



Predictive Self-Learning Content Recommendation System

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Outlines

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- Analysis
- Conclusion

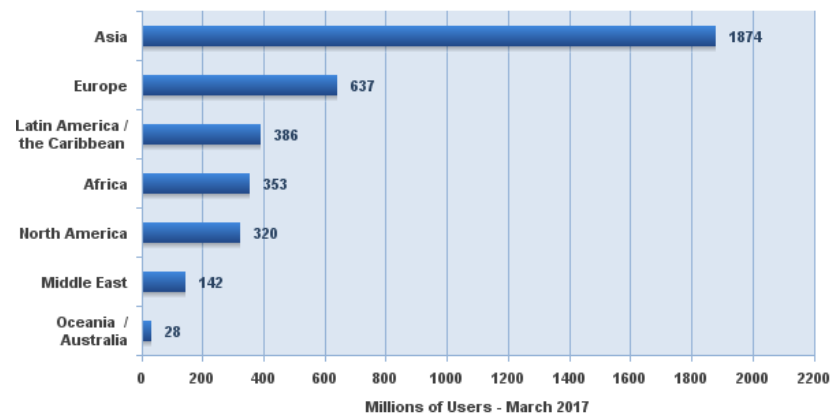


Introduction

- Millions of daily internet users
- Entertainment, Education, Shopping etc.
- Key feature of online software is recommendation system
- Well known sites:
 - Youtube
 - Netflix
 - Amazon



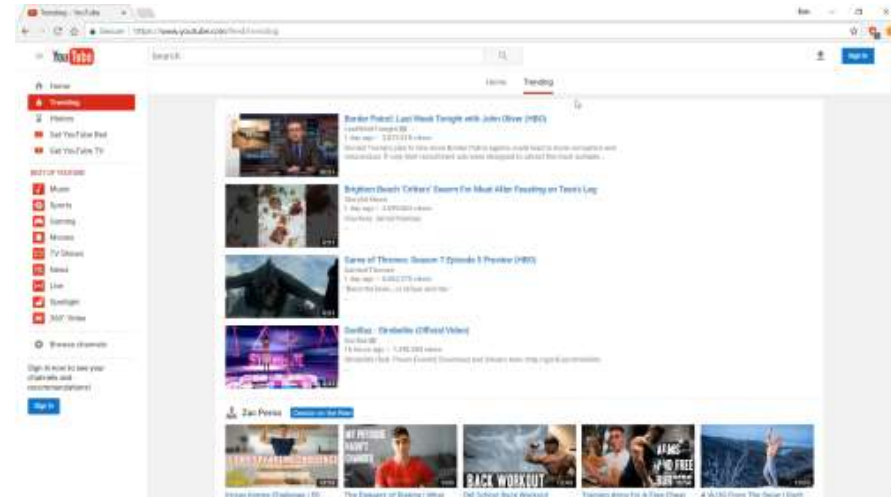
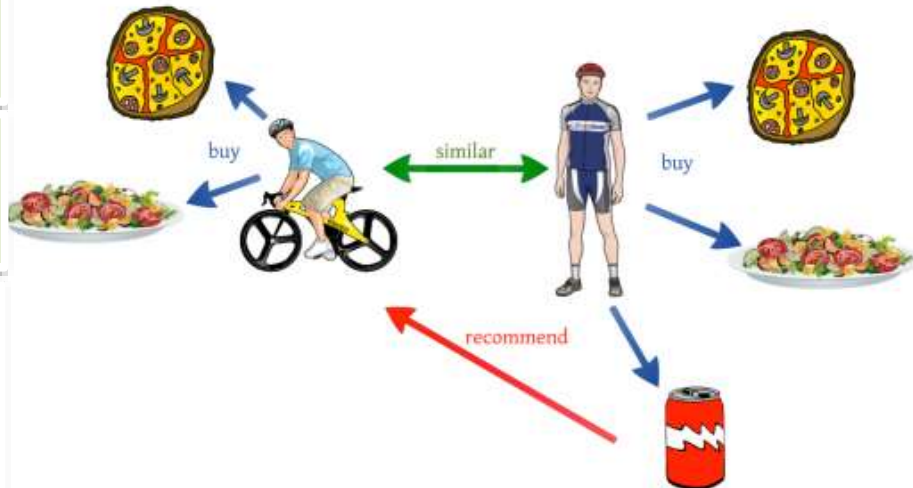
Internet Users in the World by Geographic Regions - 2017 Q1



Source: Internet World Stats - www.internetworldstats.com/stats.htm
 Basis: 3,739,698,500 Internet users estimated for March 31, 2017
 Copyright © 2017, Miniwatts Marketing Group

Recommendation System

- Suggestions





Recommendation System Metric

- Parameters
 - Related content
 - Popularity
 - Channels
 - Location
 - Past Activity
 - Language
 - User Profile



User Input

- Background information
 - Age
 - Location
 - Nationality
 - Occupation
 - Etc...

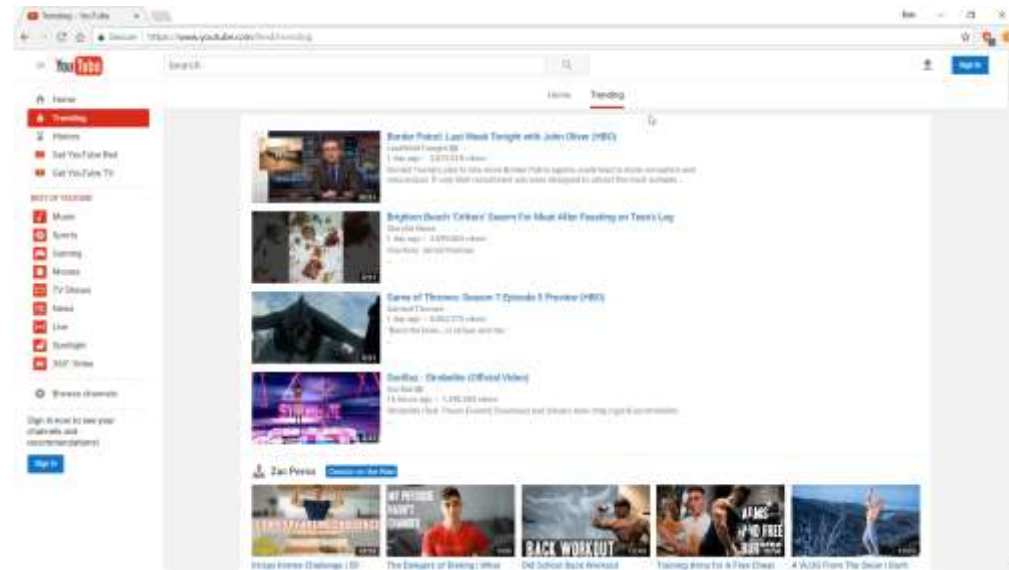


Ranking

- The most watched
- The most liked



- Input Analysis



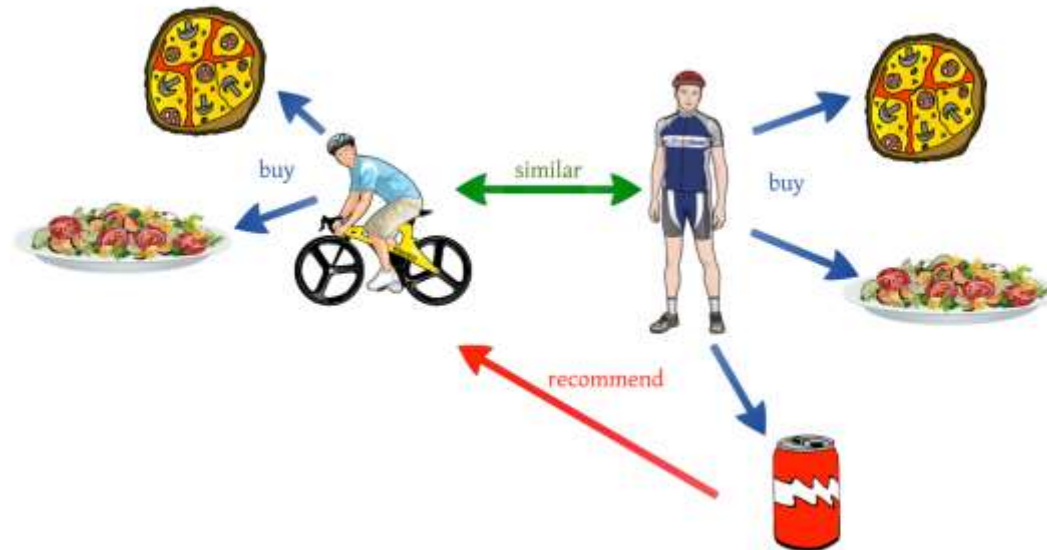
Feedback

- Accuracy
- Safety



Similarity and Grouping

- User history on products will allow the system to produce more suggestions.





Problem

- Many parameters to consider
- Which parameters are more important for which user



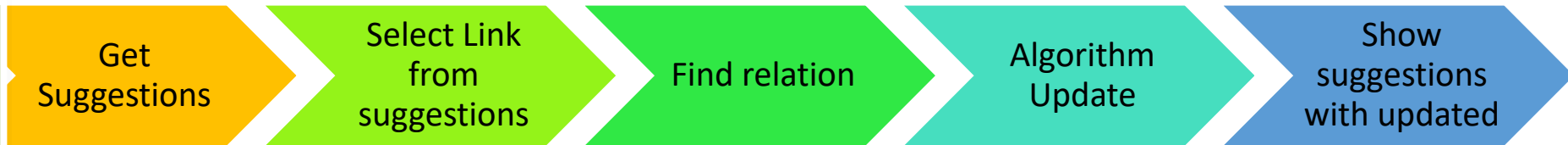


Objective

Propose a predictive self-learning recommendation system that using history information and analyze the user behaviors for the future activity. Then, use a behavior analyzer to update the prediction system by monitoring users selections from suggested contents.



System Flow Model



Get Suggestions

Select Link from suggestions

Find relation

Algorithm Update

Show suggestions with updated

Introduction

Proposed

Analysis

Result

Conclusion

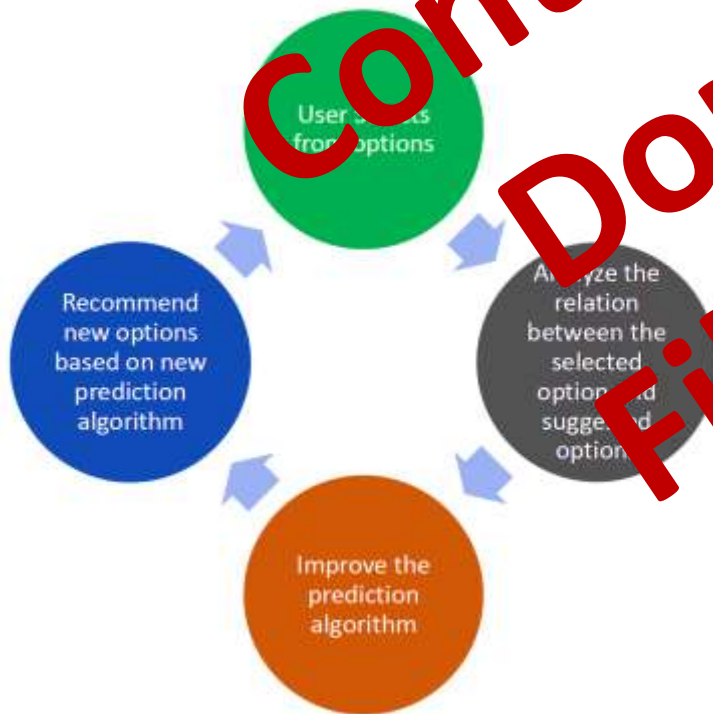
System Metrics

$$R = \alpha U_c + \beta (F_p - F_n) + \left(\gamma \frac{P_l}{10} + \eta \frac{P_o}{10} + \kappa \frac{P_n}{10} + \varsigma \frac{p_i}{10} \right) + \psi O_c$$

$$\min_{x^1, \dots, x^{nm}} \frac{1}{2} \sum_{i=1}^{n_m} \sum_{j:r(i,j)=1} \left((\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2$$

Parameters	
U_c	User Clicks
F_p and F_n	Positive and negative feedback
P_l	Location
P_o	Occupation
P_n	Nationality
p_i	Interests
O_c	Overall clicks

System Cycling



Continuous Double Filtering

Algorithm 1 Algorithm to improve recommendation systems

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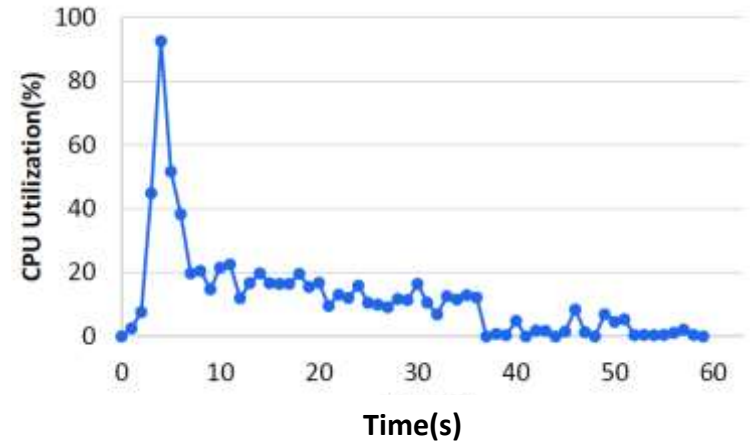
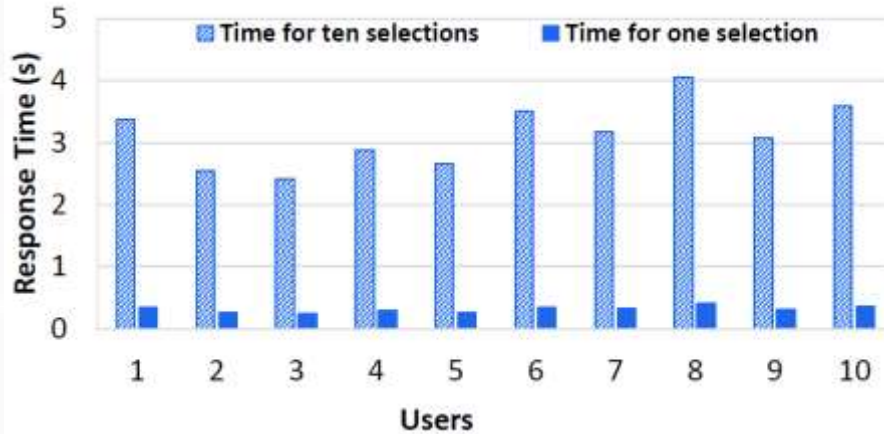
require:
  input - user profiles and past activities
  output - suggestions
1: procedure
2:   while selection do
3:     display suggestions
4:     get user selections
5:     if selection in DB then
6:       display the content
7:       create a relation: selected and suggested
options
8:       update user recommendation system
9:       display some suggestions according to the
new recommendation and some based on the previous
recommendation system
10:    end if
11:  end while
12: end procedure
  
```



Simulation-based Analysis

- Data Type – Meta Data from YouTube
- Test Cases
 - Response Time
 - CPU Utilization
 - Suggestion Uniqueness
- Simulation Design
 - Java Implementation
 - Quad Core 2.4GHz, 16GB Memory, 32MB cache

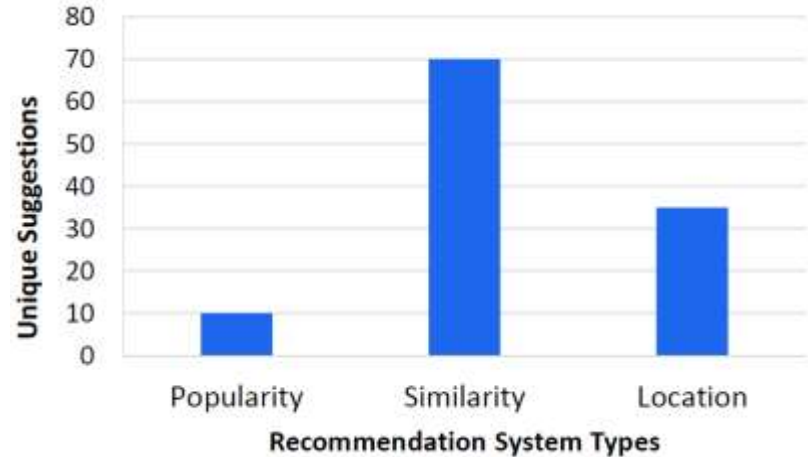
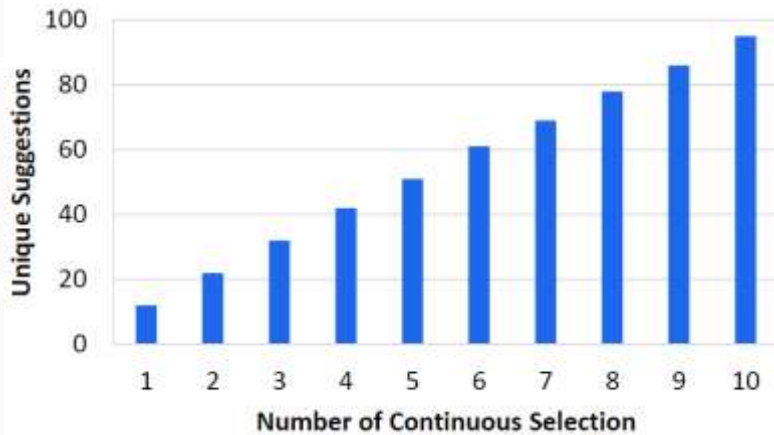
Results



- User selection response time for:
 - One selection
 - Ten selections

- CPU Utilization over 60 seconds

Results



- Unique results returned by the system after continuous user selections over 10 rounds.

- Comparison of unique suggestions return by different recommendation systems

Conclusion and Future Works

Predictive Self-Learning Recommendation System.

Analyzed according to integrity, CPU performance and Time efficiency.

Need more experiment.

Creating relation between medias should be investigated more.

Thank You

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