Music & the Internet
MUMT301

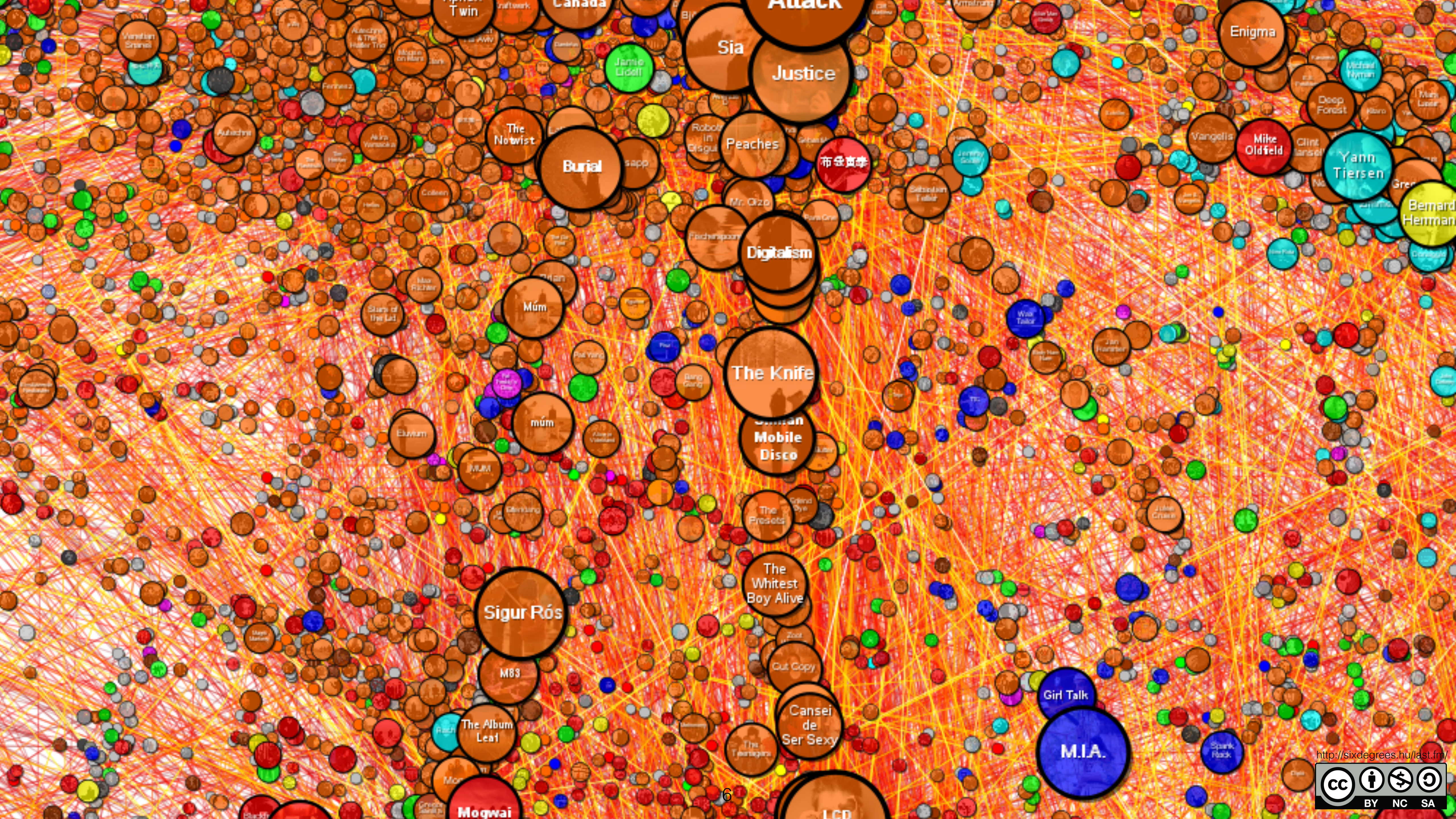
Gabriel Vigliensoni
Schulich School of Music
McGill University

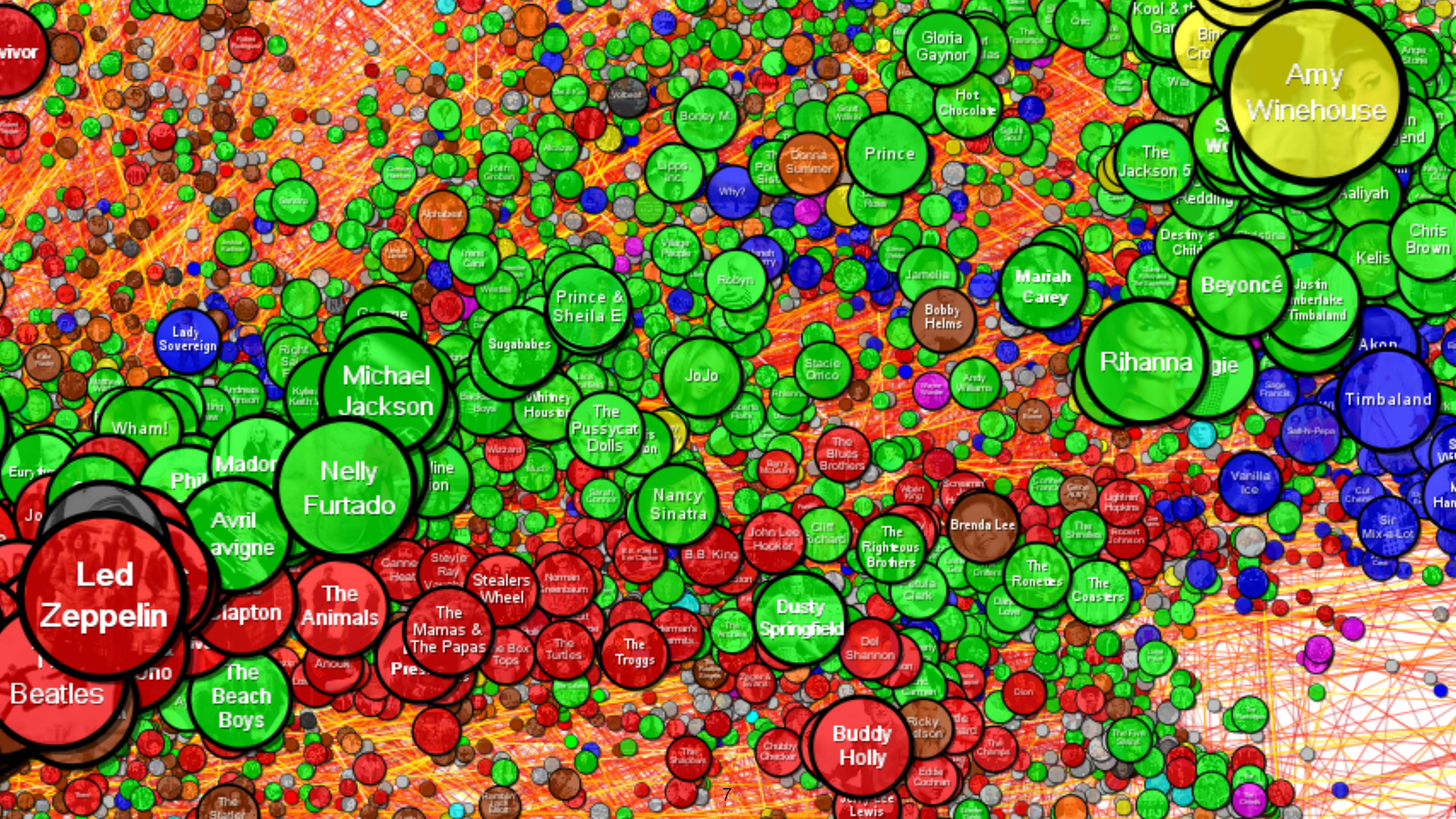
Plan

- Music recommendation systems
- Mid-term preparation
- DOM Model, JavaScript
- Potential final projects

Automatic **music recommendation** systems:
Do **demographic**, **profiling**, and **listening** context features improve their performance?

http://sixdegrees.hu/last.fm/


Twin
Canada
Attack
Sia
Justice
Enigma
Jamie Lidell
The Notwist
Burial
Peaches
Mr. Oizo
Digitalism
Múm
The Knife
Mobile Disco
múm
Sigur Rós
M83
The Whitest Boy Alive
Cut Copy
Cansei de Ser Sexy
The Album Leaf
Mogwai
Girl Talk
M.I.A.
Vangelis
Mike Oldfield
Yann Tiersen
Deep Forest


Amy Winehouse
Gloria Gaynor
Hot Chocolate
Boney M.
Prince
Donna Summer
The Jackson 5
Aaliyah
Chris Brown
Kelis
Beyoncé
Mariah Carey
Bobby Helms
Rihanna
Timbaland
Akon
Prince & Sheila E.
Robyn
Lady Sovereign
Michael Jackson
Sugababes
JoJo
Wham!
Whitney Houston
The Pussycat Dolls
Nelly Furtado
Avril Lavigne
Nancy Sinatra
The Blues Brothers
Vanilla Ice
Sir Mix-a-Lot
Brenda Lee
The Righteous Brothers
The Ronettes
The Coasters
Led Zeppelin
Beatles
The Beach Boys
The Animals
Stealers Wheel
The Mamas & The Papas
The Turtles
The Troggs
B.B. King
John Lee Hooker
Dusty Springfield
Del Shannon
Buddy Holly
Ricky Nelson
Eddie Cochran
Jerry Lee Lewis

Motivation

- To improve **recommendation accuracy** of automatic music recommendation systems

- By understanding what, **when**, and **where** people listens to music

- By characterizing people's **listening behaviour**

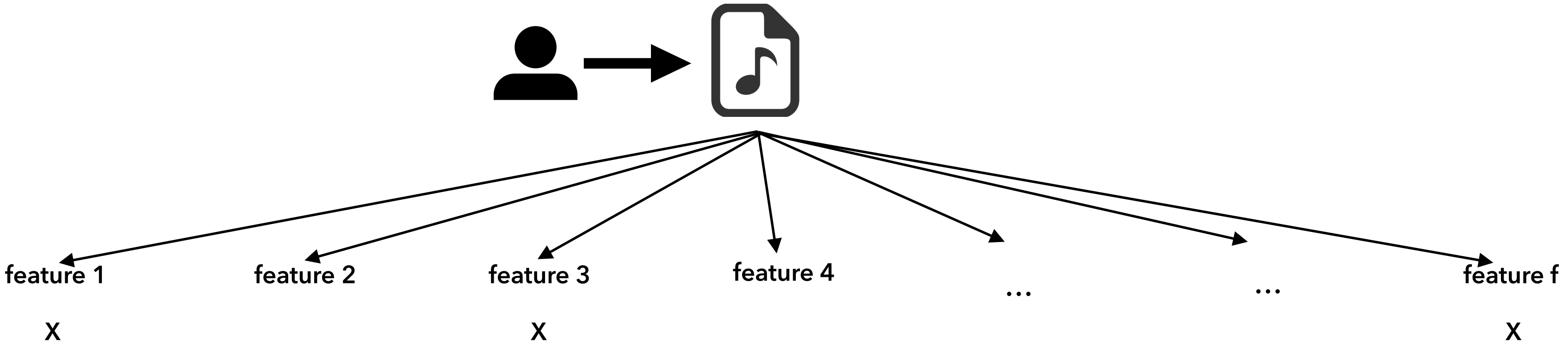
- Performing a **data-centric** instead of ethnocentric **music listening research**

Music recommendation approaches

- Content-based
- Collaborative filtering

Music recommendation approaches

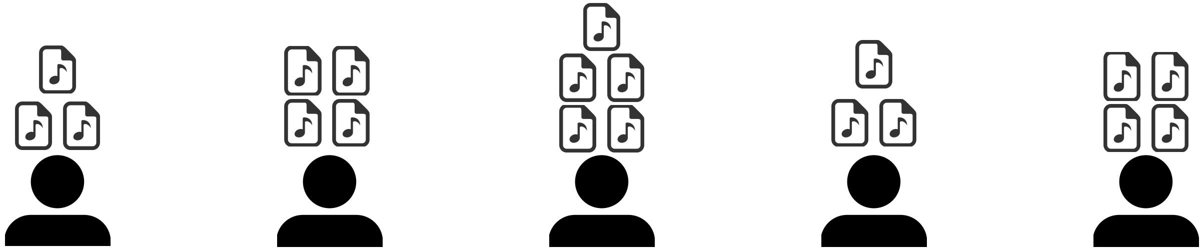
Content-based



	feature 1	feature 2	feature 3	feature 4	...	...	feature f
music item 1		X					X
music item 2	X	X			X		
music item 3		X			X		X
music item 4			X			X	
...				X			
...		X			X		
music item i	X		X				X

Music recommendation approaches

Collaborative filtering



user/artist	beatles	rolling	bsabbath	metallica	miles	coltrane	autechre	dpunk	reich	bartok
a	5	4			3	2	4		4	5
b	5	4		2				2	3	
c	4		3		3		5	4		
d	5			1	5	4				1
e	5				4		1		1	1

Music recommendation approaches

Collaborative filtering

User similarity

user/artist	beatles	rolling	bsabbath	metallica	miles	coltrane	autechre	dpunk	reich	bartok
a	5	4	3	3	3	2	4	3	4	5
b	5	4	2	2	5	3	3	2	3	2
c	4	4	3	1	3	3	5	4	5	3
d	5	4	2	1	5	4	3	2	2	1
e	5	3	2	1	4	3	1	1	1	1

Jaccard similarity
Intersection of sets

	a	b	c	d
b	0.33			
c	0.33	0.25		
d	0.50	0.25	0.25	
e	0.71	0.25	0.43	0.43

Cosine vector similarity
Angle of vectors in space

	a	b	c	d
b	0.99			
c	0.98	0.92		
d	0.82	0.98	0.99	
e	0.79	0.98	0.81	0.99

Pearson correlation
Distance of points in space

	a	b	c	d
b	0.93			
c	0.52	0.20		
d	-0.39	0.96	-0.51	
e	-0.06	1.00	-0.30	0.94

Music recommendation approaches

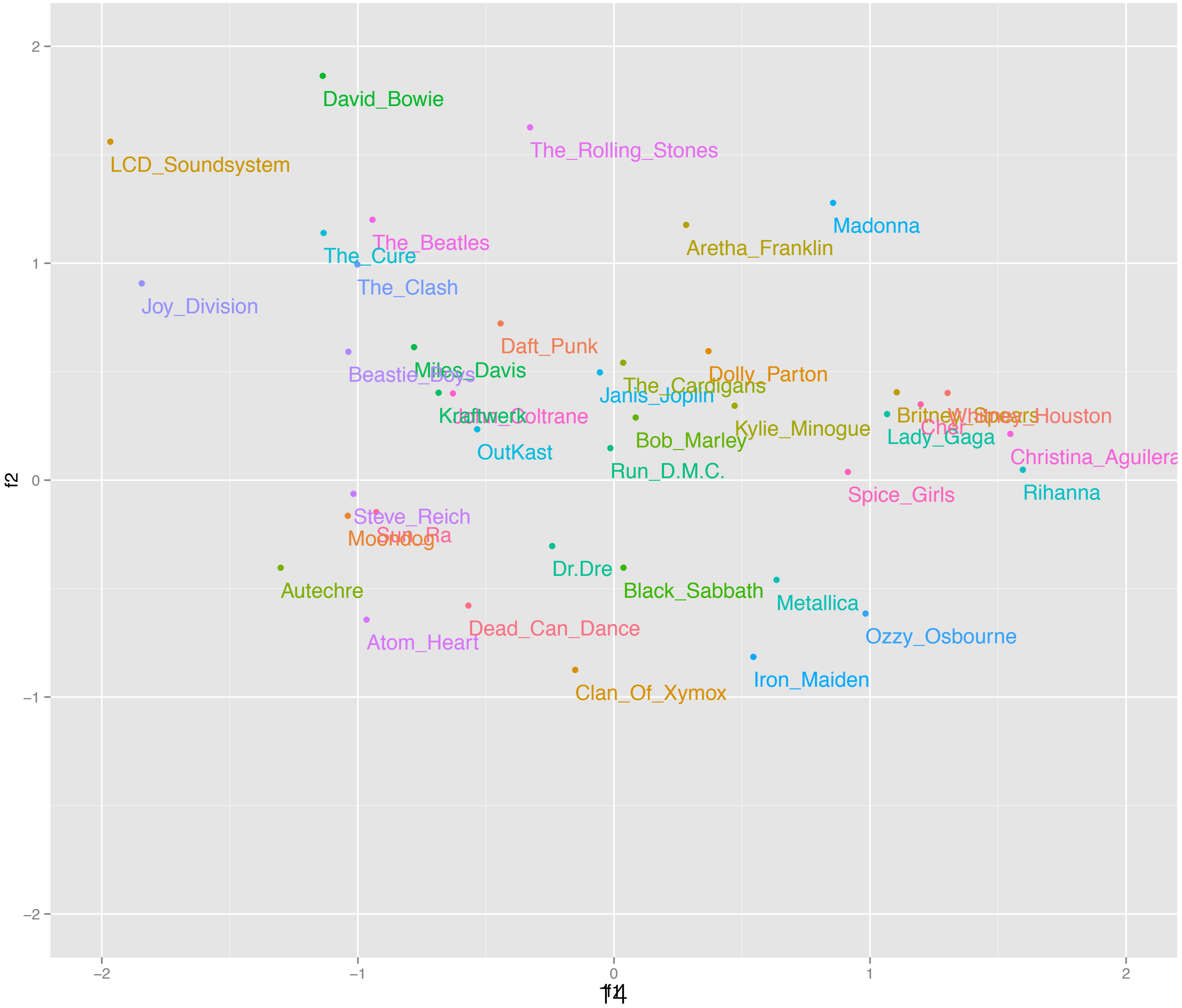
Collaborative filtering

Model-based

		factor 1	-0.188	-0.015	-0.006	0.069	-0.472	-0.353	0.238	0.078	0.168	0.481
		factor 2	-0.074	-0.001	-0.002	-0.014	-0.042	0.036	0.171	0.035	0.083	-0.186
factor 1	factor 2	**user/artist**	**beatles**	**rolling**	**bsabbath**	**metallica**	**miles**	**coltrane**	**autechre**	**dpunk**	**reich**	**bartok**
0.440	0.001	**a**	5	4	3	2	3	2	4	3	4	5
-0.009	-0.010	**b**	5	4	3	2	4	3	3	2	3	4
0.315	0.118	**c**	4	4	3	2	3	3	5	4	3	4
-0.634	0.115	**d**	5	4	3	1	5	4	3	3	2	1
-0.092	-0.229	**e**	5	3	2	1	4	3	1	2	1	1

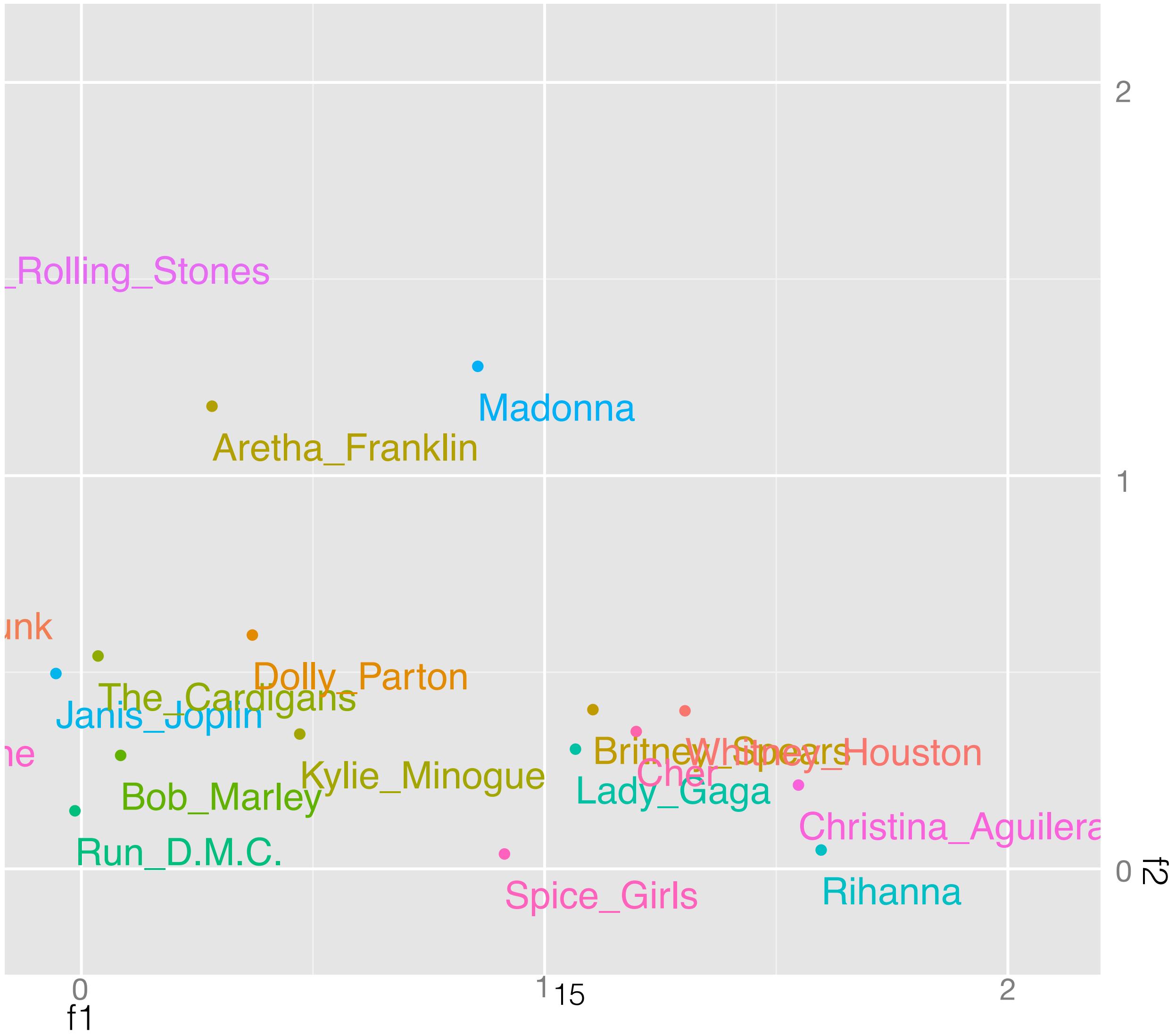
Music recommendation approaches

Latent factors models



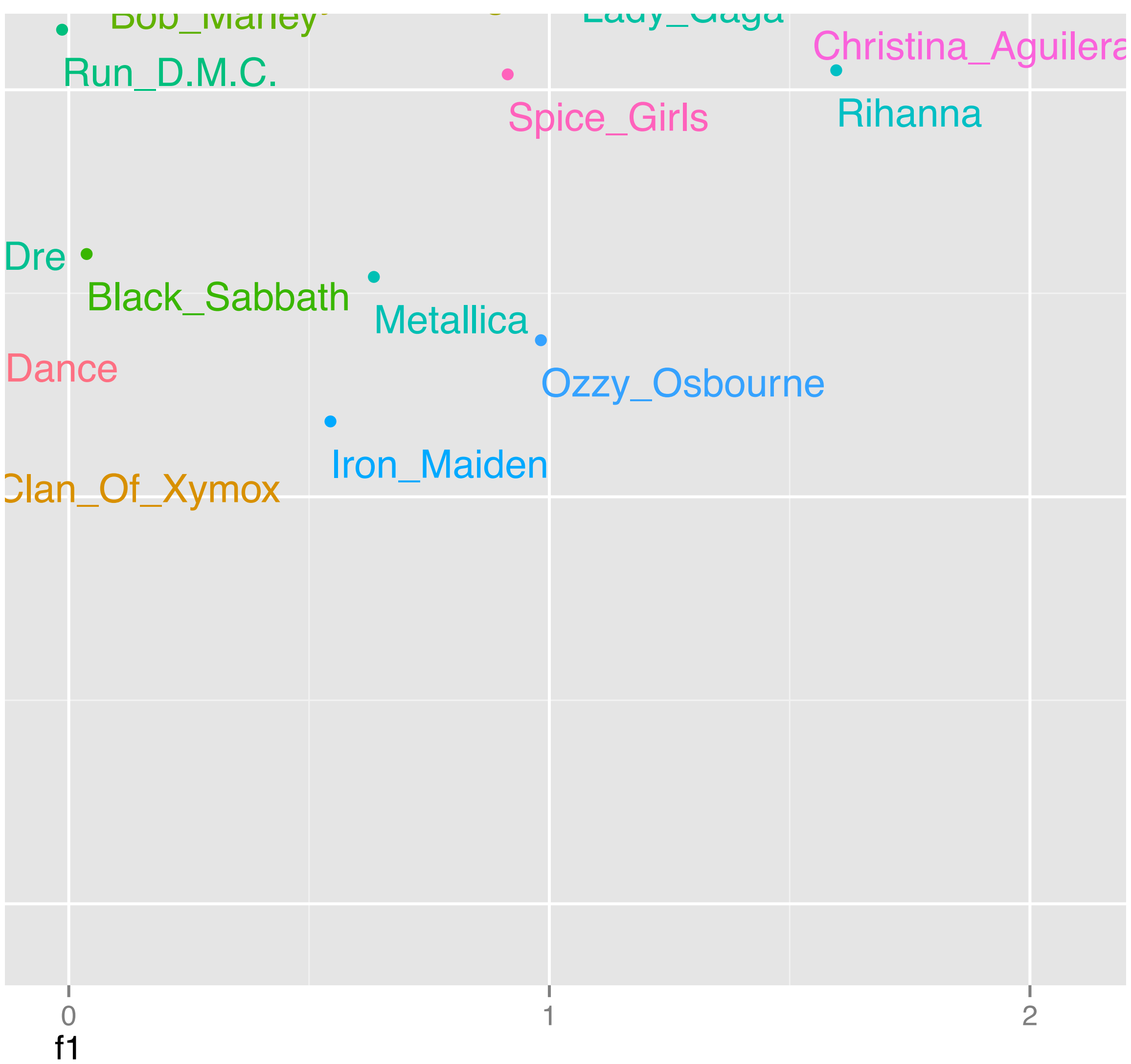
Music recommendation approaches

Latent factors models



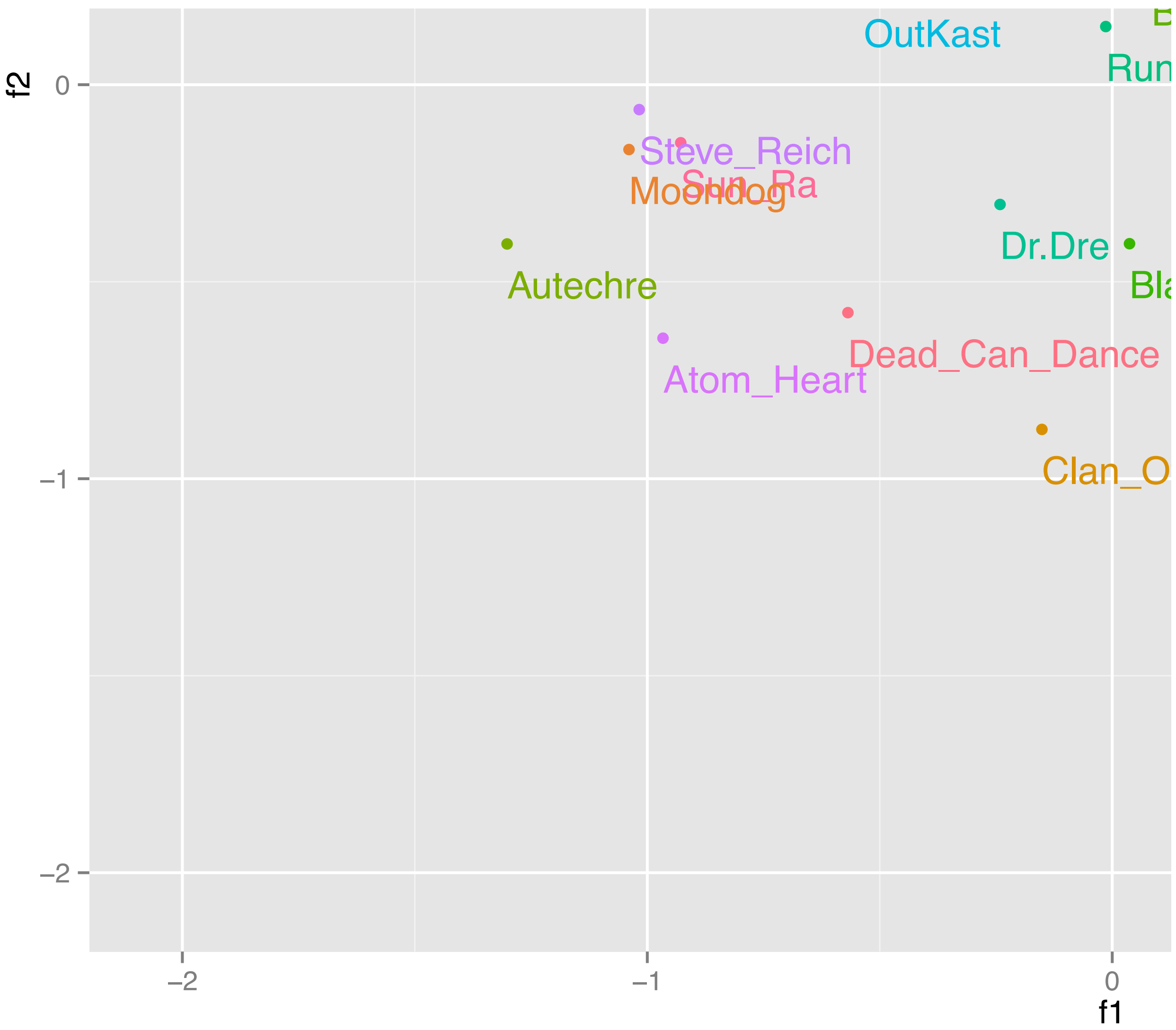
Music recommendation approaches

Latent factors models

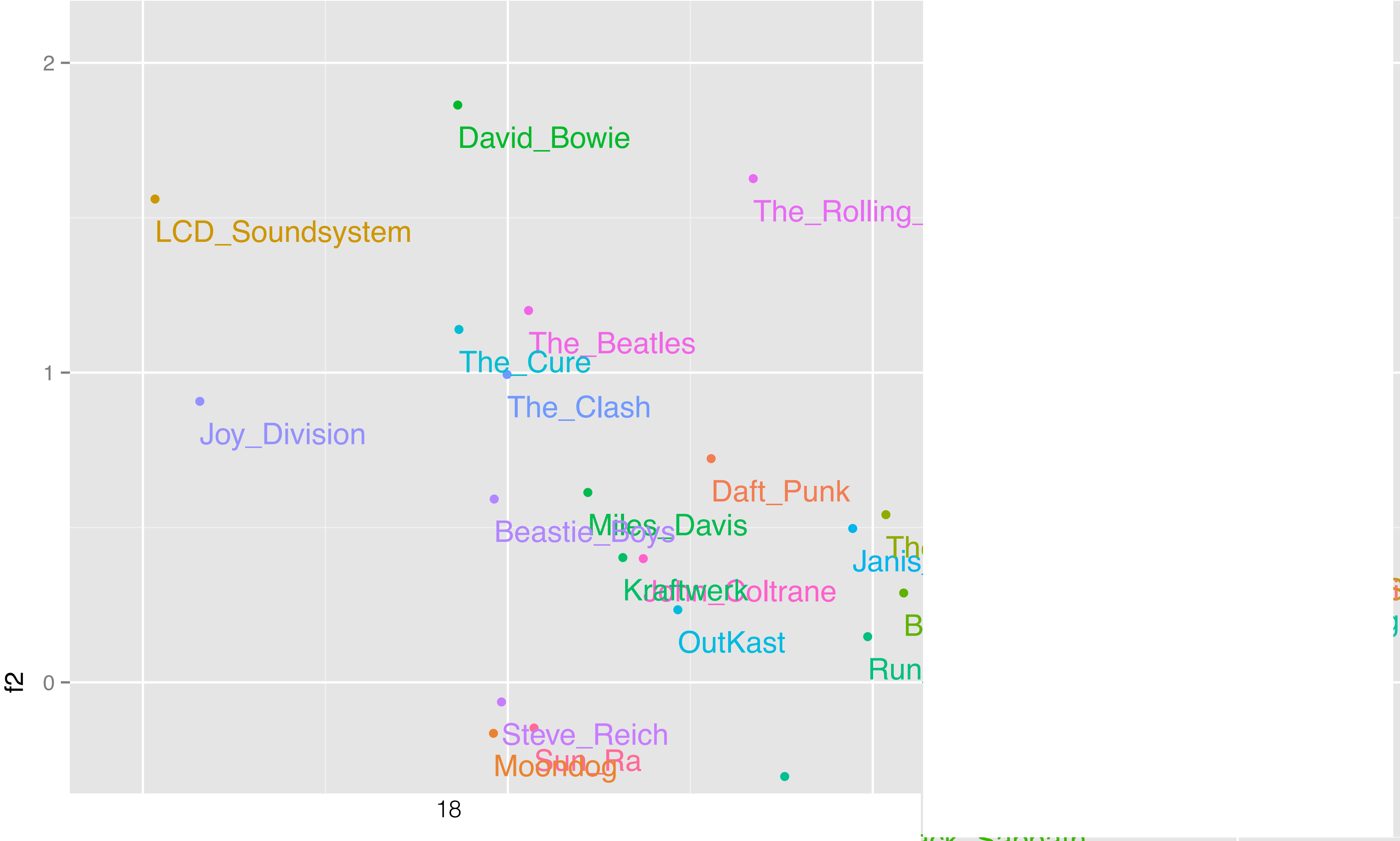


Music recommendation approaches

Latent factors models

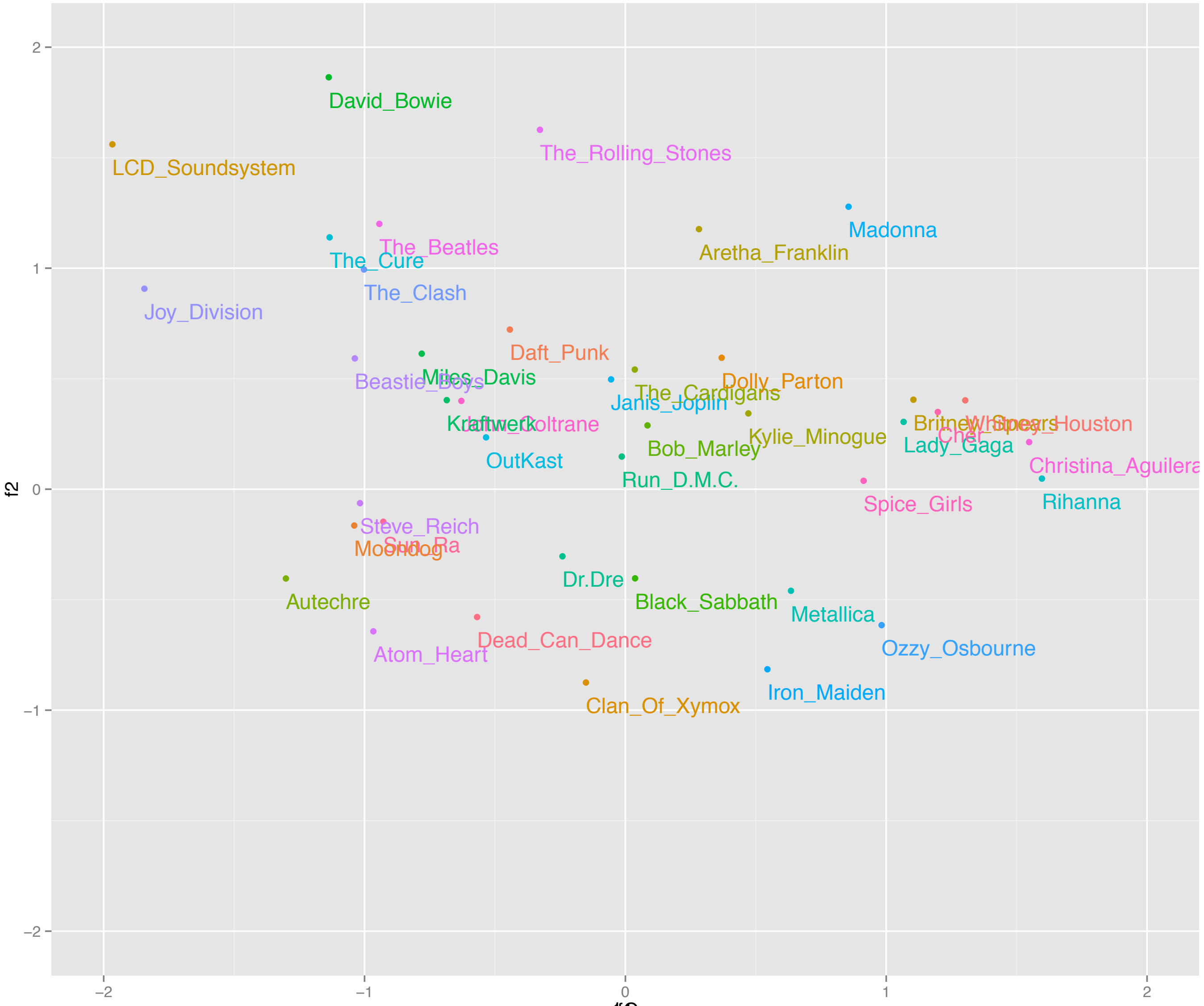


Music recommendation approaches
Latent factors models



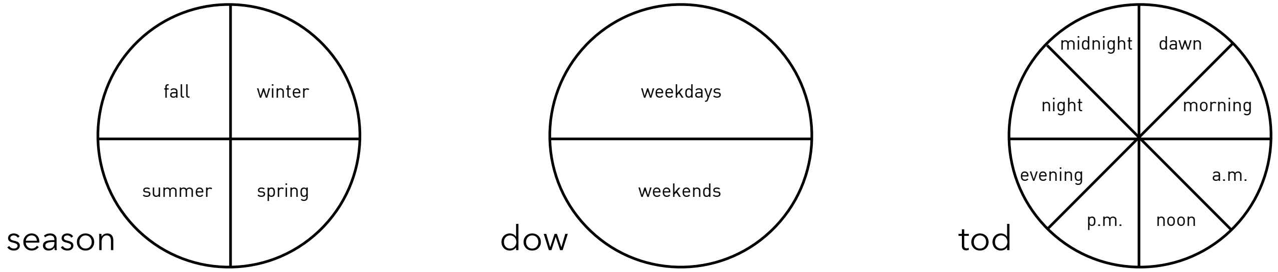
Music recommendation approaches

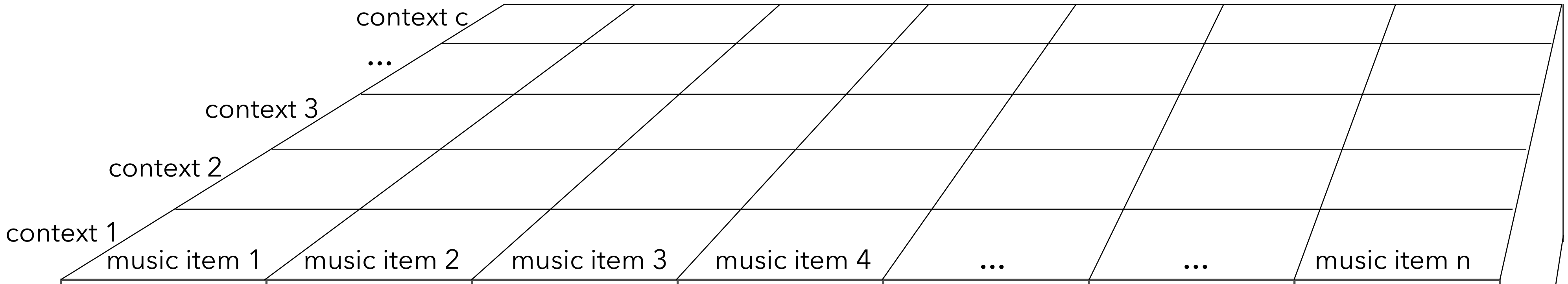
Latent factors models



Music recommendation approaches

Incorporating context into the model





	music item 1	music item 2	music item 3	music item 4	...	...	music item n
user 1		x					x
user 2	x	x			x		
user 3		x			x		x
user 4			x			x	
...				x			
...		x			x		
user m	x		x				x

Music recommendation approaches

Incorporating side features into the model

				factor1	-0.1250	-0.0758	0.2597	-0.4078	0.3469	0.4341	0.8519	0.5257	0.7062	-1.6830
				factor2	0.3663	0.2352	-0.1869	-0.3558	0.9251	0.8393	-0.8159	-1.2368	-0.8491	-0.0734
gender	**age**	**factor1**	**factor2**	**user/artist**	**beatles**	**rolling**	**bsabbath**	**metallica**	**miles**	**coltrane**	**autechre**	**dpunk**	**reich**	**bartok**
m	o	-0.7364	-0.5380	**a**	5	4	3	3	3	2	4	4	4	5
f	o	0.4071	0.3544	**b**	5	4	3	2	4	3	3	2	3	4
m	y	0.6459	-1.1424	**c**	4	3	3	1	3	2	5	4	5	1
m	y	0.8063	0.6618	**d**	5	4	3	1	5	4	4	2	4	1
f	y	-1.0800	0.7037	**e**	5	4	2	2	4	3	1	0	1	5
m	o	-0.0002	0.0000	**f**	5	4	2	2	4	3	4	3	4	4

side feature	value	factor 1	factor 2
age	o	-0.3872	-0.1737
age	y	0.1648	0.4031
gender	m	0.3986	-0.1552
gender	f	-0.3539	0.1451

Rendle, Steffen. "Factorization machines." In IEEE 10th International Conference on Data Mining, pp. 995-1000. 2010.

Research Project

- 1M listeners' listening histories
- Listening history > 2 years
- Average logs per day > 10
- LastFM API

UserID	age	country	gender
playcount	usertype	lifetime	registration time
timestamp	ArtistID	AlbumID	SongID

Listening histories

```
1215399979 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab d9b7388e-a155-436c-bdc1-ab0a12567980 230f484e-1d62-4405-8758-f2123864c358
1215399474 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab d9b7388e-a155-436c-bdc1-ab0a12567980 0771ae03-acb4-43ce-85c9-3602aabcd736
1215399033 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab d9b7388e-a155-436c-bdc1-ab0a12567980 0ae30644-0363-4d9d-bf52-2e49939c0fb1
1215398687 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab d9b7388e-a155-436c-bdc1-ab0a12567980 0c9a06d3-2614-4998-be91-c060aea7bd11
1215282573 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab e233c4ef-783f-3d1d-b024-dafd9076325b 00343efa-29e9-4fc2-91c9-d74e22c0fee4
1215282230 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab bcce51ff-7fae-4b4d-98f1-771f1c767f14 0366c477-0e8a-4612-8b69-cd73b120b1ec
1215281947 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab aef5108a-3dc0-3ba7-bfd7-dc95a3b186fe 01a9a99f-1567-4a06-991f-82605adb85b6
1215281672 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab aef5108a-3dc0-3ba7-bfd7-dc95a3b186fe 01b85e0a-4cd1-49fa-88c4-43ee48d97464
1215281225 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab fed37cfc-2a6d-4569-9ac0-501a7c7598eb 00c081da-b833-45db-8899-358ea0cc8509
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1215223742 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab fed37cfc-2a6d-4569-9ac0-501a7c7598eb c43d82d1-d998-45e7-9929-ab75e2188802
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1215222857 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab 05c4412c-002d-496a-9914-b6fdbc647992 59de2738-2d34-417f-be82-a5e7ae9f2b45
1215221262 b0fe8ef0-d59b-4d41-afee-2d21b59112ab 7007cf99-0f38-3838-bd73-3c7db5158311 620e6357-9a6f-4a16-901f-644ac72d98ea
1215221093
1215220625 a9044915-8be3-4c7e-b11f-9e2d2ea0a91e baf8b67c-7ca3-484f-ac5a-14c116b7e280 3d9a8a4b-3965-4ec3-873f-9bc117818ead
1215220357 a9044915-8be3-4c7e-b11f-9e2d2ea0a91e
1215220083
1215144740 b0fe8ef0-d59b-4d41-afee-2d21b59112ab 7007cf99-0f38-3838-bd73-3c7db5158311 620e6357-9a6f-4a16-901f-644ac72d98ea
1215139921 65f4f0c5-ef9e-490c-aee3-909e7ae6b2ab d9b7388e-a155-436c-bdc1-ab0a12567980 0771ae03-acb4-43ce-85c9-3602aabcd736
```

Dataset

Dataset	Listeners	Logs	Artists	Albums	Tracks	
	594K	27MM	555K	900K	7M	
Listener's	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Age (years)	0	21	24	25.4	27	113
Number of logs	7K	24K	37K	49K	60K	998K
Logs lifetime (days)	731	1192	1653	1721	2188	3929
Gender	Declared	Non-declared		Female	Male	
(%)	81.6	18.4		28.70	71.30	
User type	Alumni	Moderator	Staff	Subscriber	User	
(number and %)	70 (~0%)	21 (~0%)	33 (~0%)	14K (2.4%)	580K (97.6%)	

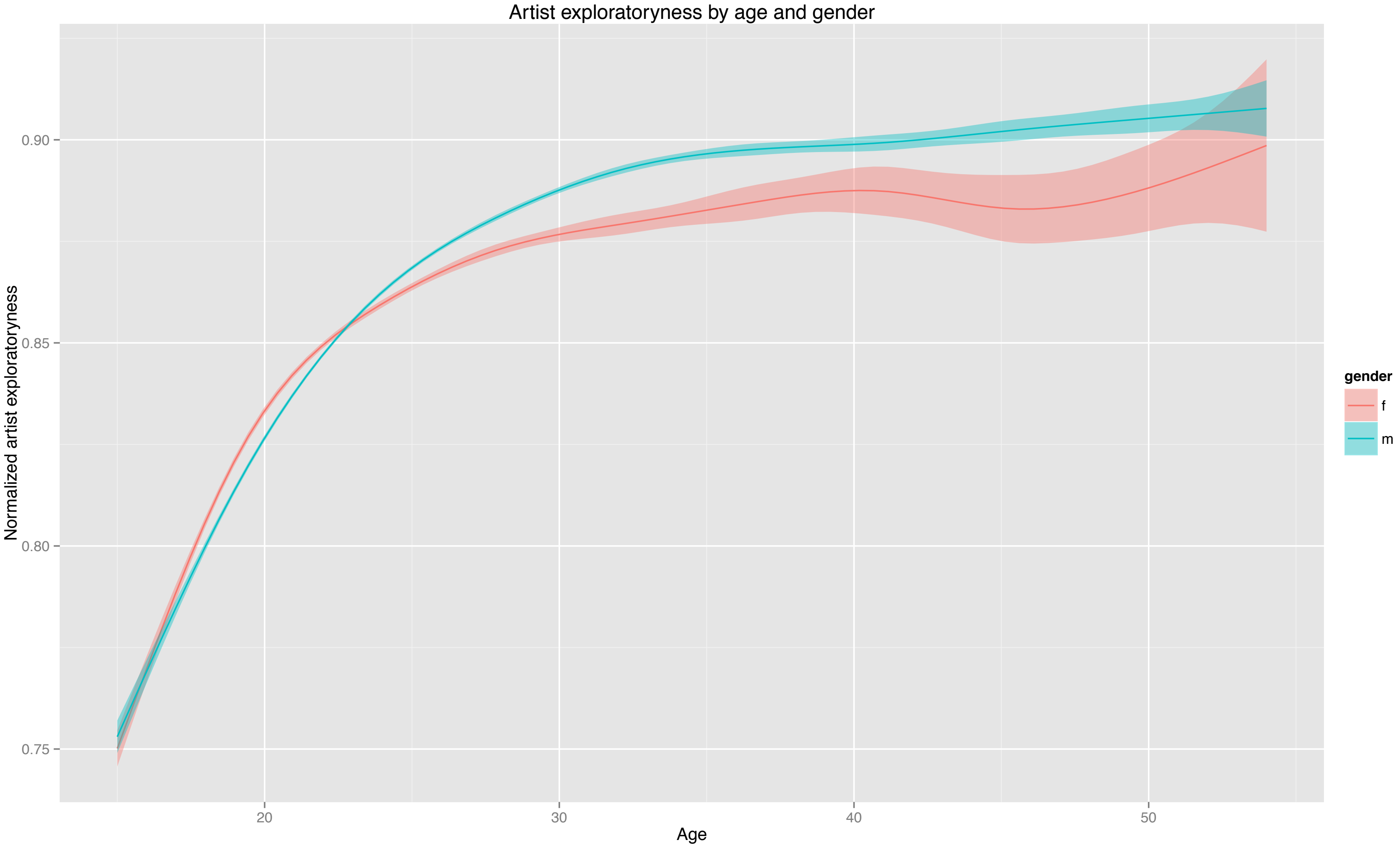
Profiling features

Exploratoryness

How much does a listener explore music?

Profiling features

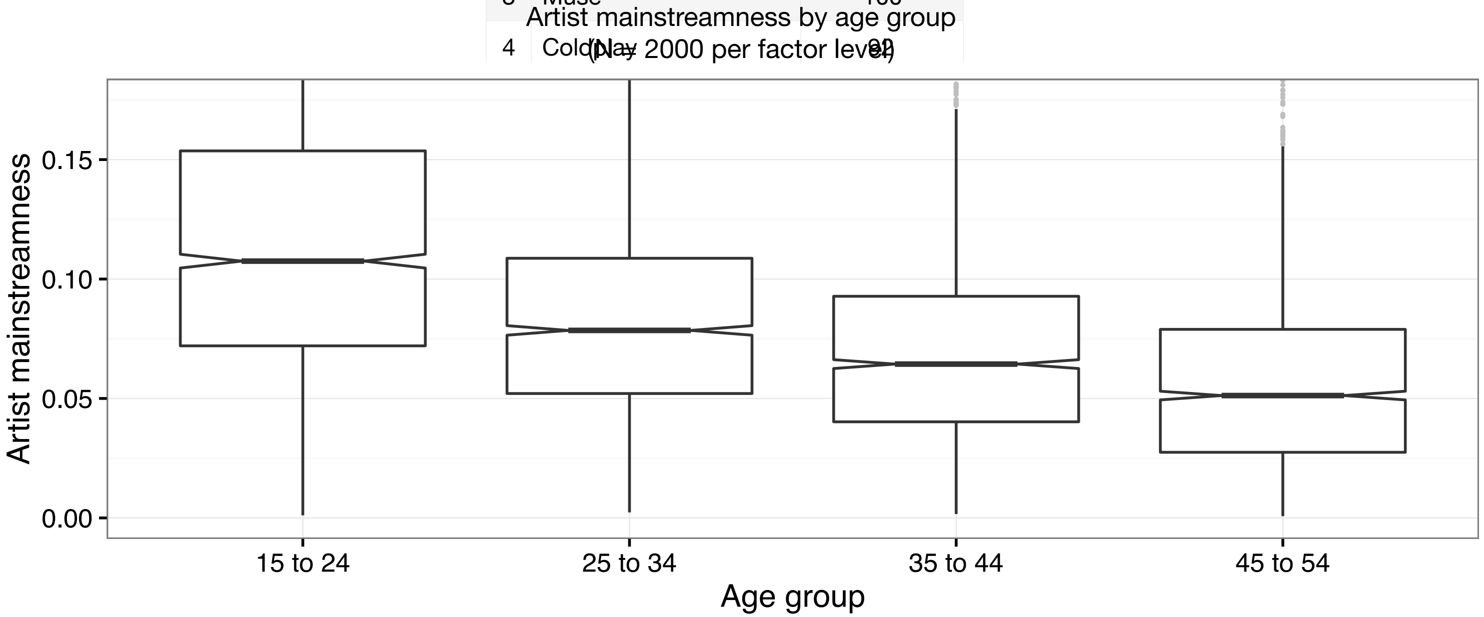
Exploratoryness



Profiling features

Mainstreamness

R	Artist Name	No Logs (M)
1	The Beatles	149
2	Radiohead	140
3	Muse	100
4	Coldplay	92
16	Foo Fighters	54
17	Daft Punk	52
18	Britney Spears	50
19	Green Day	50
20	Iron Maiden	50



Side data into recommendation model

Feature combinations

DEMOGRAPHIC
a: age group
g: gender
c: country

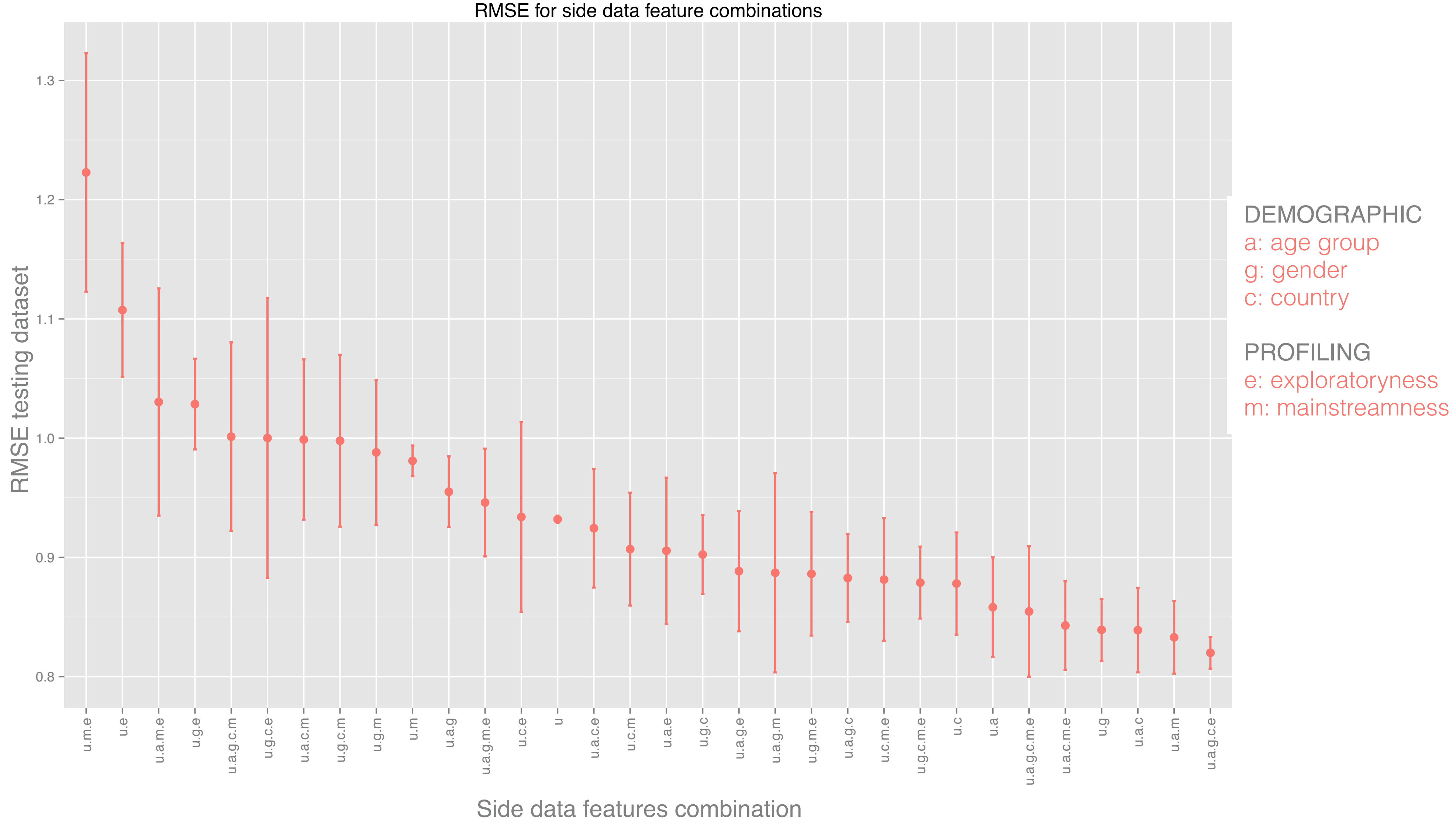
PROFILING
e: exploratoryness
m: mainstreamness

FEATURE COMBINATIONS

a
a,g
a,c
a,e
a,m
a,g,c
a,g,e
a,g,m
…
g
g,c
g,e
…
a,g,c,e,m

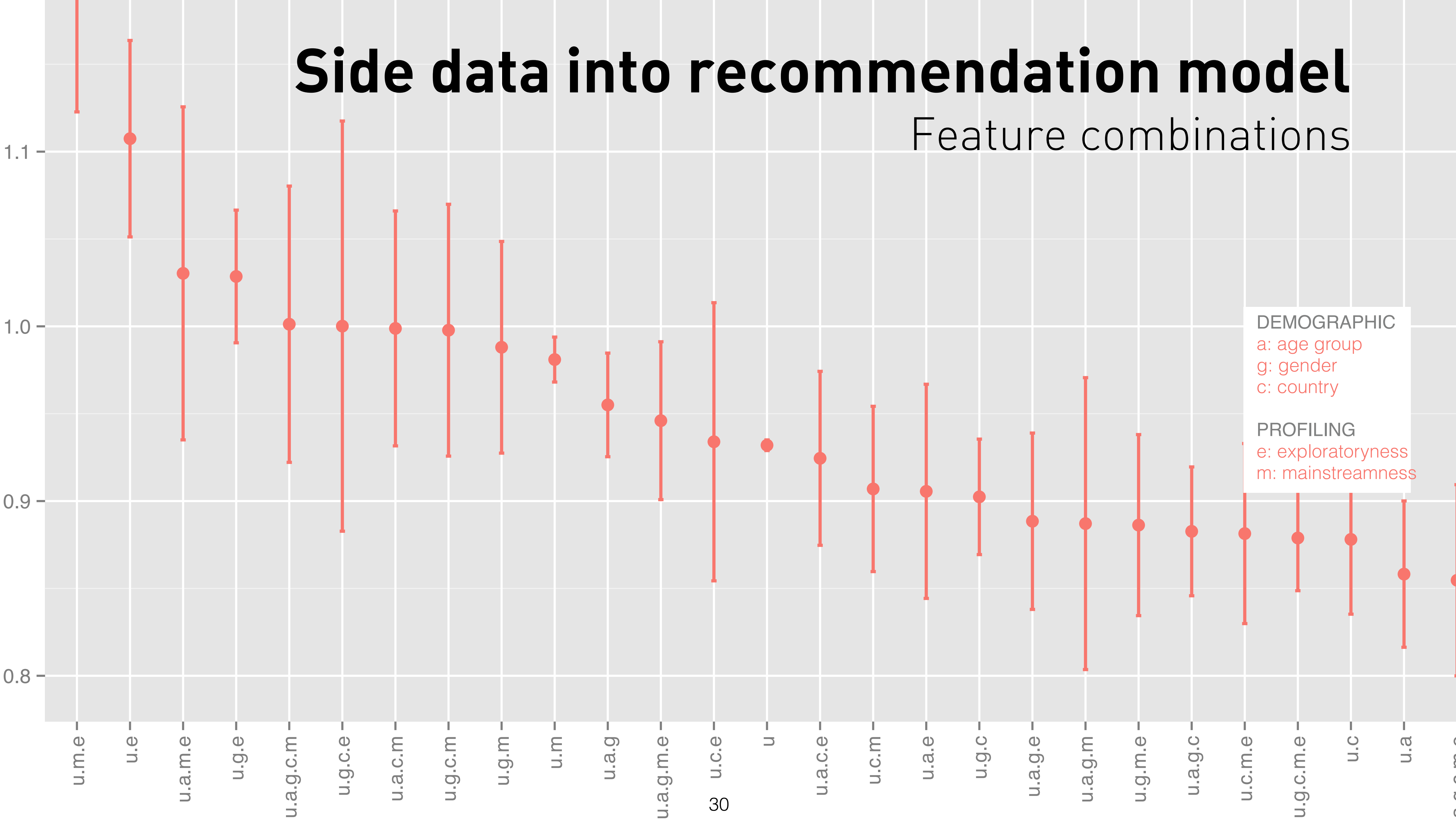
Side data into recommendation model

Feature combinations



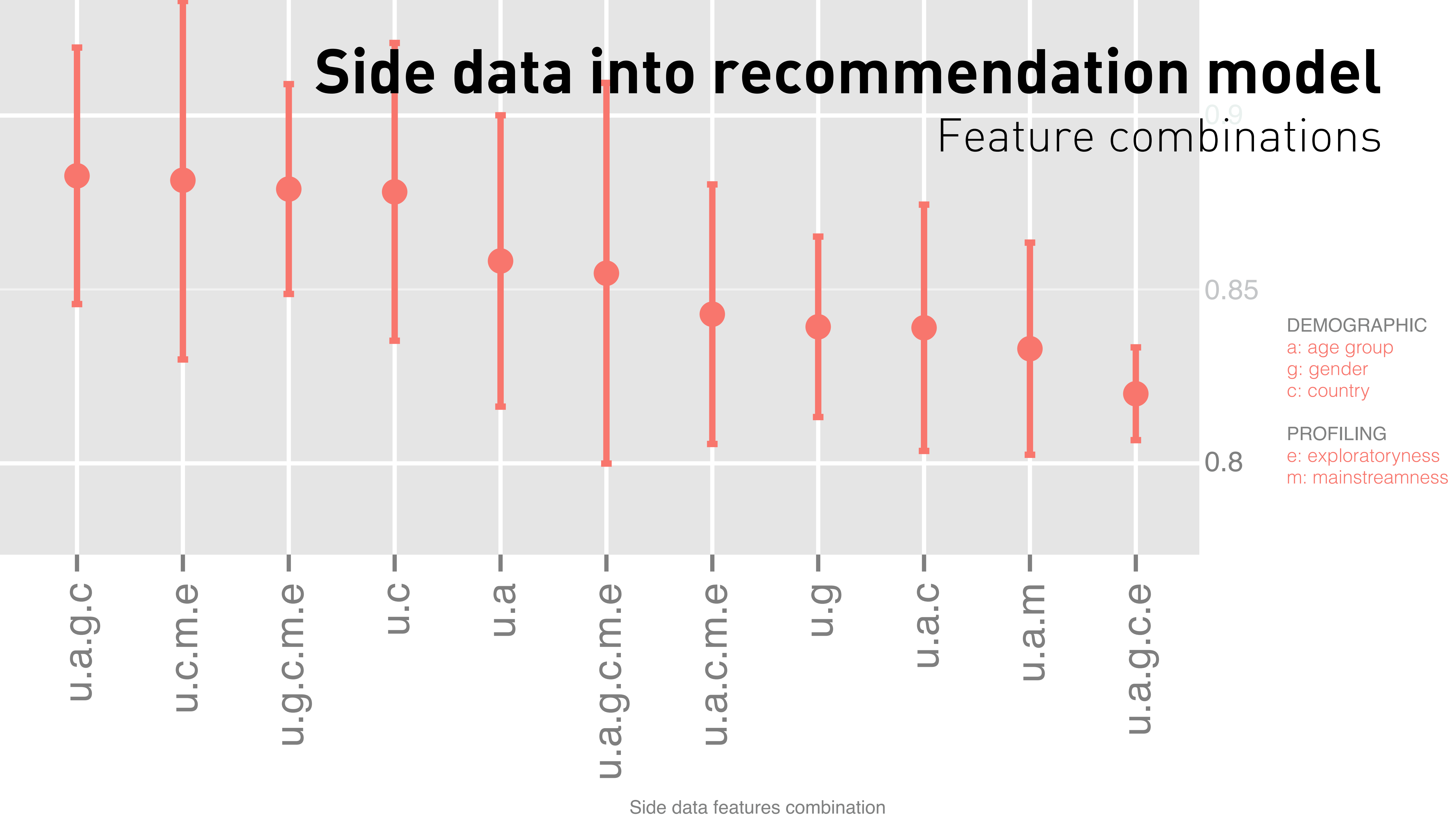
Side data into recommendation model

Feature combinations



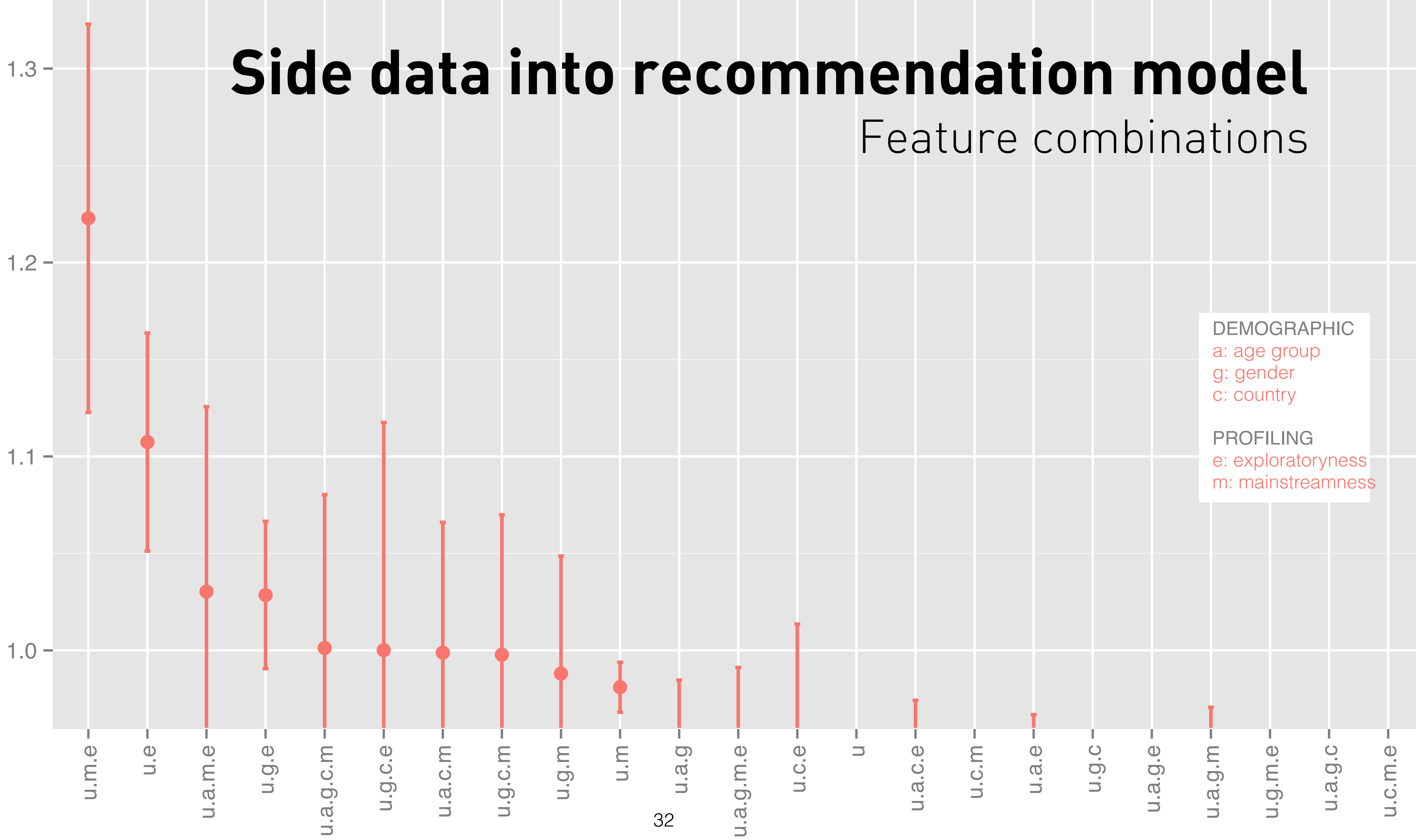
Side data into recommendation model

Feature combinations



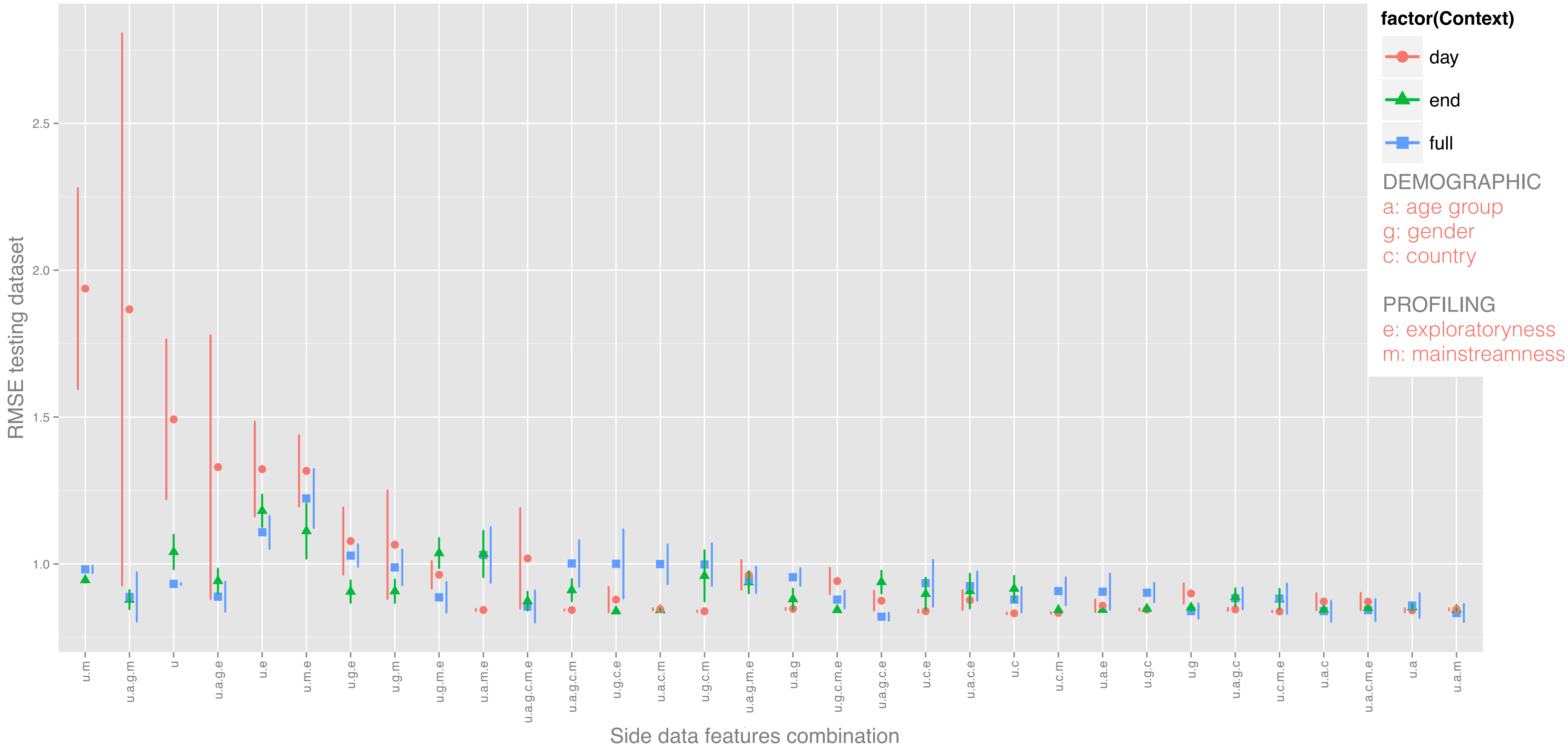
Side data into recommendation model

Feature combinations



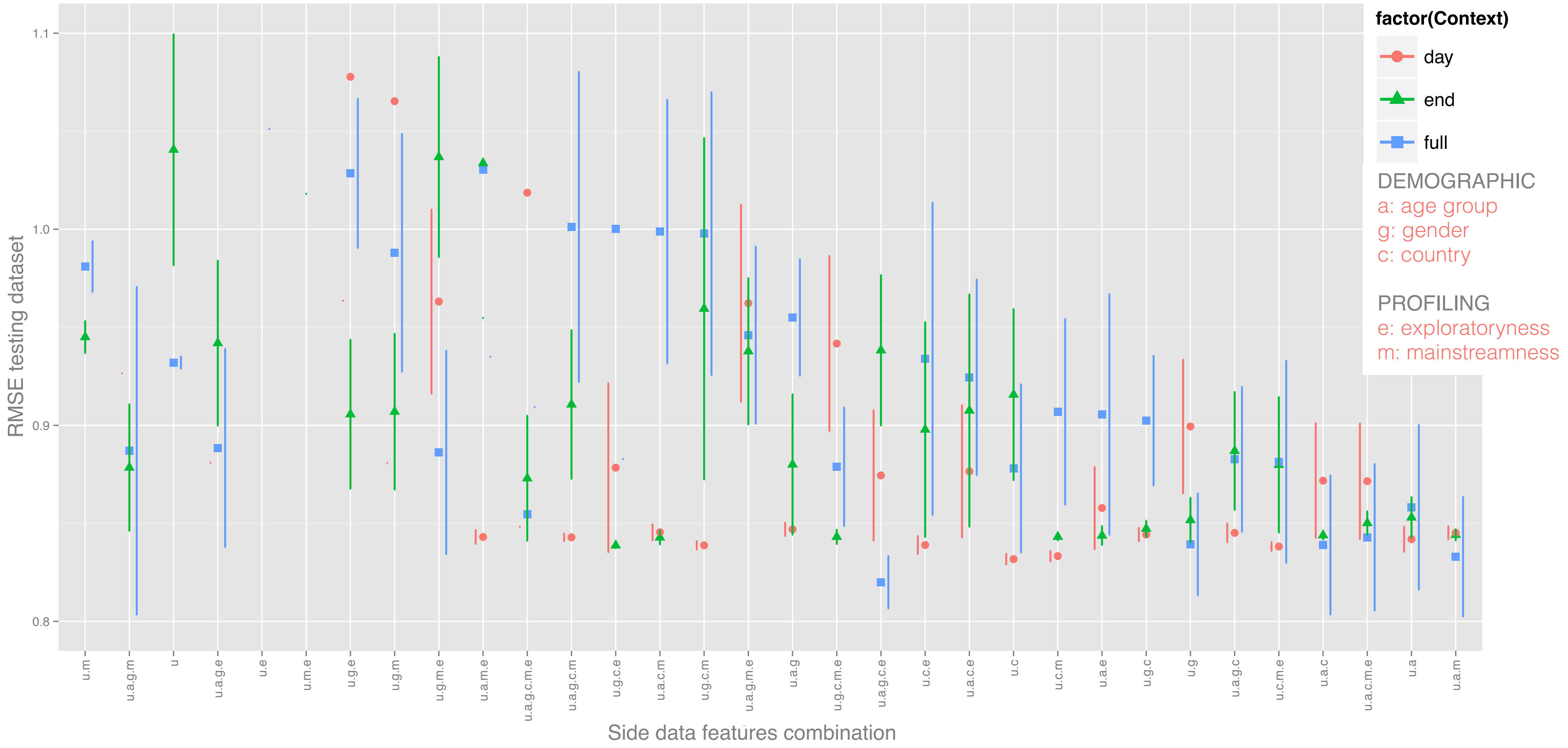
Side data into recommendation model

Context data: weekdays vs. weekend



Side data into recommendation model

Context data: weekdays vs. weekend



Final remarks

- Artist recommendation model improves by using all **user demographic features** together (5%)

- It improves even more if listener profile of **exploratoryness** is added (12%)

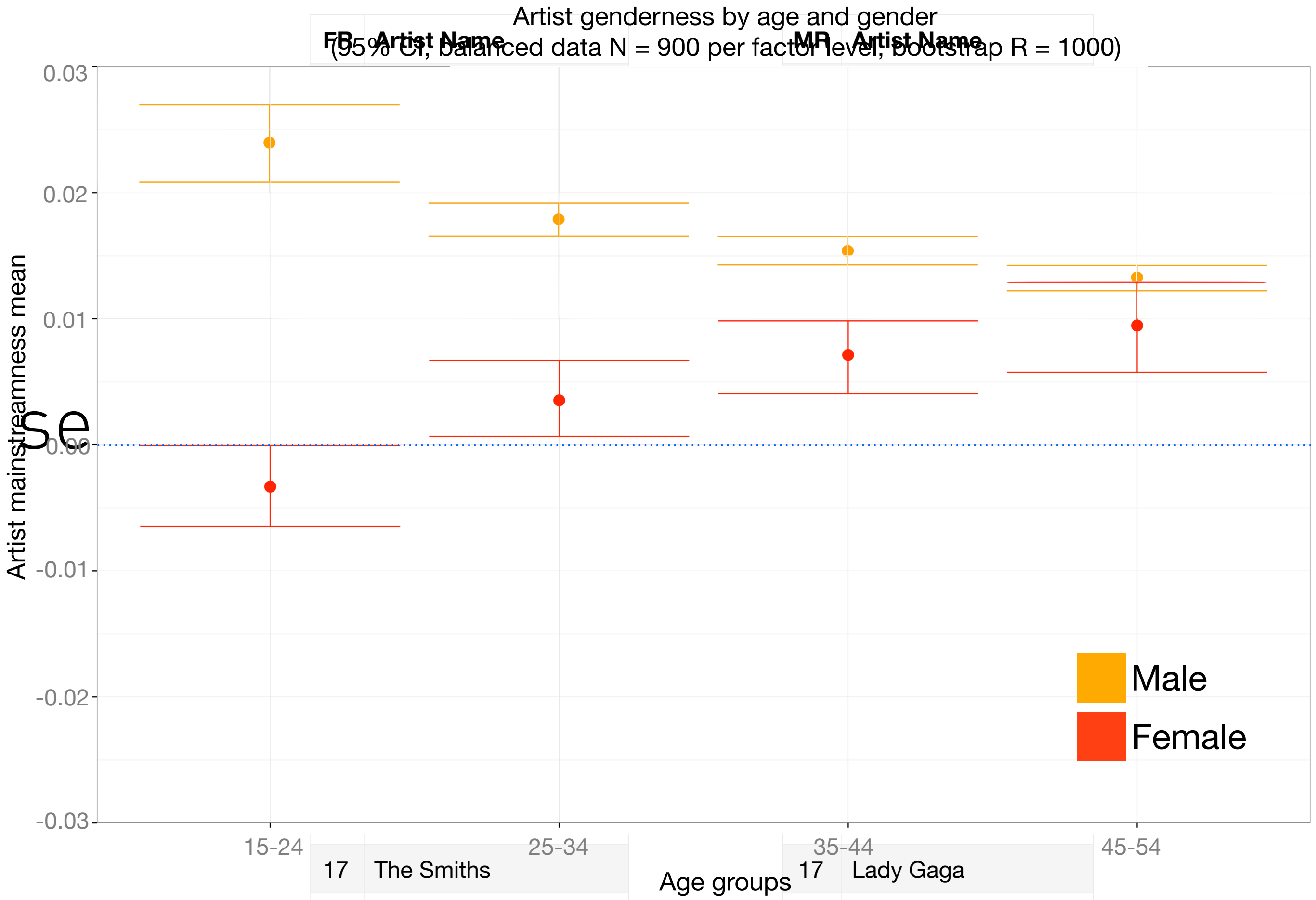
- In general, models with better performance are created if split week data is used. However, the best combination of features achieves the best performance by **using full-week data**

- Demographics and profiling features improve the recommendation accuracy of recommendation model. Further research is needed to determine if listening context improves the recommendation

Profiling features

Genderness

Does se ... erence?



FR	Artist Name
17	The Smiths
18	Nirvana
19	My Chemical Romance
20	The Cure

MR	Artist Name
17	Lady Gaga
18	Rammstein
19	Led Zeppelin
20	Britney Spears

Music recommendation approaches

Collaborative filtering

User similarity

user/artist	beatles	rolling	bsabbath	metallica	miles	coltrane	autechre	dpunk	reich	bartok
a	5	4			3	2	4		4	5
b	5	4		2				2	3	
c	4		3		3		5	4		
d	5			1	5	4				1
e	5				4		1		1	1

Pearson correlation

$$PC(u,v) = \frac{\sum_{i\in I}(r_{ui}-\bar{r}_u)(r_{vi}-\bar{r}_v)}{\sqrt{\sum_{i\in I}(r_{ui}-\bar{r}_u)^2 \sum_{i\in I}(r_{vi}-\bar{r}_v)^2}}$$

	a	b	c	d
b	0.93			
c	0.52	0.20		
d	-0.39	0.96	-0.51	
e	-0.06	1.00	-0.30	0.94

Cosine vector similarity

$$\cos(\mathbf{x}_a, \mathbf{x}_b) = \frac{\mathbf{x}_a^\top \mathbf{x}_b}{\|\mathbf{x}_a\|\|\mathbf{x}_b\|} = \frac{\sum_{i\in I_{uv}} r_{ui} r_{vi}}{\sqrt{\sum_{i\in I_u} r_{ui}^2 \sum_{j\in I_v} r_{vj}^2}}$$

	a	b	c	d
b	0.99			
c	0.98	0.92		
d	0.82	0.98	0.99	
e	0.79	0.98	0.81	0.99

Jaccard similarity

$$JS(A,B) = \frac{|A\cap B|}{|A\cup B|}$$

	a	b	c	d
b	0.33			
c	0.33	0.25		
d	0.50	0.25	0.25	
e	0.71	0.25	0.43	0.43

Music recommendation approaches

Incorporating context into the model

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i \, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \mathbf{v}_i, \mathbf{v}_j \rangle \, x_i \, x_j \qquad \langle \mathbf{v}_i, \mathbf{v}_j \rangle := \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f}$$

Rendle, Steffen. "Factorization machines." In Data Mining (ICDM), 2010 IEEE 10th International Conference on, pp. 995-1000. IEEE, 2010.

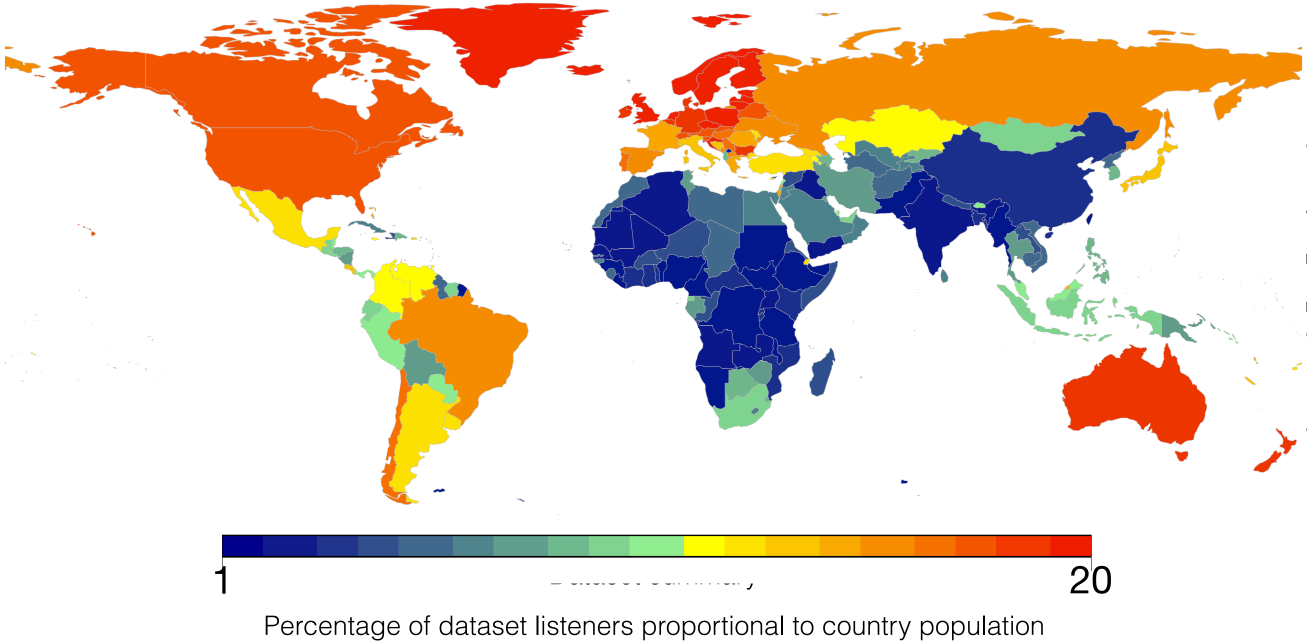
gender	age	user/artist	beatles	rolling	bsabbath	metallica	miles	coltrane	autechre	dpunk	reich	bartok
m	o	**a**	5	4			3	2	4		4	5
f	o	**b**	5	4		2				2	3	
m	y	**c**	4		3		3		5	4		
m	y	**d**	5			1	5	4				1
f	y	**e**	5				4		1		1	5
m	o	**f**										

user	factor 1	factor 2
a	-0.7364	-0.5380
b	0.4071	0.3544
c	0.6459	-1.1424
d	0.8063	0.6618
e	-1.0800	0.7037
f	-0.0002	0.0000

item	factor 1	factor 2
beatles	-0.1250	0.3663
rolling	-0.0758	0.2352
bsabbath	0.2597	-0.1869
metallica	-0.4078	-0.3558
miles	0.3469	0.9251
coltrane	0.4341	0.8393
autechre	0.8519	-0.8159
dpunk	0.5257	-1.2368
reich	0.7062	-0.8491
bartok	-1.6830	-0.0734

side feature	value	factor 1	factor 2
age	o	-0.3872	-0.1737
age	y	0.1648	0.4031
gender	m	0.3986	-0.1552
gender	f	-0.3539	0.1451

Dataset



Scr

ax
13
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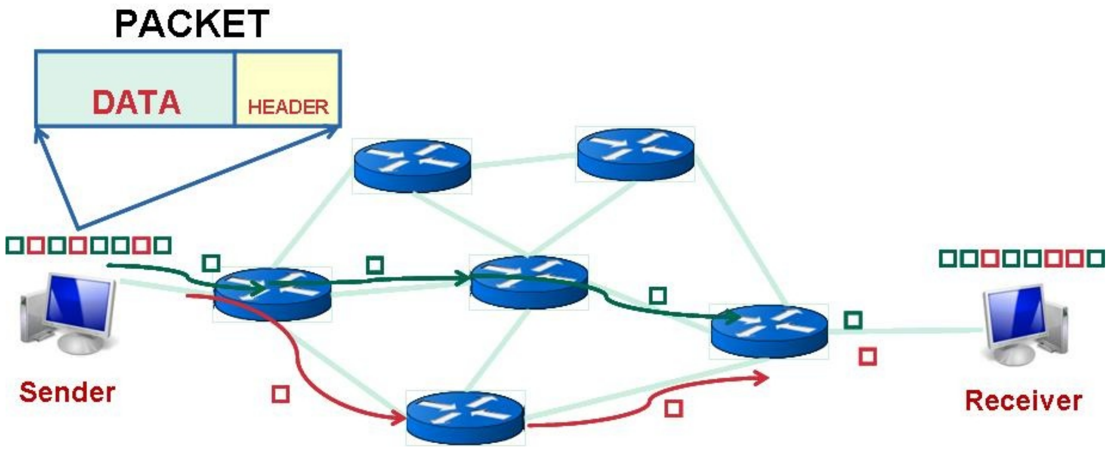
Mid-term review

New music economy

- Three dimensions (tensions) between the old music economy (OME) and the new music economy (NME)
  - Connectivity vs. control
  - Service vs. product
  - Amateur vs. professional

Packet switching



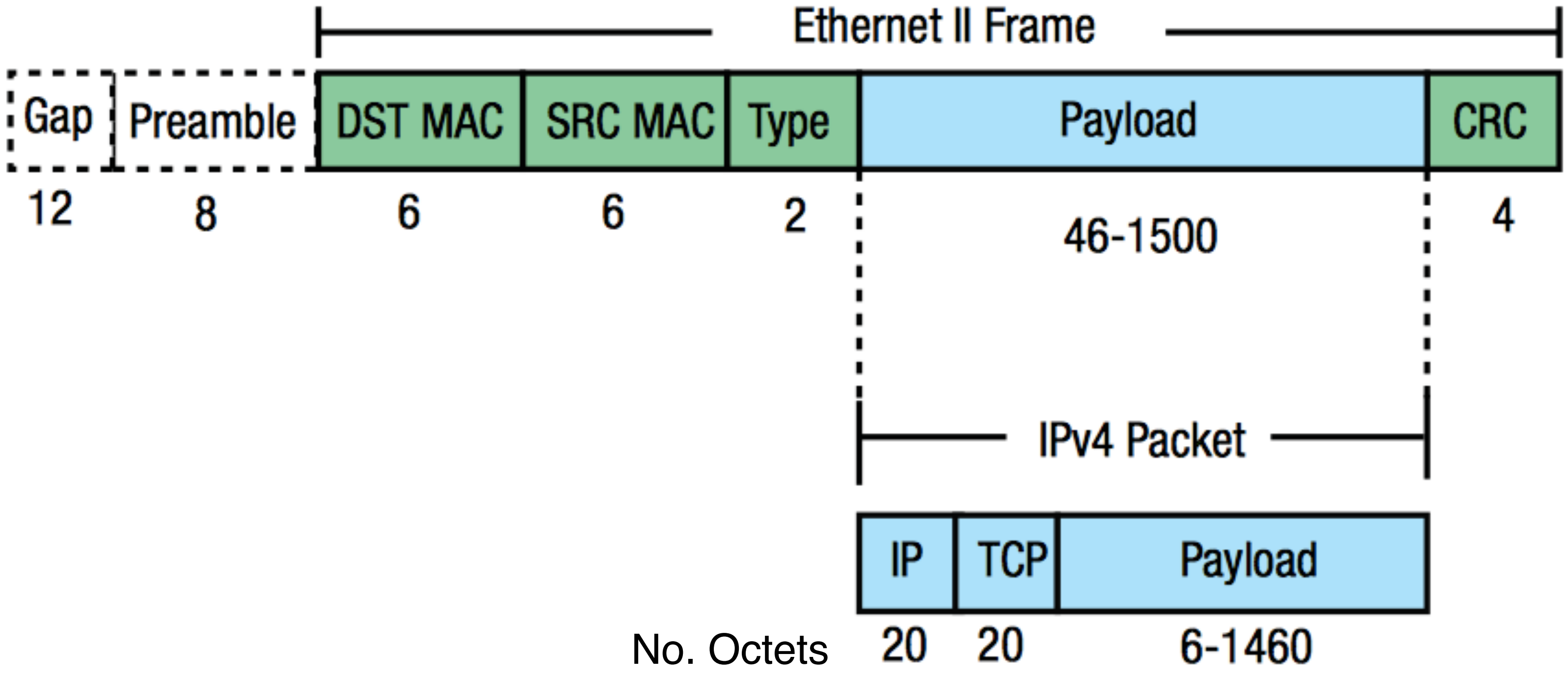
Taken from http://computernetworkingsimplified.com/physical-layer/overview-circuit-switching-packet-switching/

Internet technologies

- Ethernet
- TCP/IP
- OSI Model
- IP Addresses
- DNS
- Ports
- DHCP
- FTP
- SSH
- HTTP

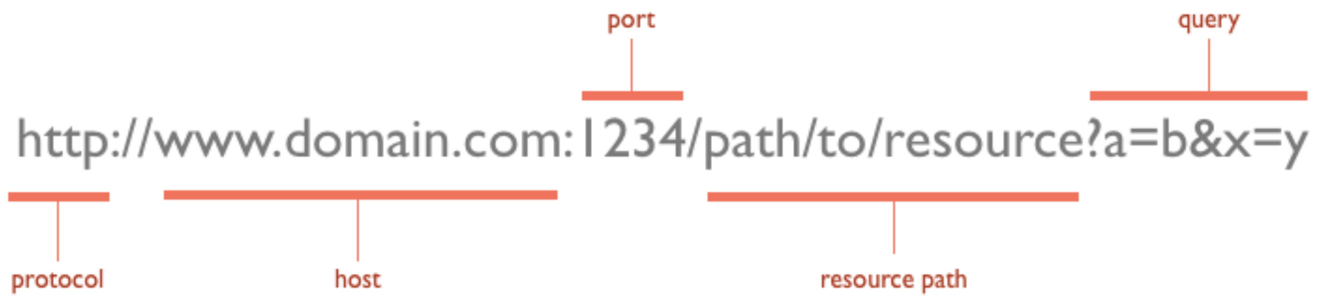
Complete Ethernet Packet

Taken from openmicrolab.com



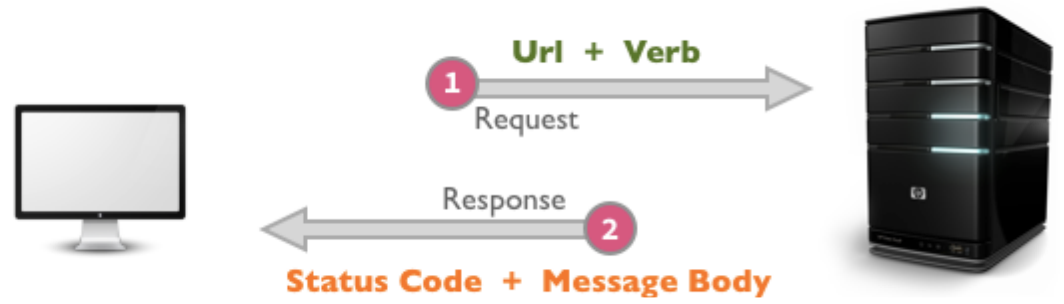
HTTP requests

- Request messages are at the heart of web communications using HTTP
- These messages are sent using URLs (Uniform Resource Locators)



HTTP

- “The first version of the protocol had only one method, namely GET, which would request a page from a server. The response from the server was always an HTML page.” (T. Berners-Lee)



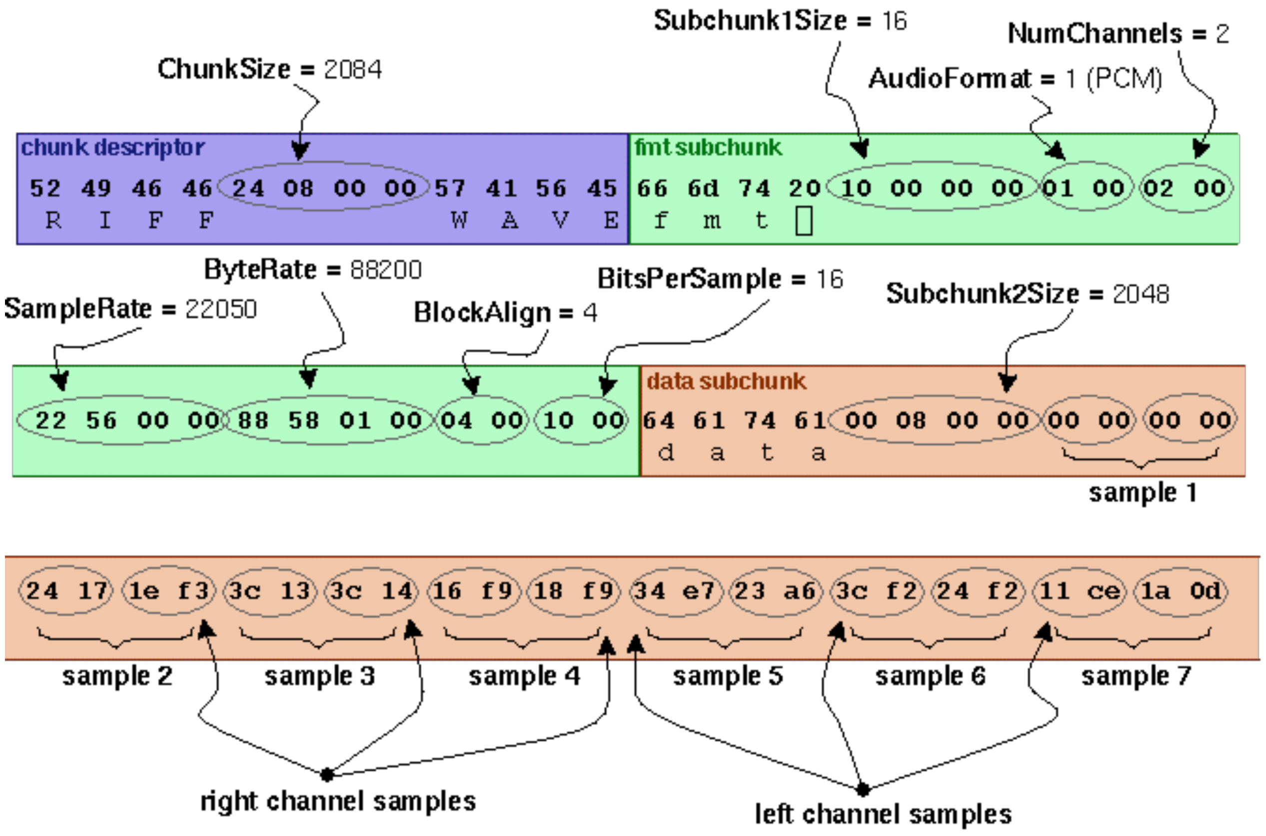
Taken from http://code.tutsplus.com/

- However, these days there are some other HTTP “verbs” that allow us to perform other actions on resources:
    - GET: fetch an existing resource
    - POST: create a new resource
    - PUT: update an existing resource
    - DELETE: delete an existing resource

Sound file formats

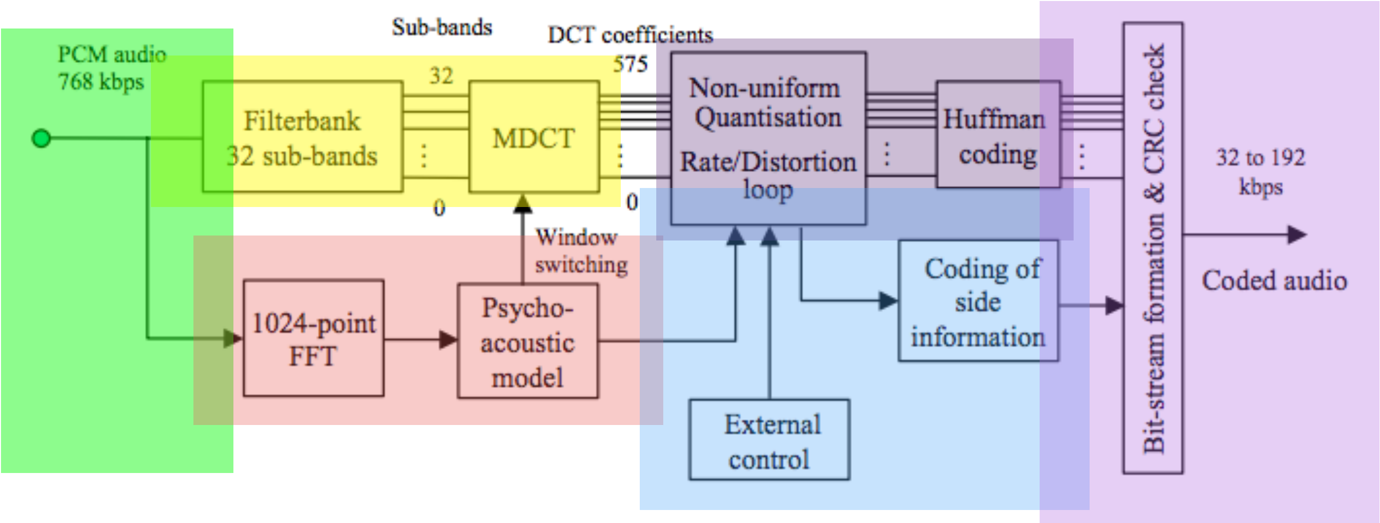
- Broadly speaking, sound content is delivered in two format categories:
    - As **structured audio**
        - Sounds are generated in a dynamic manner at runtime
        - MIDI, MODs (e.g., trackers)
    - As **recorded sound**:
        - often called *waveform* sound
        - audio data can be stored in
            - **uncompressed** formats
            - **compressed** formats
                - **Lossy** formats
                - **Lossless** formats

Uncompressed formats
The Canonical WAVE file format



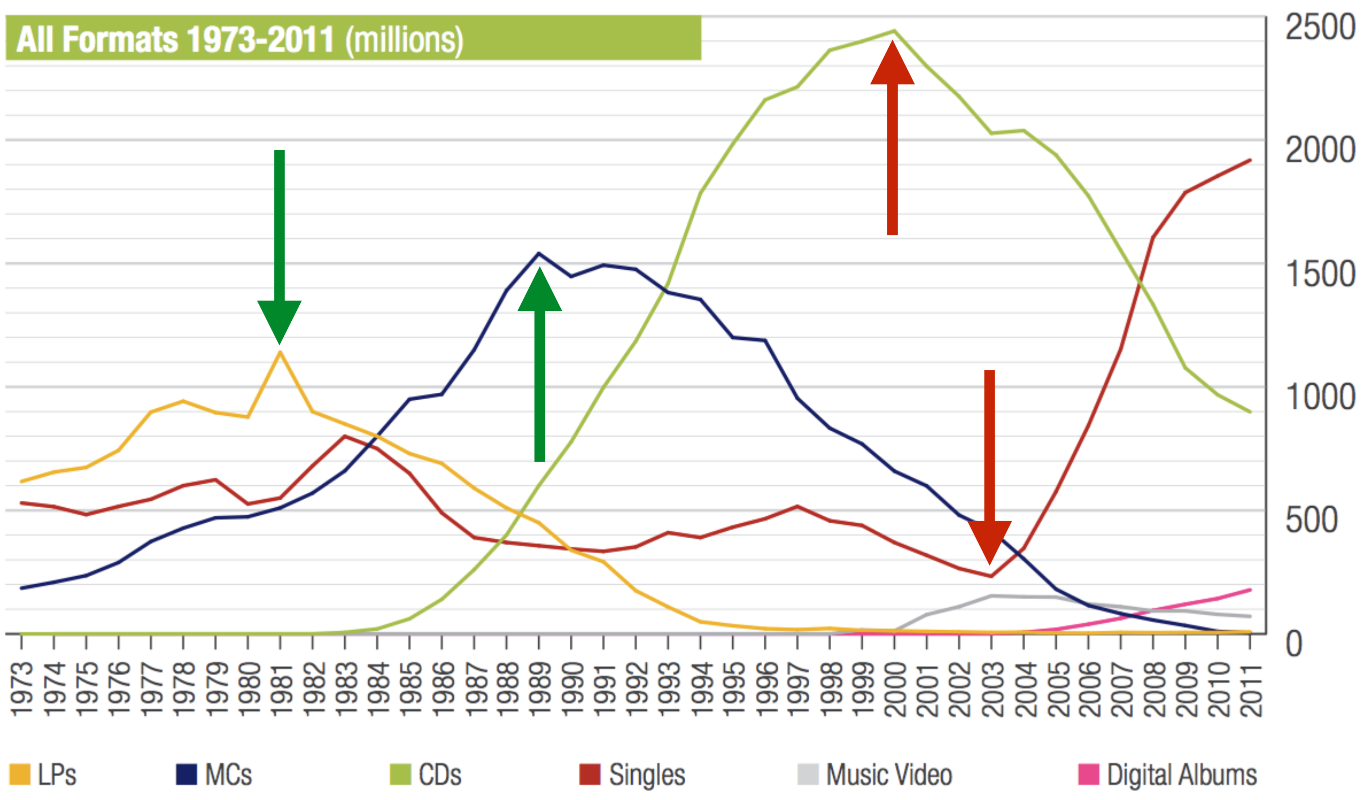
Taken from http://soundfile.sapp.org/doc/WaveFormat/

MPEG-1 Layer-3 encoder diagram



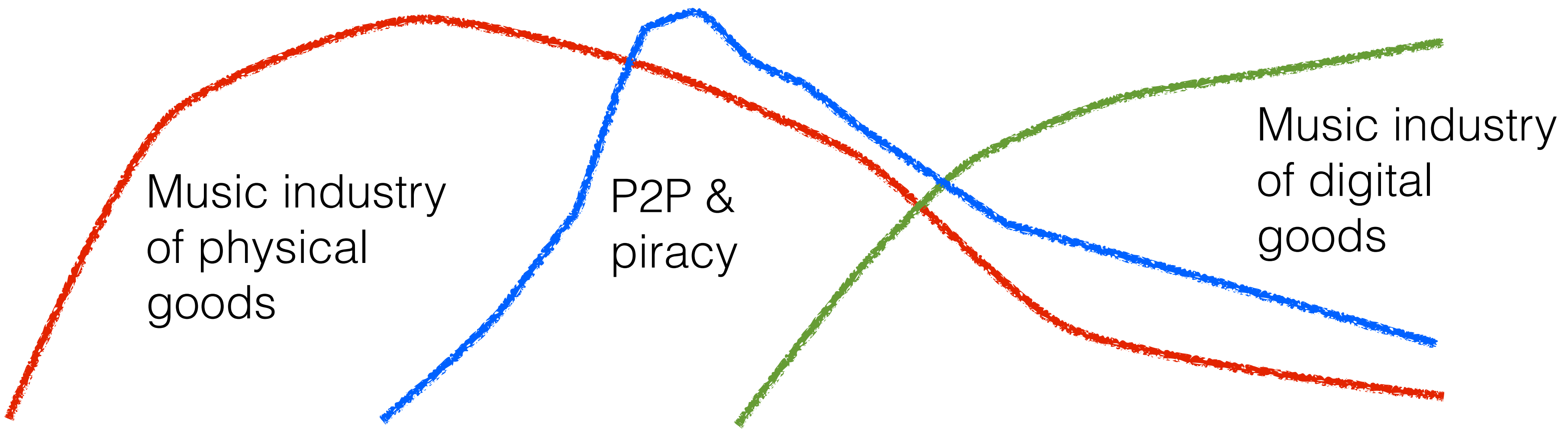
Taken from Brandeburg, K. 1999. MP3 and AAC explained. In Proceedings of the AES 17th International Conference on High Quality Audio Coding

Global music sales by format



Taken from Record Industry in Numbers 2011 (IFPI)

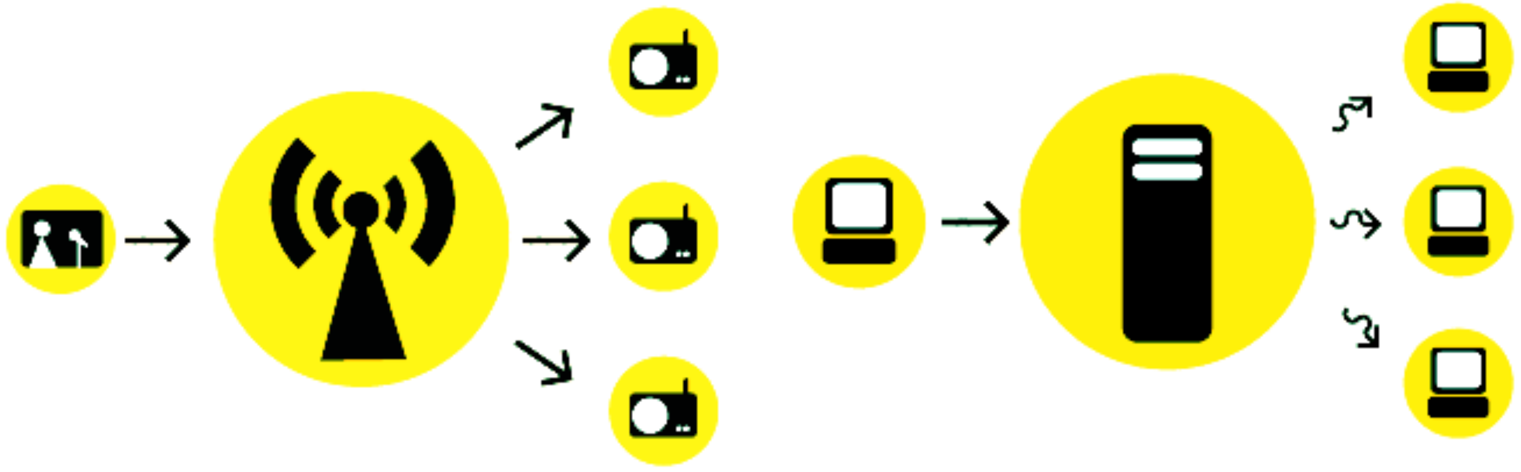
Music industry

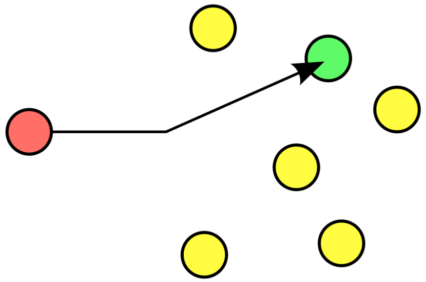


Digital music distribution models

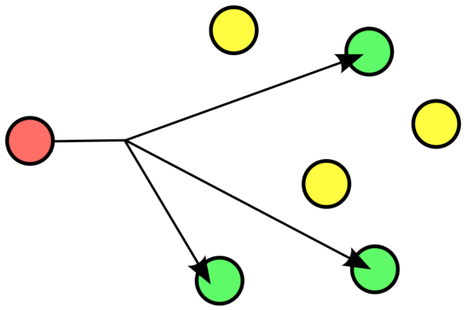
- Music stores (buy to own)
- Music tracks are delivered online
- Music locker (cloud based)
- Music streaming via subscription

Internet Radio broadcasting





Unicast: Sends IP packets to identified recipients on a network, with added bandwidth



Multicast: sends IP packets to a group of hosts on a network, with no added bandwidth, and not requiring prior knowledge of who or how many receivers there are.

Mid-term potential questions

Class 7
- Music recommendation systems
  - How does content-based recommendation work?
  - How does collaborative filtering recommendation work?

Class 6
- Internet radio:
  - Differences between unicast and multicast streaming?

Class 5
- Music distribution
  - In the context of music sales, the year 2000 has been established as an inflection point, in which the ever-growing music industry stop its growth. Explain what happened year, and how the music industry changed.
  - How the music industry recovered from the inflection point established in the year 2000?
- Digital music distribution models
  - Provide the characteristics of the different current models of digital music distribution

Class 4
- Sound file formats
  - What is the main difference between "structured audio" and "recorded sound." Provide at least one name of a structured audio file format.
  - What is the main differences between lossy and lossless compression?
  - Provide an explanation about the perceptual model in which MPEG-3 Layer 1 is based

Class 3
- Internet technologies
  - Explain briefly how does Ethernet work
  - What is the Internet Protocol Suite (TCP/IP)
  - What is a port in the context of computer networking?
  - Can you explain the five constituent parts in this URL:
    - http://www.domain.com:1234/path/to/resource?a=b&x=y

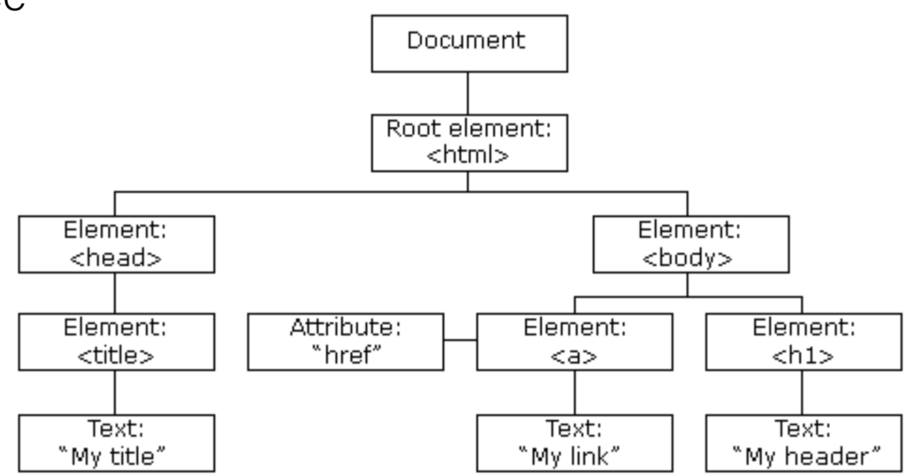
Class 2
- Internet, WWW, and HTML
  - Explain the difference between the Internet and the web (WWW)
  - Explain what is HTML

Class 1
- The old and the new music industry
  - Explain the tensions between the new and the old music industry in terms of
    - connectivity vs. control
    - service vs. product
    - amateurism vs. professionalism

BREAK

DOM

- The Document Object Model: platform- and language-neutral interface that allow programs and scripts **to dynamically access and update the content, structure and style of documents.**
- The nodes of every document are organized in a tree structure, called the DOM tree



- HTML DOM@W3schools
- With the object model, JavaScript gets all the power it needs to create dynamic HTML

HTML DOM and forms

mumt301.github.io

Potential final projects

- History of the recording industry in the age of the Internet
- Statistical / historical analysis of music industry based on web-based data
- Study of international music copyright laws
- Substantial music composition (20-30 min) strictly using web resources with substantial write up (2-3 pages)
- Comprehensive comparison of on-demand music streaming services
- Music recommendation site
- Music playlist maker