Sistemas Recomendadores IIC-3633

Recomendación basada en contexto

Esta clase

1. Ideas proyectos Denis Parra
2. Recomendación utilizando información contextual

Ideas de proyectos: Denis Parra

Contexto

Un factor importante a considerar en las recomendaciones.

Componentes del contexto

1. ¿Estás de humor cuando consumes el ítem?
2. ¿Con quien estoy consumiendo el ítem?
3. ¿Dónde estoy consumiendo el ítem?
4. ¿Cuándo estoy consumiendo el ítem?
5. Ocasión especial

Componentes del contexto

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Context-aware recommendation (CARS)

Recomendación basada en filtrado colaborativo

Users X Items → Ratings (o interacciones)

Recomendación contextual

Users X Items X Context → Ratings (o interacciones)

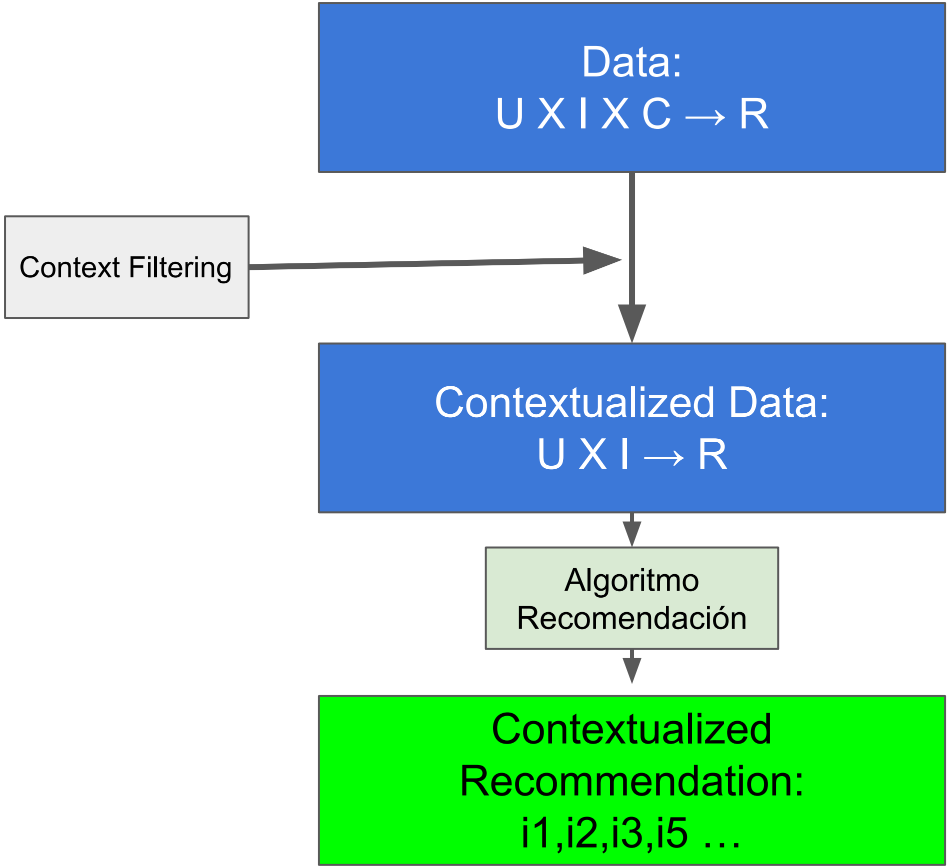
Set de datos de User-Item-Context

User	Item	Who	Where	When	Rating
U1	M1	Kids	Home	Weekend	5
U1	M2	Family	Theater	Weekend	4
U1	M3	Partner	Event	Weekday	5
U2	M1	Friends	Home	Weekend	3
U2	M2	Family	Home	Weekday	4
U3	M2	Kids	Theater	Weekday	2
U3	M3	Partner	Home	Weekend	1
U2	M3	Partner	Home	Weekday	?

Tipos de recomendación contextual

1. Contextual pre-filtering
2. Contextual post-filtering
3. Contextual modeling

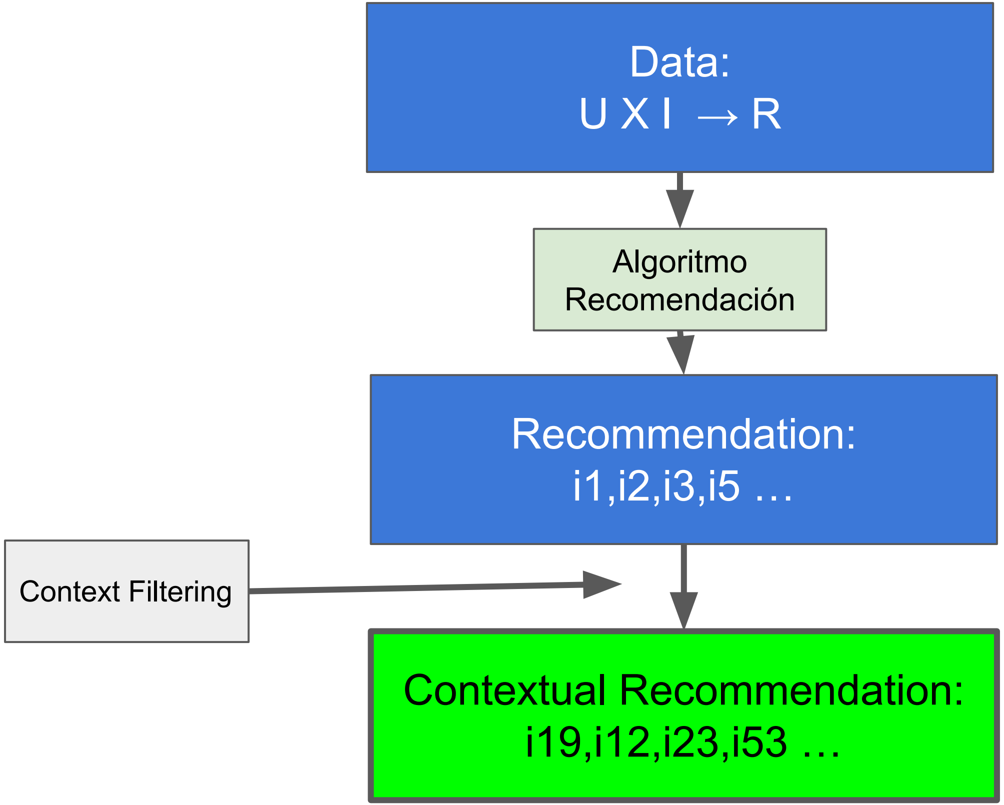
Contextual pre-filtering



ERROR COMÚN:
ESCOGER UN CONTEXTO DEMASIADO ESPECÍFICO.

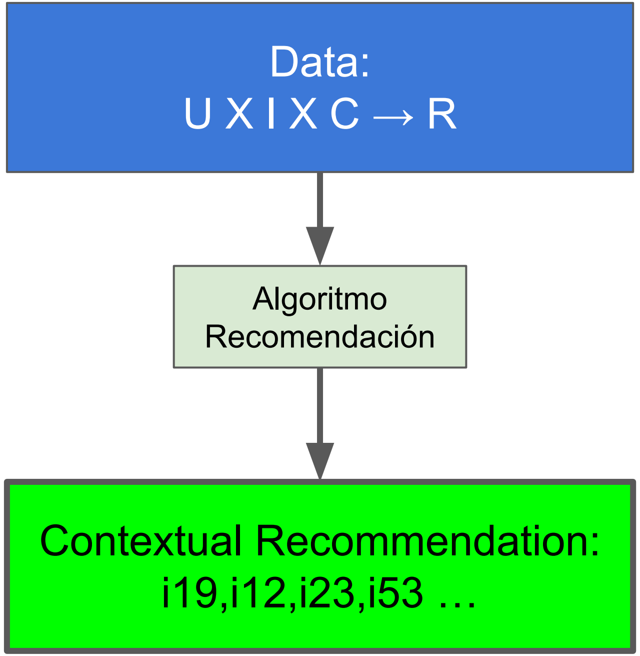
BUEN CONTEXTO:
- DIA / NOCHE
- INVIERNO
- LOCAL DE MACUL

Contextual post-filtering



IGNORAMOS EL CONTEXTO ANTES DE HACER LA RECOMENDACION

Contextual modeling



APRENDE VECTORES:

- USUARIO
- ITEM
- CONTEXTO

INCORPORA EL CONTEXTO EN EL MODELO

Deviation-based context-aware matrix factorization

¿Cuál es la desviación de los ratings?

Contextual rating deviation (CRD).

Ver la desviación del rating dados los distintos contextos.

Deviation-based context-aware matrix factorization

Context	Location	Time	Who
C1	Home	Weekend	Family
C2	Home	Weekend	Friend
C3	Home	Weekday	Family
C4	Home	Weekday	Friend
C5	Theater	Weekend	Family
C6	Theater	Weekend	Friend
C7	Theater	Weekday	Family
C8	Theater	Weekday	Friend

Deviation-based context-aware matrix factorization

Context	Location	Time	Who
C1	Home	Weekend	Family
C8	Theater	Weekday	Friend
CRD(Dim)	0.8	-0.2	0.1

Repite el mismo proceso para todos los pares de contextos…

Usuarios han dado

- +0.8 rating para contexto de Cine comparado con Hogar
- -0.2 rating menos para Dia de semana que para Fin de semana.
- +0.1 rating cuando ve la película con Amigos que con Familia

Deviation-based context-aware matrix factorization

Avg Rating

User-item interaction

$$r_{uic1,c2,....} = \mu + b_{\mu} + b_{i} + P_{U}^{T} q_{i} + \sum_{j=1}^{N} CRD(C_{j})$$

User Bias

Item Bias

Contextual Rating

Contextual Rating Deviation

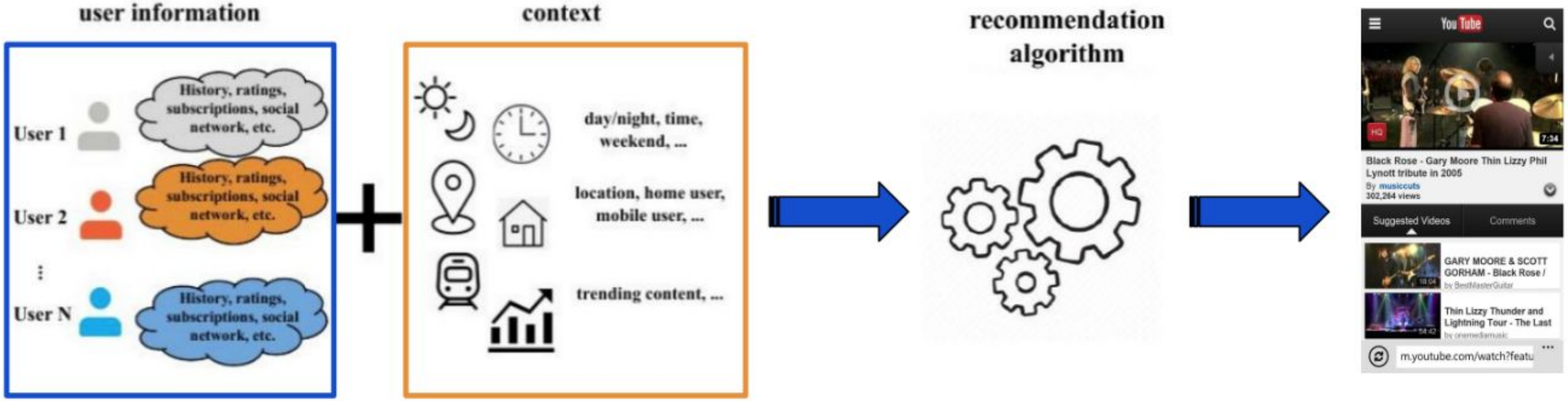
Towards QoS-Aware Recommendations

P. Sermpezis, S. Kastanakis, J. I. Pinheiro, F. Assis,
M. Nogueira, D. Menasche, T. Spyropoulos

FORTH
INSTITUTE OF COMPUTER SCIENCE

EURECOM
Sophia Antipolis

Context-aware Recommendation Systems



- Recommendations are based on:
  - user information: user interests, history, content/user similarity scores, etc.
  - context information: location, time, type of device, etc.

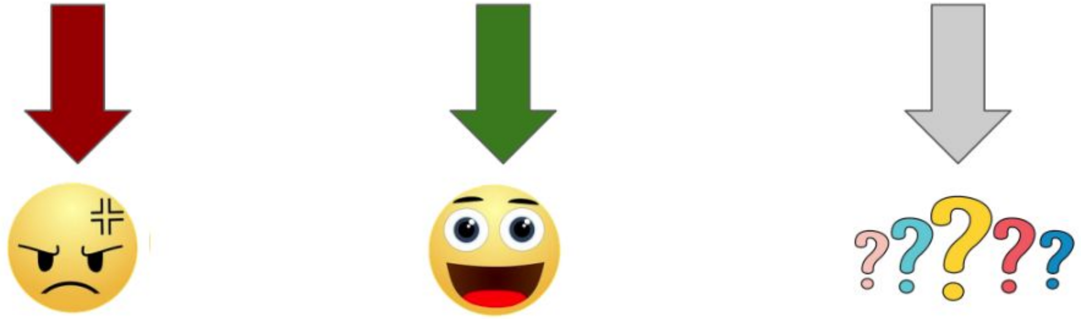
QoS as a dimension of Context

- The <u>quality of service (QoS)</u> may affect users' experience (QoE)
  - e.g., rebufferings → poor experience, abandon service
  - e.g., available video quality → affect user preferences
    "I'd like to watch a sports video... hmm, only available in 144p... let's pick a music clip..."

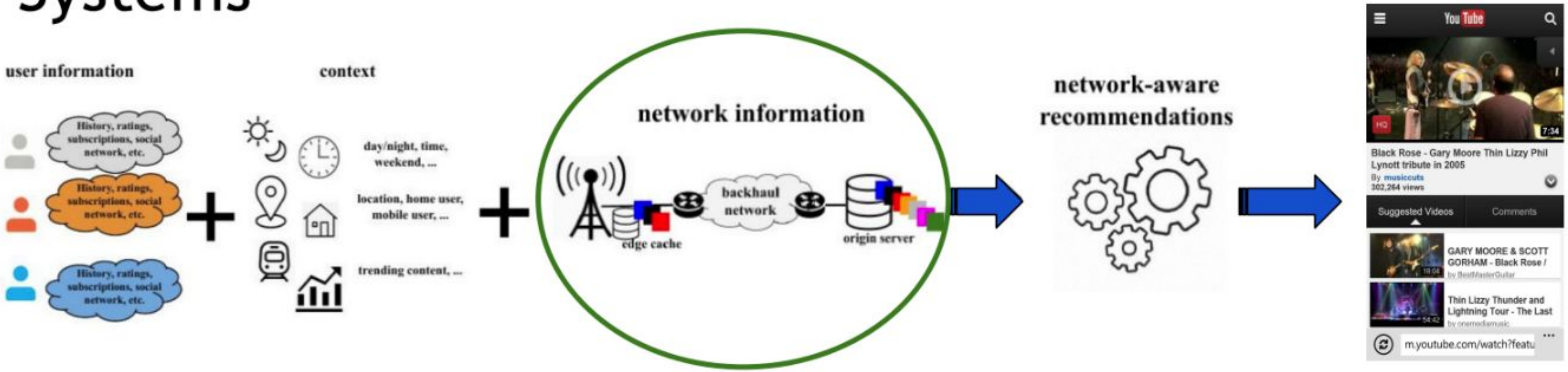
- RecSys for multimedia services are currently agnostic to the QoS !
  - QoS has not yet been considered a dimension of the "Context"

A simple example

Interest	★★★★★	★★★★★	★★☆☆☆
Quality of Service	★★☆☆☆	★★★★★	★★★★★



What we propose: QoS-aware Recommendation Systems



- Benefits from QoS-aware RS:
  - network performance ✓ *(tested in previous works)*
  - user experience ? *(not studied, only speculated)*

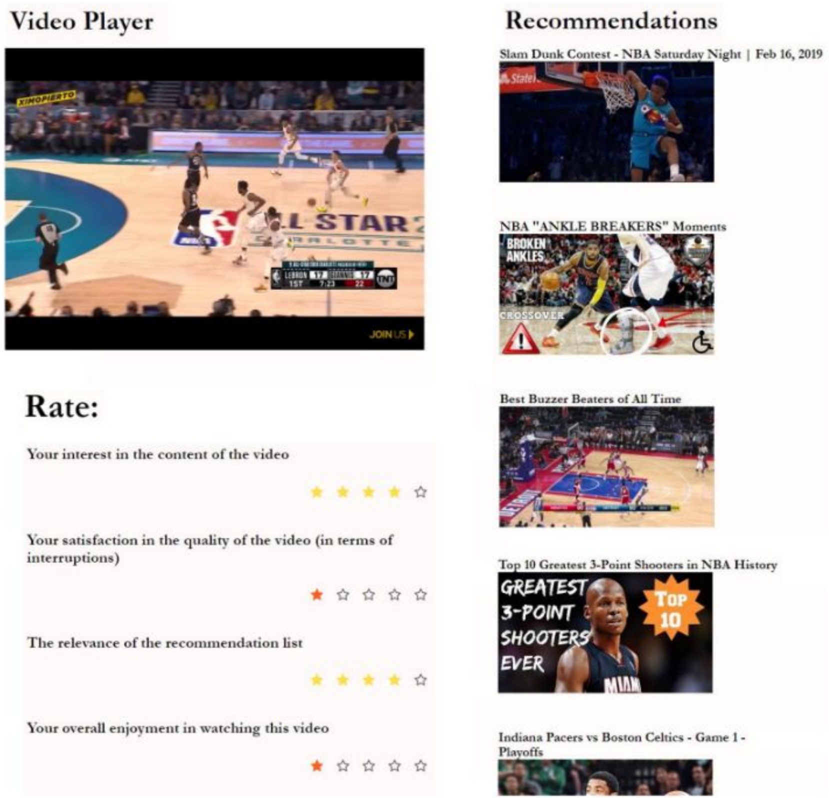
Goals & Contributions

- **Goal:** provide initial experimental results for the feasibility and design of QoS-aware RSs
    - *"Will users follow QoS-aware recommendations?"*
    - *"Do QoS-aware recommendations improve the user experience? how much?"*
    - *"What is more important: the user <u>interest</u> in a video, or the video <u>QoS</u>?"*

- **Contributions:**
    - Experimental platform (video service, QoS impairments, QoS-aware RS)
    - Experiments with users, data collection, analysis of results → provide initial answers
    - Model QoE as a function of user interest and QoS

Experiments

- Video Player (YouTube API)
  - high QoS videos
  - low QoS videos
- Recommendation List (YouTube API)
  - QoS-aware recommendations
  - Original YouTube recommendations
- Ratings
  - ***Interest***: user interest in watched video
  - ***QoS***: quality of the video
  - ***QoR***: relevance of recommendations
  - ***QoE***: overall experience



Take-home Message

- What we did:
  - QoS as context → QoS-aware recommendations
  - Real user experiments → evidence for QoS-aware RS feasibility & effect on QoE
  - Model QoE as a function of *user interest* and *QoS*
- Key findings:
  - Users are willing to follow QoS-aware recommendations
  - QoS-aware RSs bring a positive impact on user satisfaction and engagement
  - QoS should be considered a context dimension, when designing RSs
- Future work:
  - Initial results are promising → more research is needed
  - We want your feedback! (we're mainly computer networking researchers)

Contextual Personalized Re-Ranking of Music Recommendations through Audio Features

B. Gong, M. Kaya, N. Tintarev

25-09-2020

TUDelft

Context-Aware Recommender Systems Workshop at RecSys '20

Research Questions (RQs)

1. How are *contextual conditions* of different contextual dimensions related to *audio features*?

2. How does *re-ranking*, based on audio feature representations of user preferences in different contextual conditions, affect music *recommendation accuracy*?

3. How do *global* audio feature representations of user preferences in different contextual conditions affect the re-ranking results compared to *personalized* audio feature representations of user preferences in the same contextual condition (time of day)?

Answering RQ 1

"How are contextual conditions of different contextual dimensions related to audio features?"

- Significantly correlated
- Some positively, some negatively
- Audio feature and contextual condition specific
- Audio feature *key* not suitable, *liveness* weakly suitable

Global & Personalized Audio Features Based Contextual Preference Models

- User preferences in contextual conditions
    - {energy … accousticness}
    - *morning* = {0.4 … 0.7}, *afternoon* = {0.8 … 0.3}
- Global model
    - All users' ratings for a given condition
    - Meeting attendees: *morning* = {0.4 … 0.7}
- Personalized model
    - Individual user's ratings for a given condition
    - Person A: *morning* = {0.8 … 0.7}
    - Person B: *morning* = {0.2 … 0.9}
    - Person C: *morning* = {0.2 … 0.5}

Re-ranking Score Calculation

- Euclidean distance based similarity
  - {energy, liveness, accousticness}
  - *morning* = {0.4, 0.2, 0.8}
  - Mozart = {0.2, 0, 0.95} | DJ Tiësto= {0.7, 0.9, 0.2}
  - $Sim(\vec{s_j}, G\vec{M}_{c_k}) = 1 - d(\vec{s_j}, G\vec{M}_{c_k})'$
  - Similarity to *morning*: 0.68 | 0.03
- Songs re-ranked according to their new score
  - $new\_score = \lambda * Sim(\vec{s_j}, G\vec{M}_{c_k}) + (1 - \lambda) * Rec(u, s_j, c_k)'$
- Opposite re-ranking score
  - $opposite\_score = \lambda * d(\vec{s_j}, G\vec{M}_{c_k})' + (1 - \lambda) * Rec(u, s_j, c_k)'$

Answering RQ 2

"How does *re-ranking*, based on audio feature representations of user preferences in different contextual conditions, affect music *recommendation accuracy*?"

- It can increase accuracy
  - Case specific configuration
  - Initial recommender algorithm, contextual conditions, λ etc.
- Positive songs ranked higher within top *n* songs
- Opposite re-ranking results further support

Answering RQ 3

"How do *global* audio feature representations of user preferences in different contextual conditions affect the re-ranking results compared to *personalized* audio feature representations of user preferences in the same contextual condition (time of day)?"

- Personalized models consistently outperform global models
- Individual preference models are more accurate models
- Users have different preferences for different conditions
- Computationally more expensive, but justified

Conclusion

- Significant correlation between user preferences of certain audio features and varying contextual conditions
- Vectors of audio features representing user preferences in contextual conditions
- Re-ranking using similarity scoring yields promising results
- Personalized models consistently outperform global models
- Straightforward, explainable contextual re-ranking algorithm to recommend suitable songs to users in specific contextual conditions