Examples of recommendation systems ?

What can be recommended?





How recommender systems arrived on the internet





From the street shop to the on-line shop From the material content to the digital content

Storage, shipping, duplication, costs (shops and items) have evolved, helping make large catalogues available

















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Properties of large catalogues



number of products



Margin is higher on rare items (less competition) Bonus of one-stop shopping Nice to have a large catalogue (sub-contracted ?) But need to be able to exploit it (otherwise the long train might not be beneficial)



Fig : Yin et al. PVLDB 2012 (long trail)

Large catalogue => hard to exploit to sales because querying and browsing are not so easy

Experiments show you to can make the demand much higher by adding recommendation to browsing and querying





With a good recommender system

3 approaches to content selection example : Amazon



Catalogue d'objets introuvables



Capitaine Tempête : Souvenirs

Le catalogue des objets disparus

Meurtres pour mémoire

Le coupeur de mots



Catalogue = a search space

for most user knowledge

Serendipity :

- interesting content
- that would not been found easily

Ability to jump to areas hard to reach spontaneously by querying/browsing : this is one of the goals of recommendation





- Querying, browsing (generalization) : they enable exploring the space, but most corners remain hard to reach
- is a goal, a property (not a method) consisting in finding :



From the on-line shop to the intermediation platform



The catalogue becomes even larger And plateforms can share providers :



of the search tool (including recommendation)

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The value of the portal is the catalogue AND the power

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Network effects on platforms



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cost for producer



The platform is a two-sided market (an economics concept) (providers, consumers) with cross-side network effects

ex. Uber, Airbnb, Youtube : + more consumers => better for providers + more providers => better for consumers making links = their business model !

Difficult to start a business (chicken and egg start), hence huge existing systems.

Free of charge for one side helps create dynamics on this side. Either one or the other side has to pay for the platform, sometimes both.

Recommender systems are often used for helping establish the link between customer and content from an external content provider, i.e. they operate on a plateform.

The recommender system is a core tool for building the quality of a platform UNIVERSITE DE NANTES



Stakeholders

Who does Spotify serve ?

- End-users ?
- Singers ?
- Spotify ?

Optimizing recommendation is optimization a function involving all 3





Crowdsourcing, description, evaluation





A society of data crowdsourcing and « digital labor »

- recommender systems rely massively on content provided by the crowd of users, who « collaborate » to create a corpus that benefits to « all » fourniture de contenus à recommander
- Users provide:
 - content (stuff for others to read, view, buy,...)
 - meta-data over their content and other people's content (eg film topics) Evaluations feed computation of reputation of everything on the plateform
 - - of content
 - of people (peers)



A society of data crowdsourcing and « digital labor »

- Plateforms present themselves as a community of peers+content that cooperate, to hide a centralized+commercial control and goals and favour free work by users
- They provide incentives (non financial) :
 - offer social visibility (better than IRL) to people, contents, opinion
 - social recognition of expertise and taste
 - provide everyone with numerical indicators of social position
 - privileged access to rights, content, jobs,....
- Sometimes digital labor is a real job, poorly paid as micro-tasks controlled by automata. LA MÉTHODE SCIENTIFIQUE par Nicolas Martin DU LUNDI AU VENDREDI DE 16H00 À 17H00

Listen to : (france culture)





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S'ABONNER

Digital Labor : tout clic mérite-t-il salaire ? 13/11/2019

Crowdsourcing

- Is also a scientific topic about modelling, algorithms, maths, economics.
- How to recruit and retain contributors ?
- How to design and compute incentives ?
 - evaluate quality of contributors and contributions
 - evaluation by peers, combined with
 - automated statistical analysis
 - how to combine contributions ?
 - need to aggregate evaluations and to take contributor reputation into account in this process
 - this is a joint problem that needs to be solved iteratively



Tagging is categorization but categories may overlap (multiple tags)

Simple Man-Machine Interaction :

- values but no attributes (even implicit)
- values from open vocabulary (often)
- requires little user competence
- puts little constraints on user
- -> incentive for tagging
- -> suitable for crowdsourced tagging
- Tagging your own items
- Tagging existing items

-> incentive = creators are motivated to tag their content well so that it gets retrieved by other people

Tags



Tagging

- Ecomarathon Eurospeedway Lausitz •
- Germany · Europe · 2010 · Polytech' Nantes ·
- Polyjoule prototype





Such a vocabulary (:=folksonomy) can be unstable Mercedesse

- bad for matching
- but good for including new concepts with no central control
- overall, people tend to tag using popular tags (« rich get richer »)

Tags

Ecomarathon • Eurospeedway Lausitz

Germany • Europe • 2010 • Polytech' Nantes Polyjoule • prototype

Tags given by user U2



Camion mecede 809 **Enjoliveur mercedez** Interieur cuir noir mescedes 190 **MERCEDEE E 320 avangarde**



Co-occurrence statistical analysis from tagged items

Goal : find pseudo-semantic relations between tags, by computing statistical co-occurrences.

Ex. : Polytech and Polyjoule frequently present together on Flickr

Ex. : When tag scipy on Stackoverflow, python also present 90% of time but when *python* is present, *scipy* present only 12% of time = scipy is a subpart of python (scipy is a famous python package)

These statistics are more reliable if there are few tags used many times rather than many tags used once => Use these findings for query expansion



- further possibility : consider who tags in the analysis 18

Analyze the (temporal) dynamics of tags

Goal: identify short events (vs. more stable entities)

ex. GreenCodingChallenge in Nantes with #GCLChallenge

highly active during 3 days

can also find relation to (GPS-like) geolocation, if available.









25m

JTNantes-INFO @IUTNantes_INFO #GCLChallenge @IUTNantes avec un peu de @CentraleNantes

IUTNantes-INFO @IUTNantes_INFO #GCLChallenge @IUTNantes

27m



Re-introducing some control over the vocabulary To further stabilize the vocabulary systems may suggest tags (ex. Amazon, Stackoverflow)

Mots-clés inspirés de produits similaires (De quoi s'agit-II ?)

and a state for a second fit as a second

Soyez le premier à ajouter un mot-clé pertinent (fortement associé à ce produit)

Cochez une des cases ou entrez vos propres mots-clés ci-dessous

🔲 jacques attali (10)	Crise (6)	<u>nul</u> (4)
attali (9)	escroquerie (6)	fumisterie (3)
dette publique (7)	dette (4)	
arnaque (6)	littérature de chiotte (4)	
Vos mots-clés :	Ajouter	
(Appuyer deux fois sur la touche	'T' pour accéder rapidement à la fené	être "Associer des mots-clés à ce

Avoid divergence of vocabulary : - You must use existing tag (stackoverflow when beginner) - your question is more likely to be answered if you tag according to common practice



Attempts

I tried to achieve the following by adding the code:

```
nt sum <- mtcars %>%
group_by(am, gear) %>%
summarise(n = n()) %>%
spread(key = am, value = n) %>%
mutate_each(funs(./rowSums(.)))
```

but it returns the following error:

Error: 'x' must be an array of at least two dimensions

Hence my question: how can I add extra columns with row percentage values in dplyr ?

Side points

- I would prefer blank values instead of NAs
- The table could be easily build with use of CrossTable in gmodels but I would like to stay in dplyr as I want to keep as many transformations as possible in one place

r aggregate dplyr frequency crosstab

share improve this question



Describing objects : automatically using external (web) resources for processing annotations (correcting + extending). Ex.: wikipedia



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La Citapelle-sur-Erdre est une commune française située dans le département de la Loire fr.wikipedia.org/wiki/La_Chapelle-sur-Erdre - En cache - Pages similaires

Cette ville est située à 13 km au nord de Nantes, à la confluence de l'Erdre, du

- Les communes limitrophes sont Nantes, Carquefou, Sucé-sur-Erdre, Grandchamps-
- des-Fontaines et Treillières.

Evaluating objects

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- Ratings (1,2,3,4,5), good/not good; ordering (« better than »)
- Text (algorithms for «sentiment analysis» on blogs/facebook posts/tweets/ amazon «book damaged vs. uninteresting»)
- Unary value (bought/read/like), the alternative does not necessarily mean *«bad»* but maybe *«no information»* (various possible interpretations : not seen, already bought elsewhere, ...)
- I agree, I don't agree (evaluating an evaluation)
- Agregate multiple contributions (tags, evaluations) considering reputation



