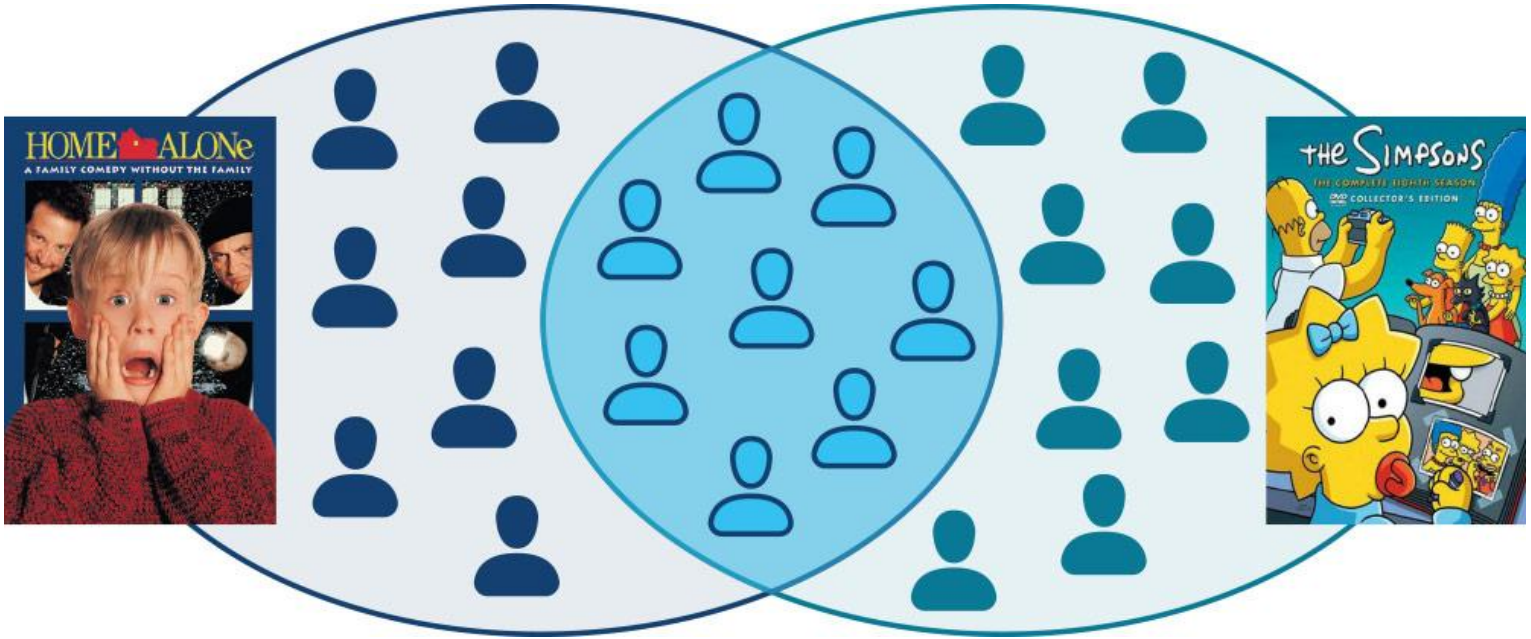

## Co-Occurence



## Collaborative Filtering

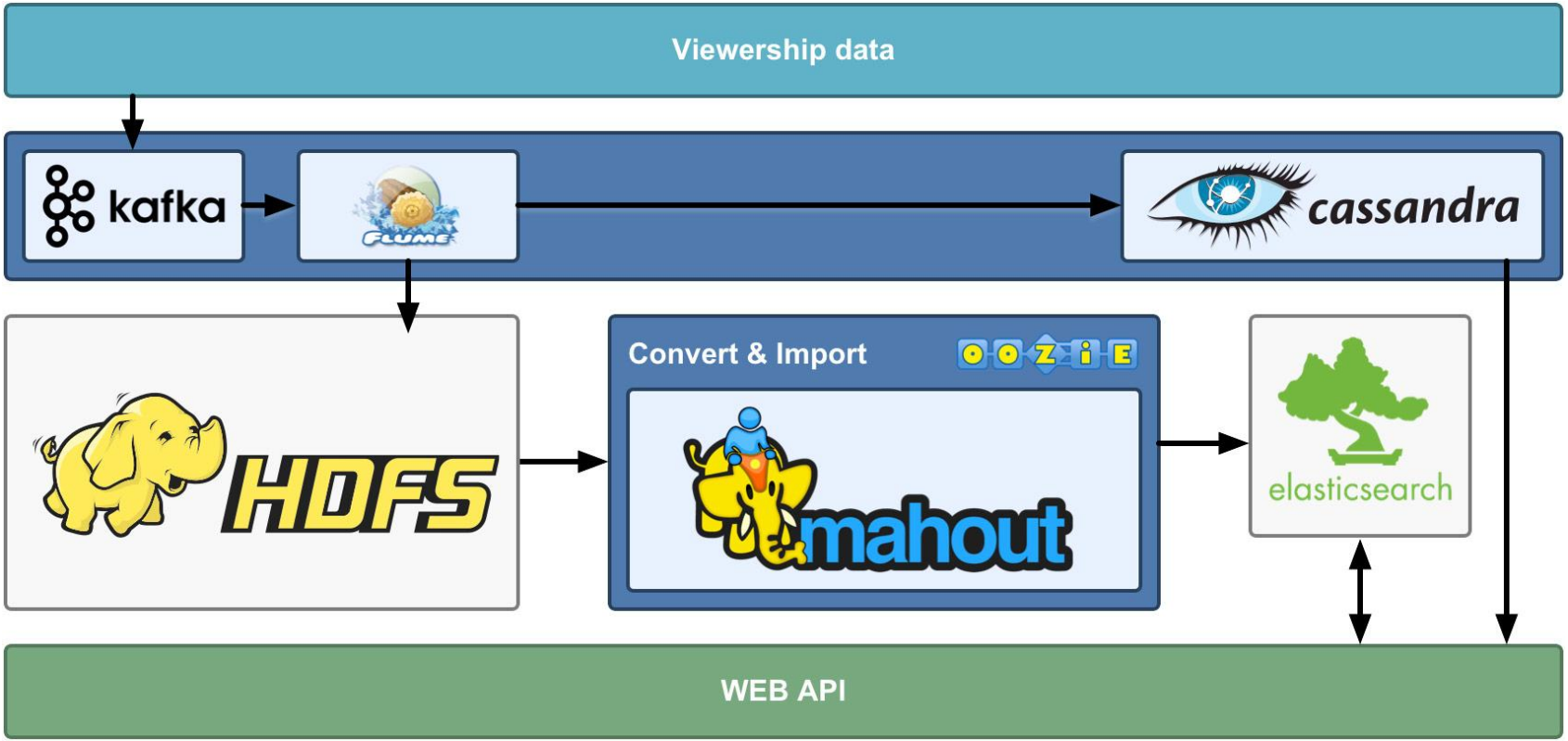



## Binary Logistic Regression



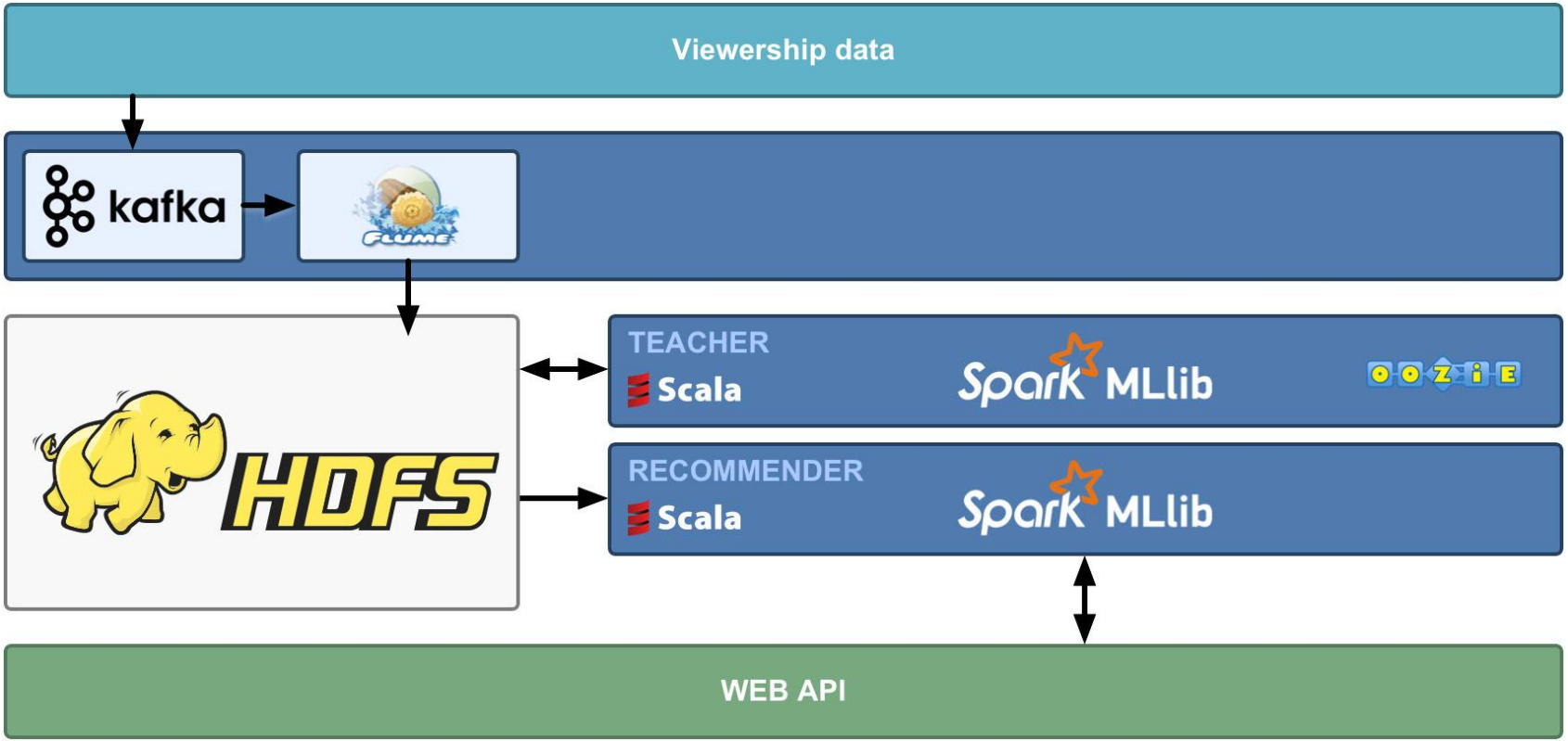

# Co-Occurence

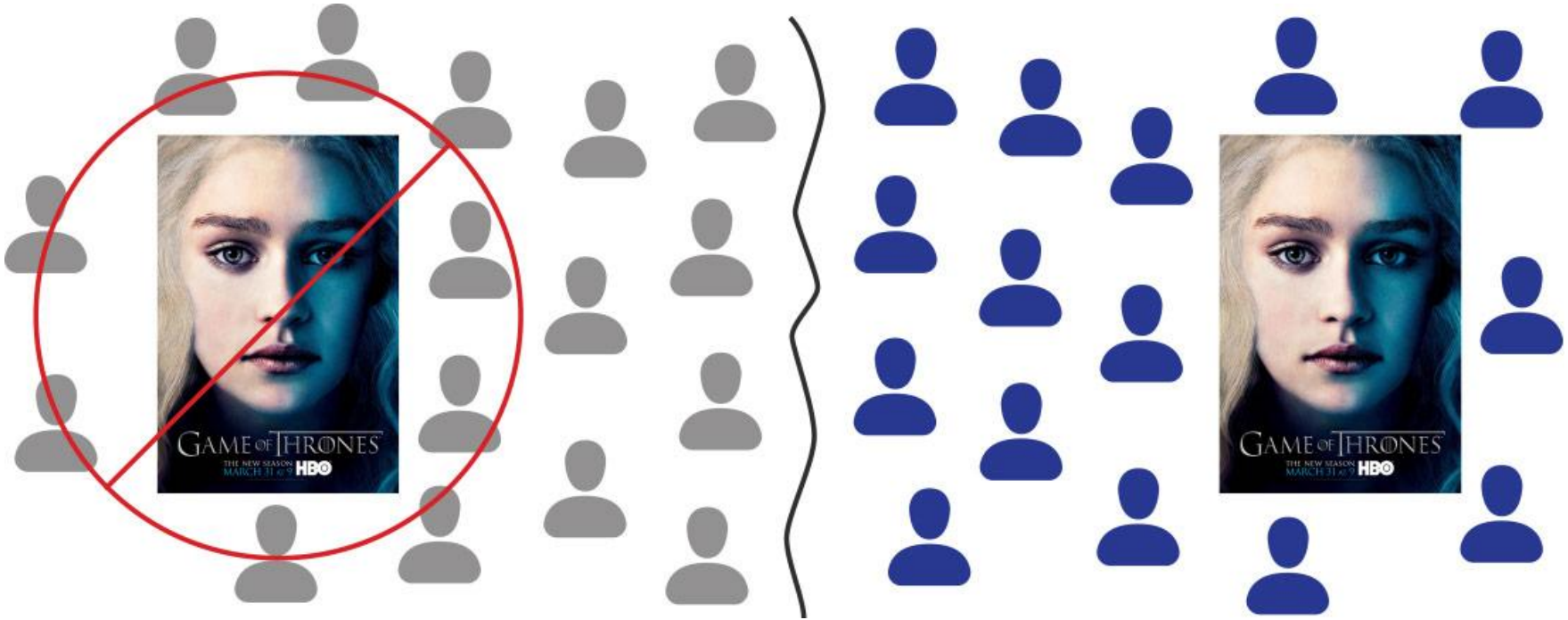
# Building a recommendation system: Co-occurrence




# Collaborative Filtering

# Building a recommendation system: Collaborative filtering





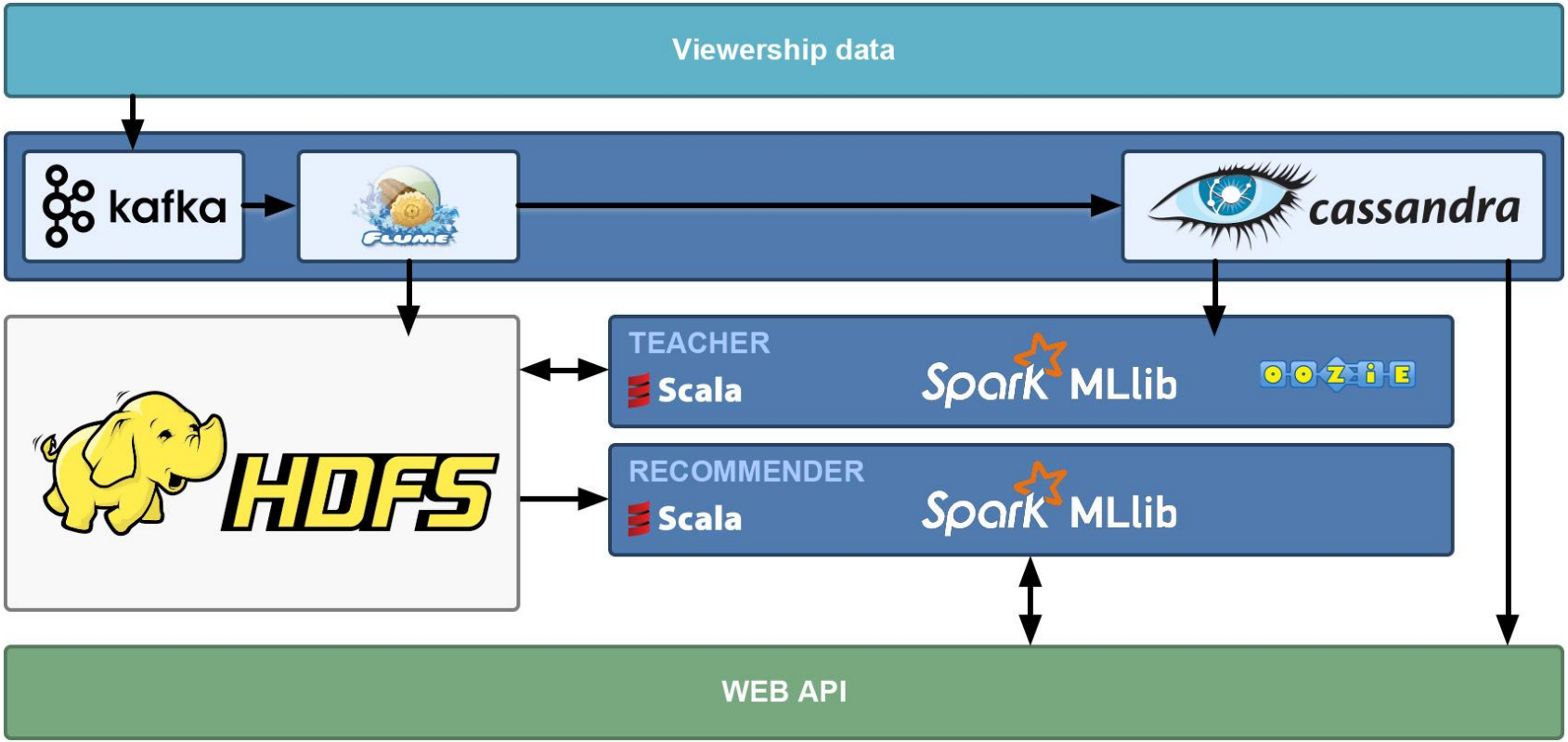

# Binary Logistic Regression

# Building a recommendation system: Regression

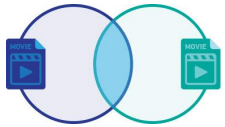
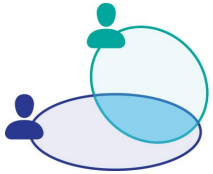
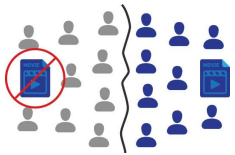
| User ID | Gender | Age | Count of viewed movies by customer | How many month customer use our services | The average duration of one film for customer | The total duration of the viewing for the entire period | The total average duration of viewing within a month | SUM_of_ Animation | SUM_of_ Comedy | ..... | title_id viewed by user |
|---|---|---|---|---|---|---|---|---|---|---|---|
| user_id 1 | X | | | | | | | | | ..... | 1 |
| user_id 2 | X | | | | | | | | | ..... | 1 |
| user_id 3 | X | | | | | | | | | ..... | 0 |
| ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... | ..... |
| user_id N | | | | | | | | | | ..... | 0 |

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}}$$

# Building a recommendation system: Regression



# Comparing algorithms

| Algorithm | Pros | Cons |
|---|---|---|
| **Co-Occurence**  | • Fast learning<br>• Good speed of work<br>• To train enough not very long history of views | • It is not possible to increase the accuracy<br>• The "cold start" problem |
| **Collaborative Filtering**  | • Fast learning<br>• Using not only the fact of views, but also ratings<br>• It predicts not only views, but also ratings | • It is not possible to add information about movies or users<br>• The "cold start" problem |
| **Binary Logistic Regression**  | • Good accuracy for the long history<br>• The ability to increase the accuracy of the method by introducing predictors | • Long time training<br>• Low precision for short history |

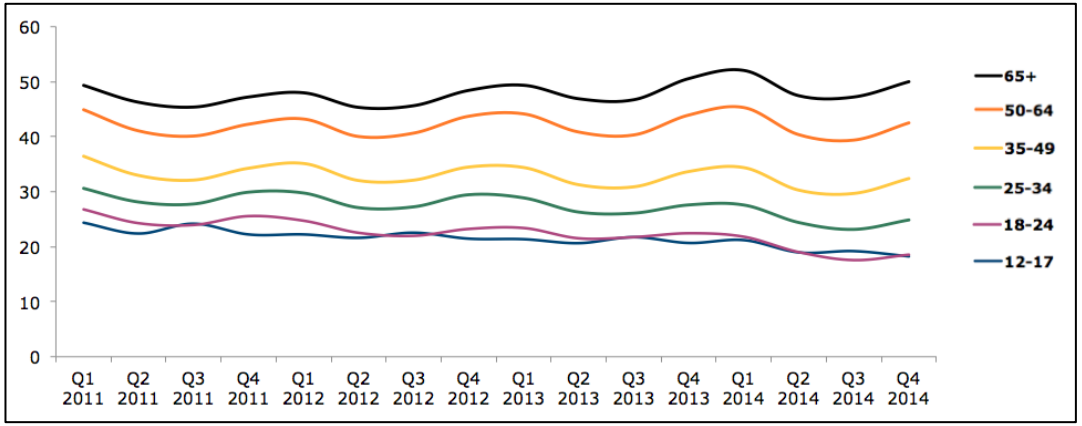
# Recommendations: KPI

| | **Dynamic dataset** (Users Activity Generator) | **Static dataset** (Movielens.org dataset) |
|---|---|---|
| **Co-occurrence** | 48 % | 7,96 % |
| **Collaborative filtering** | 27 % | 4,6 % |
| **Binary logistic regression** | 8 % | 16 % |

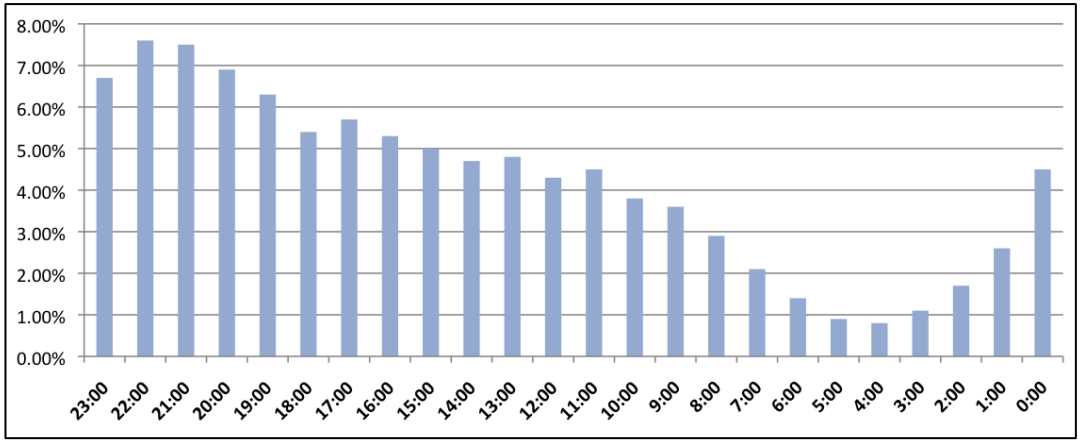
# Recommendations: KPI comparison

| | **Dynamic dataset** (Users Activity Generator) | **Static dataset** (Movielens.org dataset) |
|---|---|---|
| **Co-occurrence** | 48 % | 7,96 % |
| **Collaborative filtering** | 27 % | 4,6 % |
| **Binary logistic regression** | 8 % | 16 % |
| **Top_Hot_Rate** | **17 %** | **1.04 %** |
| **Randomly** | **0.3 %** | **0.005 %** |

# Traditional TV Viewing Trends

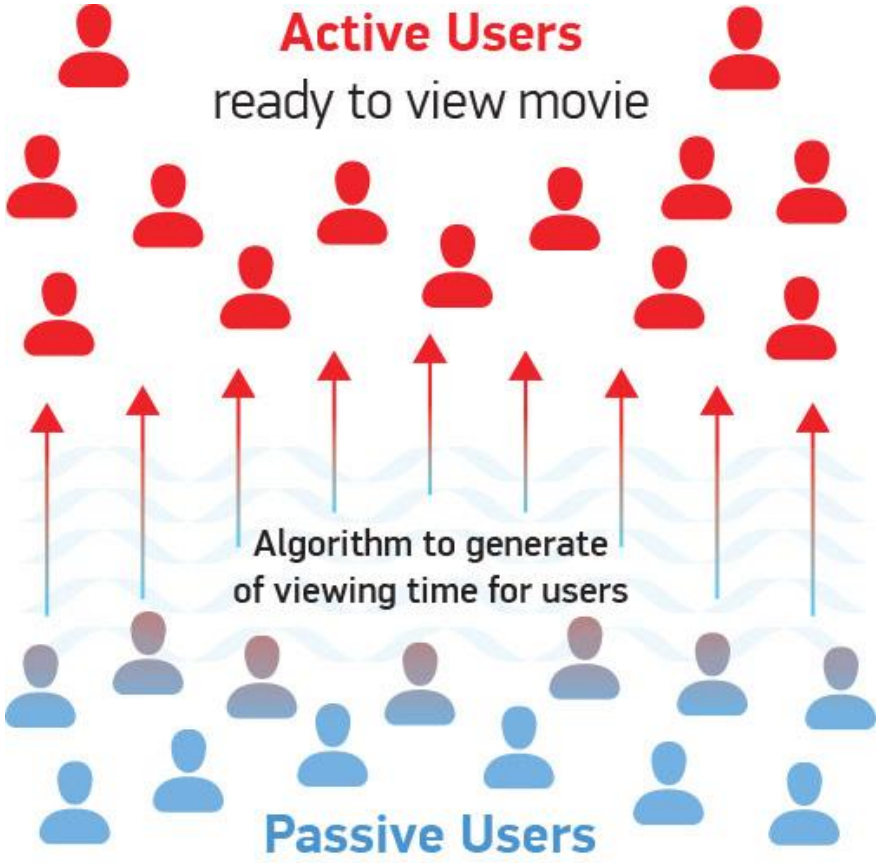



# When Are People Watching?

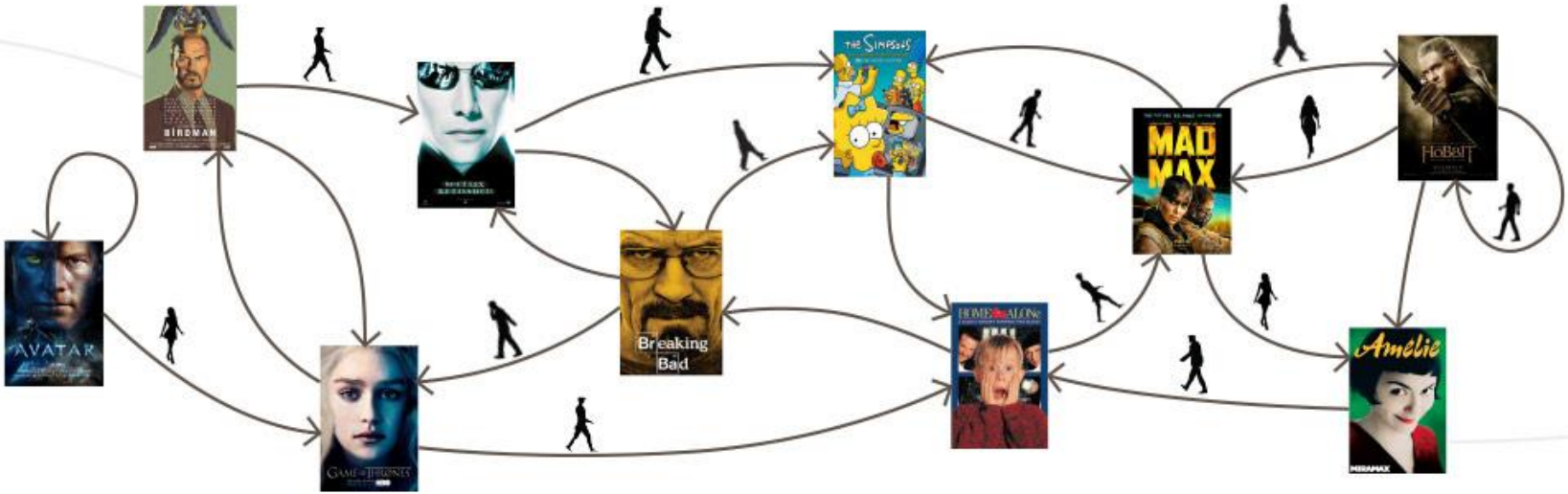


## User Parameters:

1. The first level of preference by genre
2. The second level of preference genre
3. The level of preferences of other genres
4. Sensitivity to change genres
5. Sensitivity to view the rating of films
6. Sensitivity to the release date of the film
7. Sensitivity to the duration of watching movies
8. Sensitivity to view new movies
9. The level of intensity of movies
10. The level of preference for the return of the scanned film



# Generator: viewing content generation

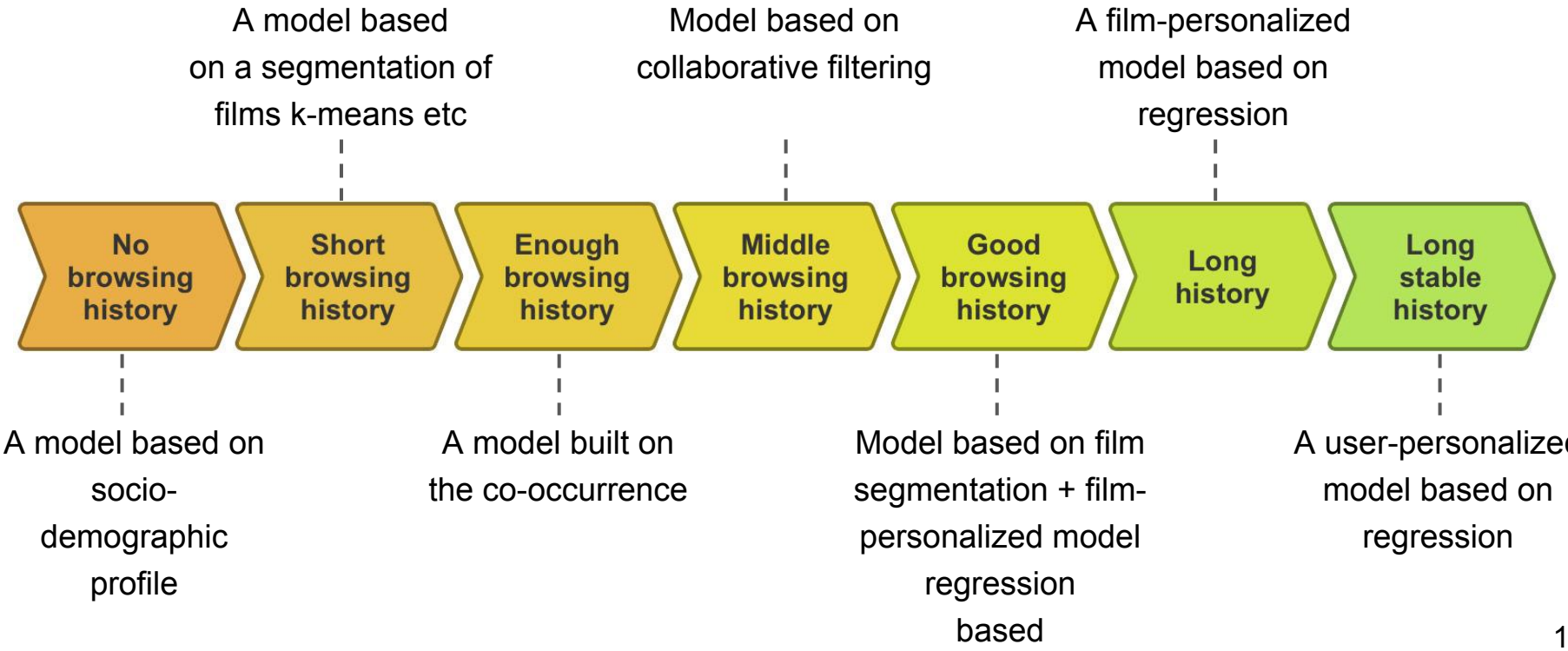



Let $X_t^{(j)}$ – an event at which to step **t** the user will watch the film **j**, then:

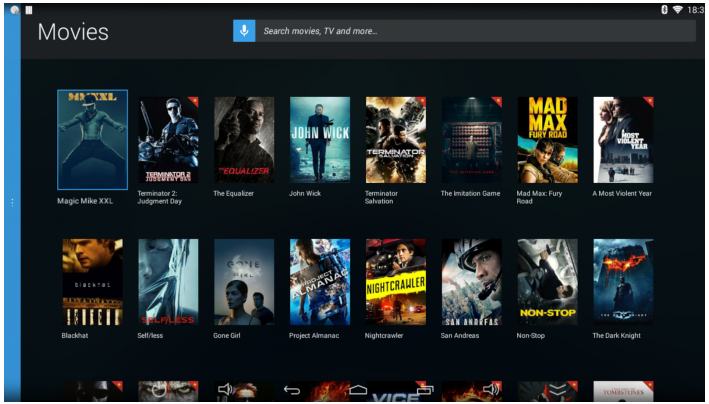
$$\hat{p}_{ji} = (1 - p_{ret}) \times \left\{ \mu\left(X_t^{(j)}, X_{t+1}^{(i)}\right) \left[ L\left(X_t^{(j)}\right)^{\frac{2}{r(Xj)}} \right] + L\left(X_t^{(j)}\right)^{\frac{2}{r(Xi)}} \left[ 1 - \mu\left(X_t^{(j)}, X_{t+1}^{(i)}\right) \right] \left[ 1 - L\left(X_t^{(j)}\right)^{\frac{2}{r(Xi)}} \right] \right\}, i \neq j$$

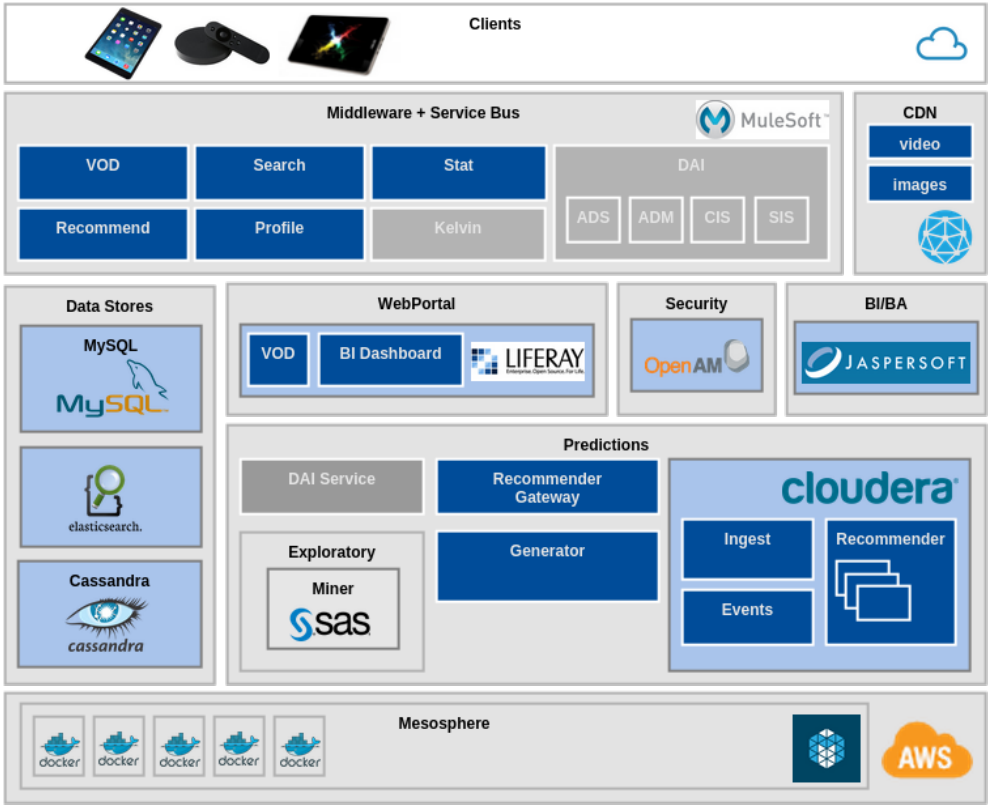
$$\hat{p}_{ji} = p_{ret} \left[ L\left(X_t^{(j)}\right)^{\frac{2}{r(Xj)}} \right], j \in S$$

# Client life cycle



Recommendation System is **only part of the bigger project**, but one of the **most crucial piece**



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