Let's bring more context into recommendations

Ex-DS Team Leader @ Sber

Artem Seleznev

@SeleznevArtem

/NameArtem

/seleznev-ar

/sel

@SeleznevArtem

/NameArtem

/seleznev-artem

/seleznev.artem.info

@SeleznevArtem

/NameArtem

/seleznev-artem

/seleznev.artem.info

User * Item > Rating > Conv. 12%

@SeleznevArtem

/NameArtem

/seleznev-artem

/seleznev.artem.info

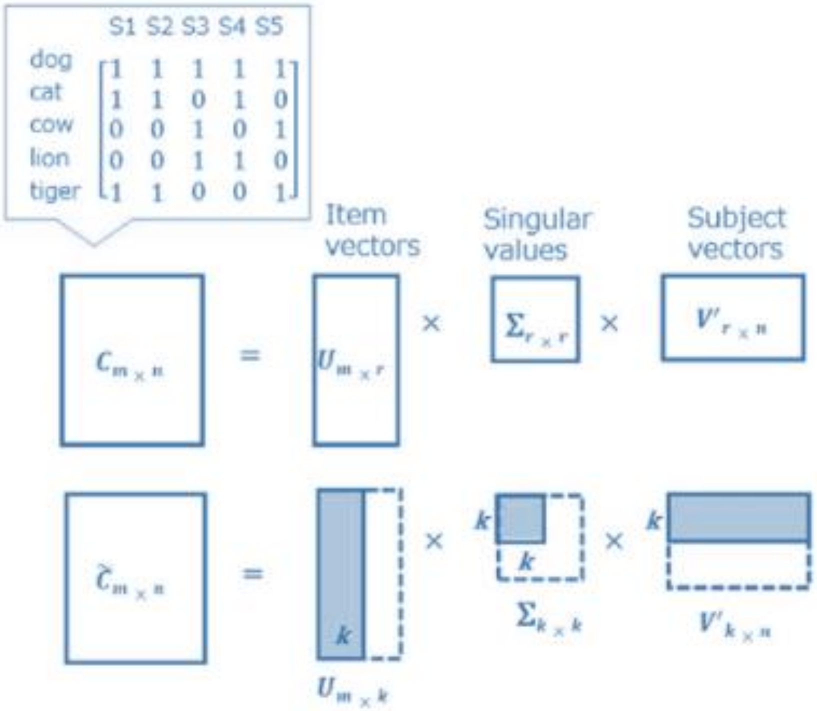
User * Item > Rating > Conv. 12%

User * Item * Context > Rating > Conv. 21%

Do you like your recommendations

?

- **Our recommendations are really boring**



- Our recommendations are really boring
  - A Classification model is a slippery slope

Day_part	Main_gen	Subcategory	Param1	Param2	Target
Noon	Adventure	55	1	3	0
Evening	Fantasy	75	1	2	1

- Our recommendations are really boring
- A Classification model is a slippery slope
- We do **NOT** use all knowledge

- Our recommendations are really boring
- A Classification model is a slippery slope
- We do NOT use all knowledge (not always)
  - Cross-Domain User Modeling
  - Attentive Collaborative Filtering
  - Self-attention models

- **Our recommendations are really boring**

- **A Classification model is a slippery slope**

- **We do NOT use all knowledge (not always)**

- **Recommendations must NOT ONLY “sell”**

Look closely at context

Look closely at context

Film

- Genre
- Subgenre
- Actors / Actresses
- Director
- Opinion
- Country

Speak the same language

Film

- Genre
- Subgenre
- Actors / Actresses
- Director
- Opinion 😱
- Country

Speak the same language

Speak the same language

Film

- Genre
- Subgenre
- Actors / Actresses
- Director
- Opinion 😱
- Country

Wine

- Aged in / Tannins
- Sugar / Taste
- Grape
- Appelcion
- Opinion 🥳
- Country / Region

1 Create
similar categories

Film-Wine

- ?
- ?
- ?

Speak the same language

1 Create
similar categories

Film-Wine

- **Key Words**
- **?**
- **?**

Type	Tannins	Grape	Actor	Country
Film	NaN	NaN	Brad Pitt	GB
Wine	High	Pino Noir	NaN	Rus

Speak the same language

1 Create similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **?**

$$TF\text{-}IDF(t_k, d_j) = TF(t_k, d_j) \cdot IDF(t_k)$$

Speak the same language

1 Create
similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **?**

$$TF\text{-}IDF(t_k, d_j) = TF(t_k, d_j) \cdot IDF(t_k)$$

$$w_{k,j} = \frac{TF\text{-}IDF(t_k, d_j)}{\sqrt{\sum_{s=1}^{|T|} TF\text{-}IDF(t_k, d_j)^2}}$$

Speak the same language

1 Create
similar categories

Film-Wine

- Key Words
- Description / Opinion
- KNN Model

Speak the same language

1 Create
similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **KNN / Seq2Seq Models**

Name	Fact_cat	Predicted
Valpolicella, Bertani	Red >Rounded >No aged	Red <Romantic <Veneto
Eld & Iagor	Melodrama >Romantic >1940th	Love <Romantic < Youngsters

Speak the same language

1 Create similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **KNN / Seq2Seq Models**

Name	Fact_cat	Predicted
Valpolicella, Bertani	Red >Rounded >No aged	Red <Romantic <Veneto
Eld & Iagor	Melodrama >Romantic >1940^{th}	Love <Romantic < Youngsters

Speak the same language

1 Create similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **KNN / Seq2Seq Models**

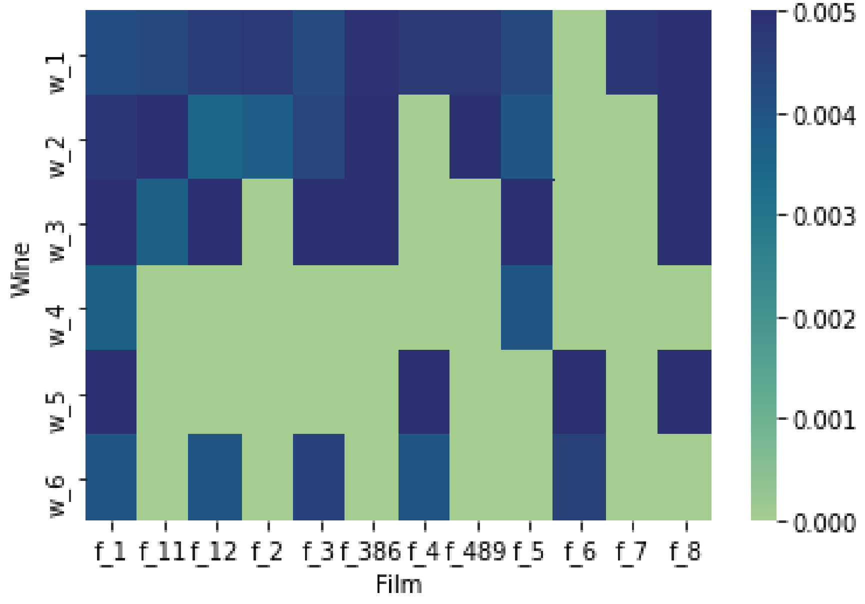
Name	Fact_cat	Predicted
Valpolicella, Bertani	Red >Rounded >No aged	Red <Romantic <Veneto
Eld & Iagor	Melodrama >Romantic >1940th	Love <Romantic < Youngsters

Speak the same language

1 Create
similar categories

Film-Wine

- **Key Words**
- **Description / Opinion**
- **KNN / Seq2Seq Models**



Speak the same language

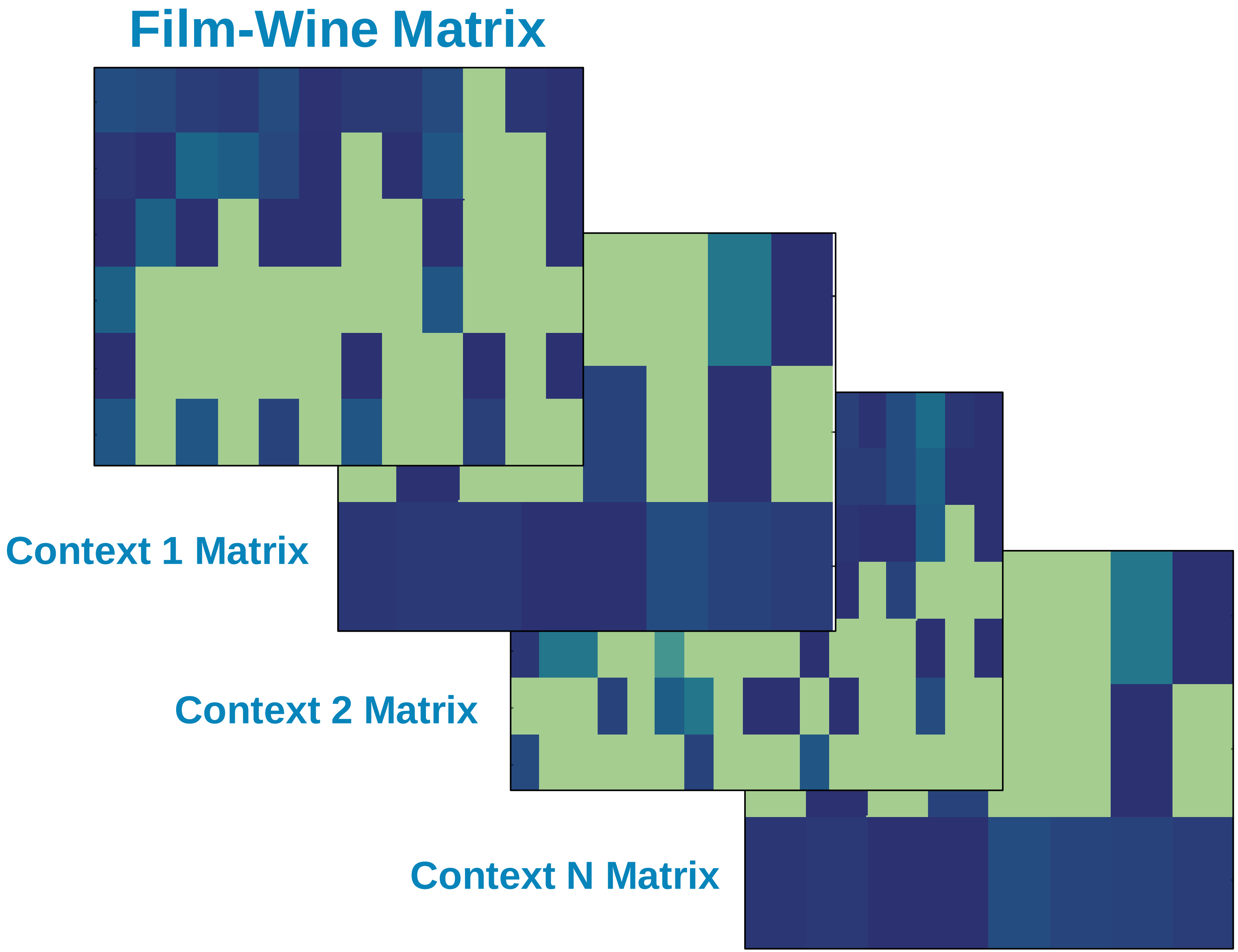
1 Create similar categories

Film-Wine Matrix

Speak the same language

1 Create
similar categories

2 Know hierarchy



Speak the same language

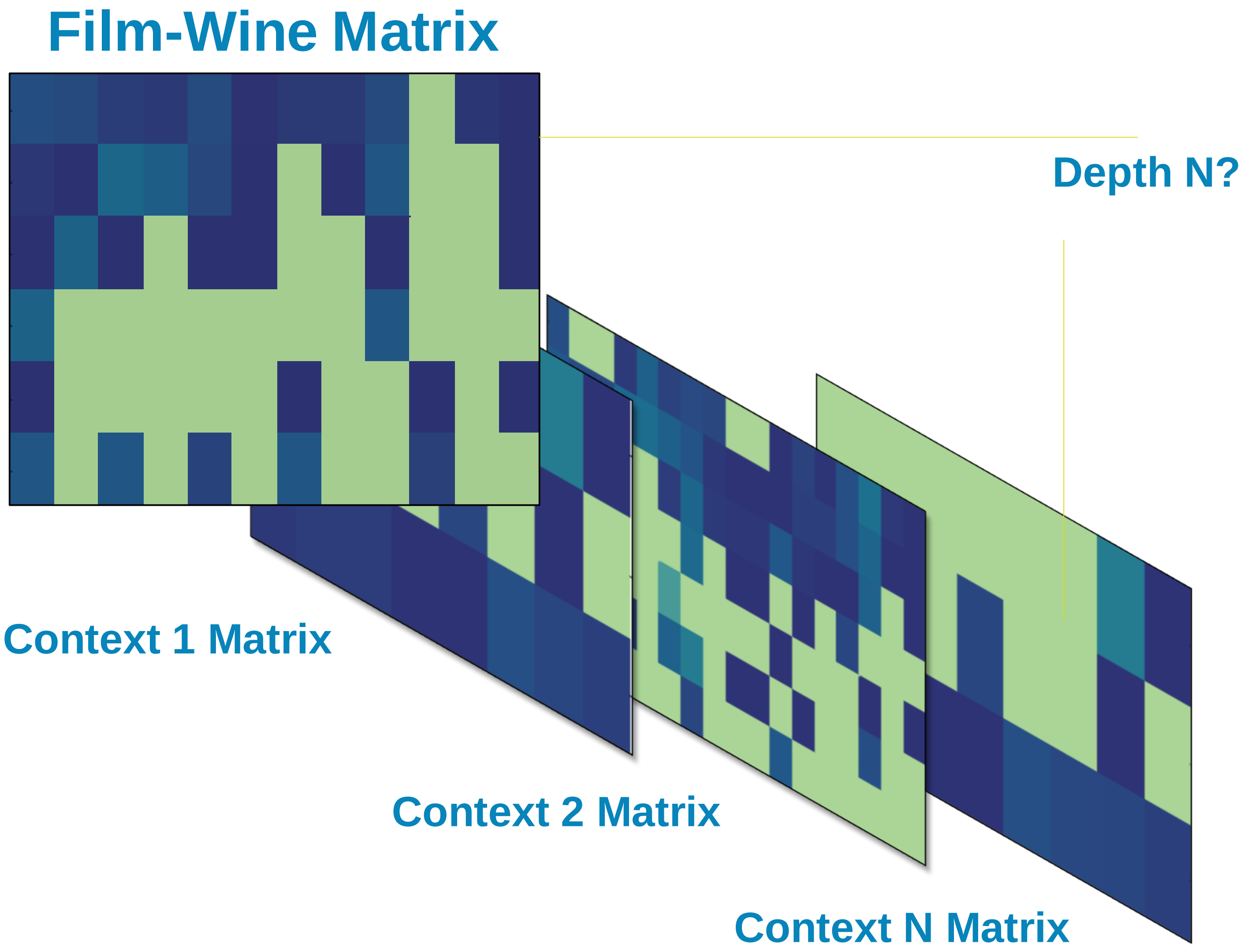
1 Create similar categories

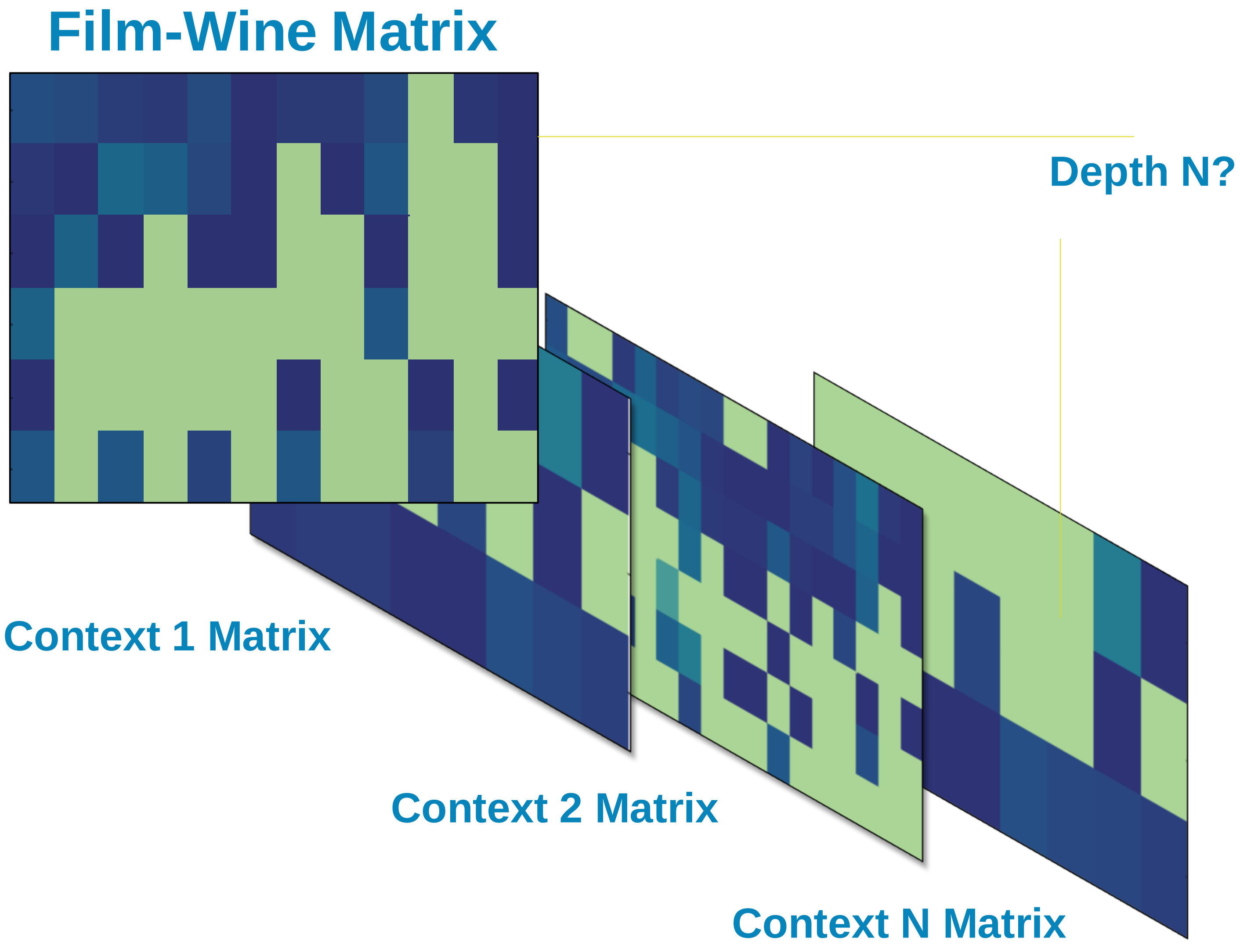
2 Know hierarchy

Speak the same language

1 Create
similar categories

2 Know hierarchy



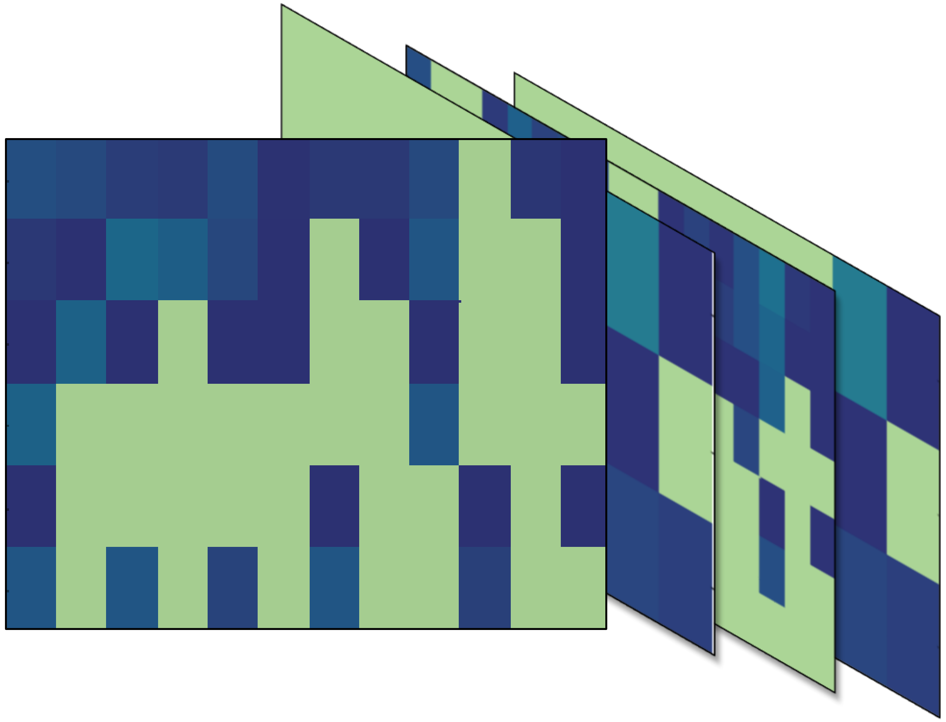


Speak the same language

1 Create
similar categories

2 Know hierarchy

! Not ALS - Based Tensor Factorization



- Quite mysterious (I want to understand)
- Restrictions in resourses

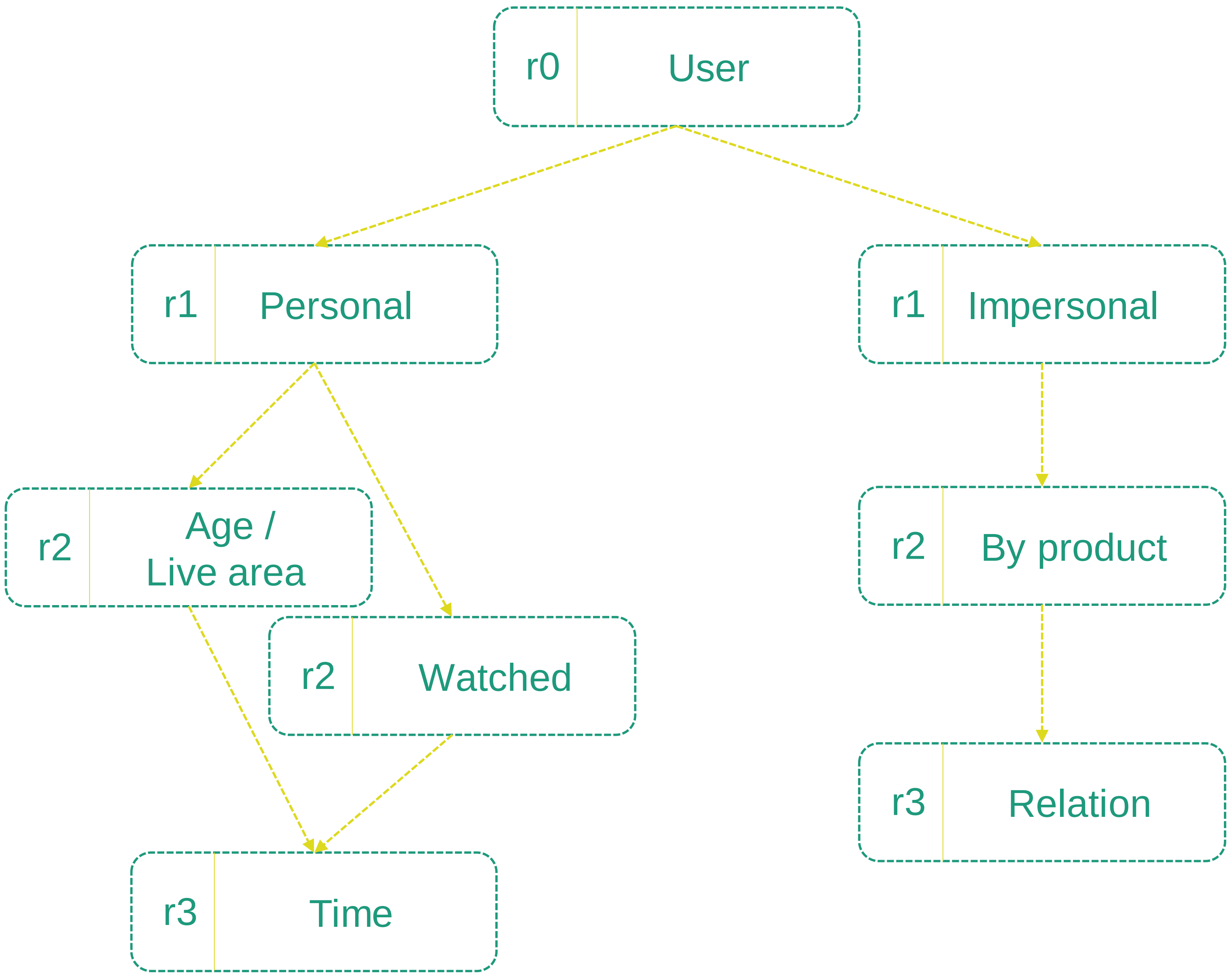
Speak the same language

!!!!!

Speak the same language

1 Create
similar categories

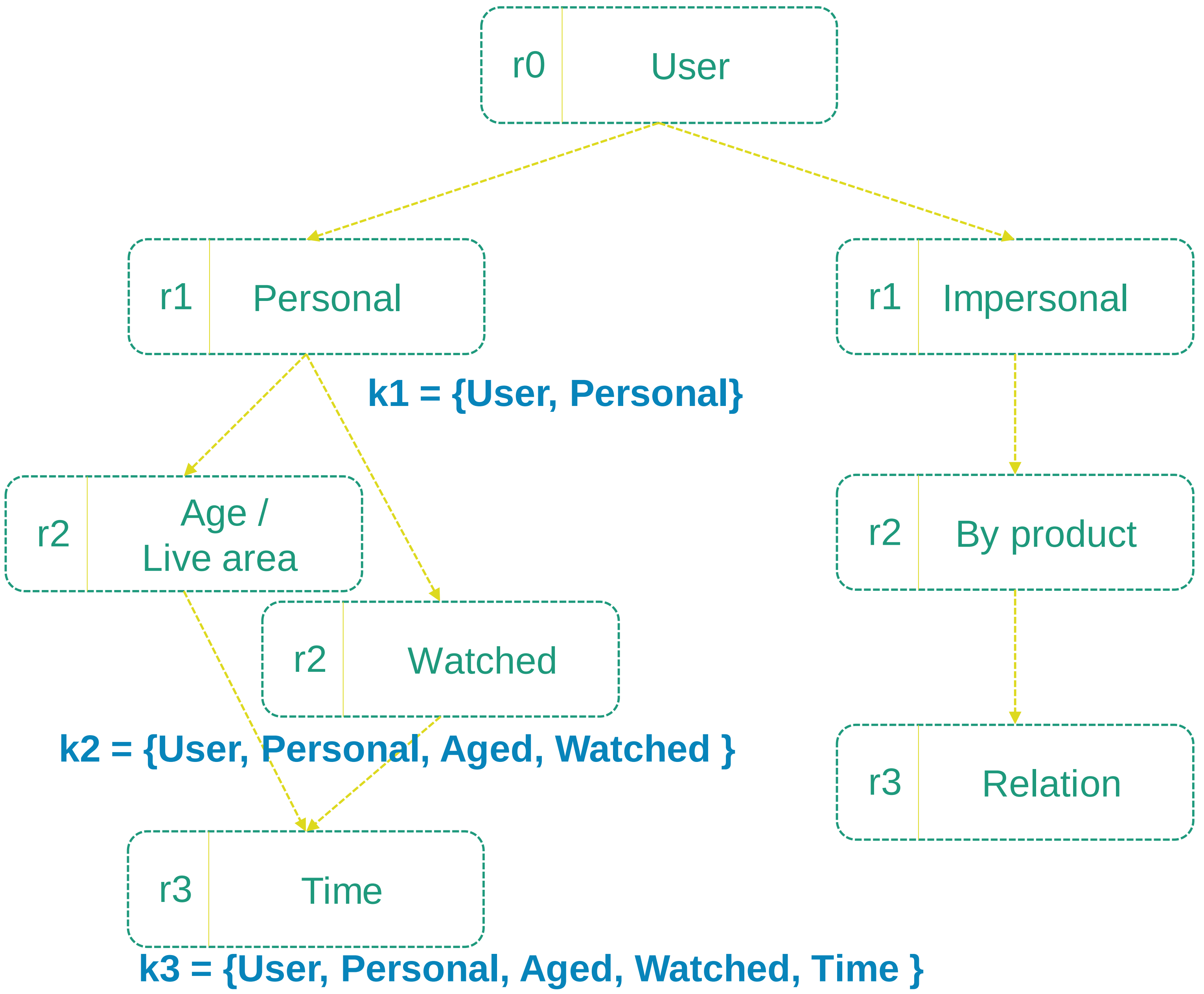
2 Know hierarchy



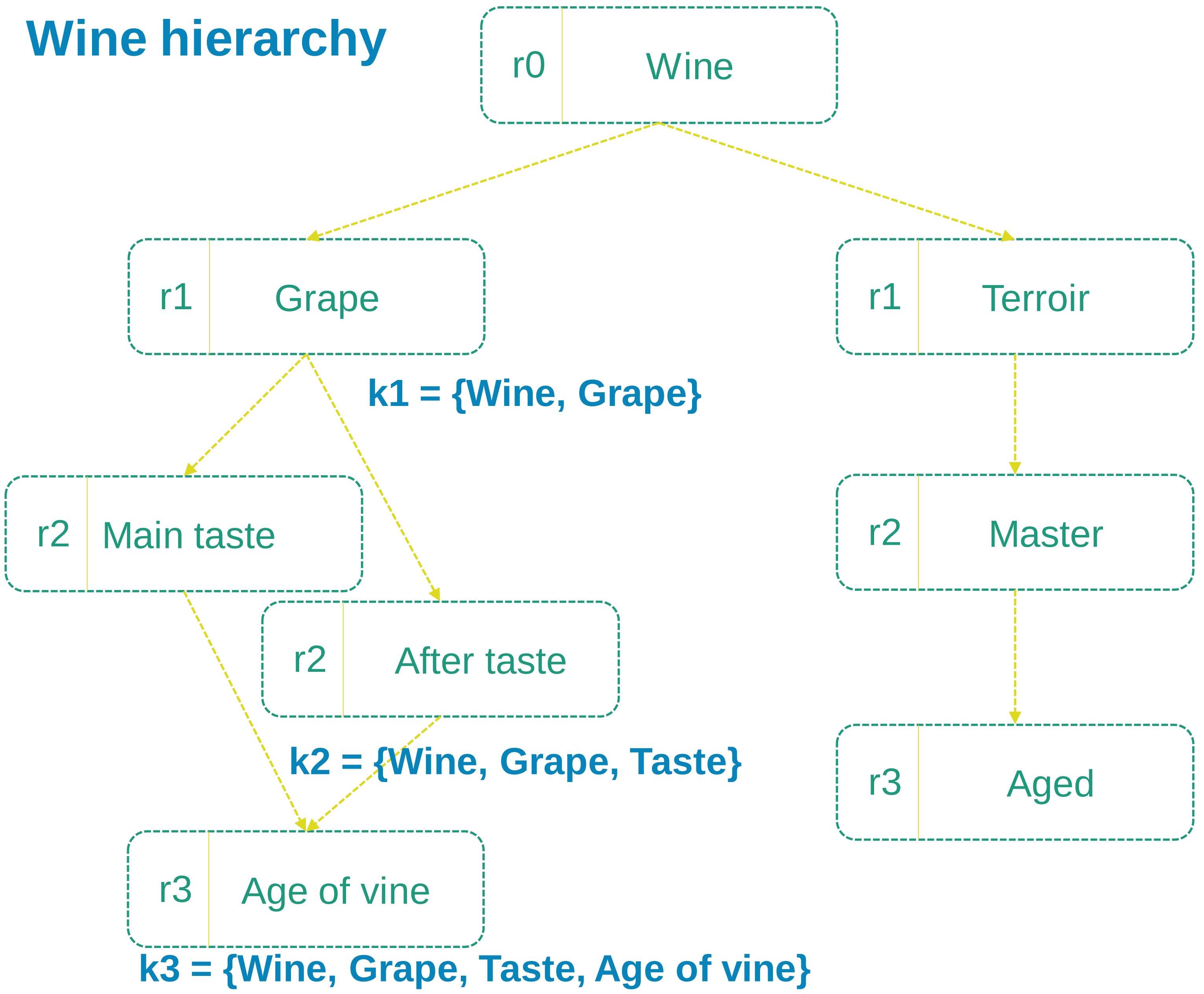
Speak the same language

1 Create
similar categories

2 Know hierarchy



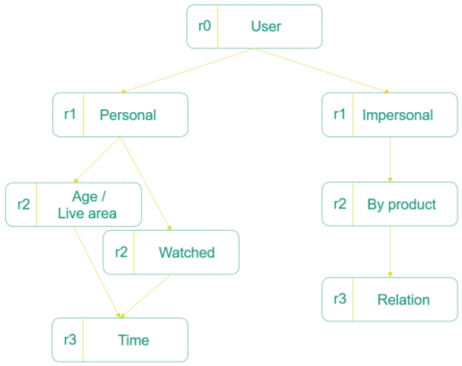
Wine hierarchy



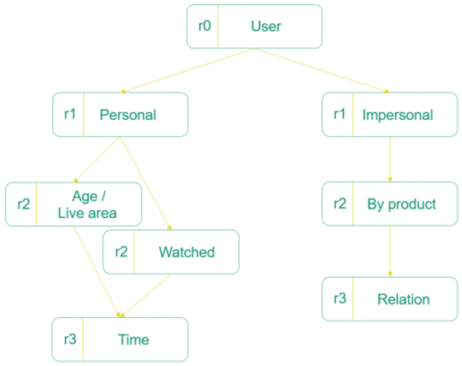
Speak the same language

1 Create
similar categories

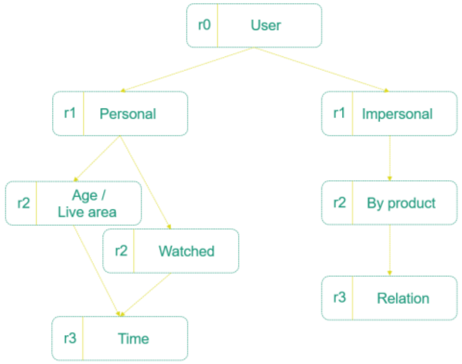
2 Know hierarchy



Explicit



Implicit



Infer

Speak the same language

1 Create
similar categories

2 Know hierarchy

X

```
IndexError: index 1969187183
```

```
MemoryError: Unable to allocate
```

Speak the same language

1 Create
similar categories

2 Know hierarchy

Pandas -> Vaex (Out-of-Core DataFrame)

```
import
df =        ?
df
```

#	id	x	y	z
0	0	1.2318683862686157	-0.39692866802215576	-0.598057746887207
1	23	-0.16370061039924622	3.654221296310425	-0.25490644574165344
2	32	-2.120255947113037	3.326052665710449	1.7078403234481812
3	8	4.7155890464782715	4.5852508544921875	2.2515437602996826
4	16	7.21718692779541	11.99471664428711	-1.064562201499939

Speak the same language

1 Create
similar categories

2 Know hierarchy

Pandas -> Vaex (Out-of-Core DataFrame)

```
import vaex
df = vaex.example()
df
```

#	id	x	y	z
0	0	1.2318683862686157	-0.39692866802215576	-0.598057746887207
1	23	-0.16370061039924622	3.654221296310425	-0.25490644574165344
2	32	-2.120255947113037	3.326052665710449	1.7078403234481812
3	8	4.7155890464782715	4.5852508544921875	2.2515437602996826
4	16	7.21718692779541	11.99471664428711	-1.064562201499939

Speak the same language

1 Create
similar categories

2 Know hierarchy

Pandas -> Vaex (Out-of-Core DataFrame)

```
df['tip_percentage'] = df.tip_amount / df.total_amount * 100  # Stores the expression
df['tip_percentage']  # compute only when needed (in this case a preview)
```

```
Expression = tip_percentage
Length: 1,173,057,927 dtype: float32 (column)
----------------------------------------------
         0        0
         1  13.6986
         2  16.6667
         3  16.5312
         4        0
       ...
1173057922  16.6667
1173057923        0
1173057924        0
1173057925        0
1173057926  16.6667
```

Speak the same language

1 Create
similar categories

2 Know hierarchy

Pandas -> Vaex (Out-of-Core DataFrame)

- There is NOT CrossTab
- Complicated integration with ML
- Does NOT support in Kedro

Speak the same language

1 Create
similar categories

2 Know hierarchy

Pandas -> Vaex (Out-of-Core DataFrame)

- There is **NOT** CrossTab
- Complicated integration with ML
- Does **NOT** support in Kedro
- Other options

Name	Easy of Adoption (1 – 10 points)	Scaling	Strategy
Dask	5	1 TB+	Cluster
Vaex	10	100 GB+	Lazy loading
Modin	10	10GB+	Cluster
Ray	7	1 TB+	Cluster

Speak the same language

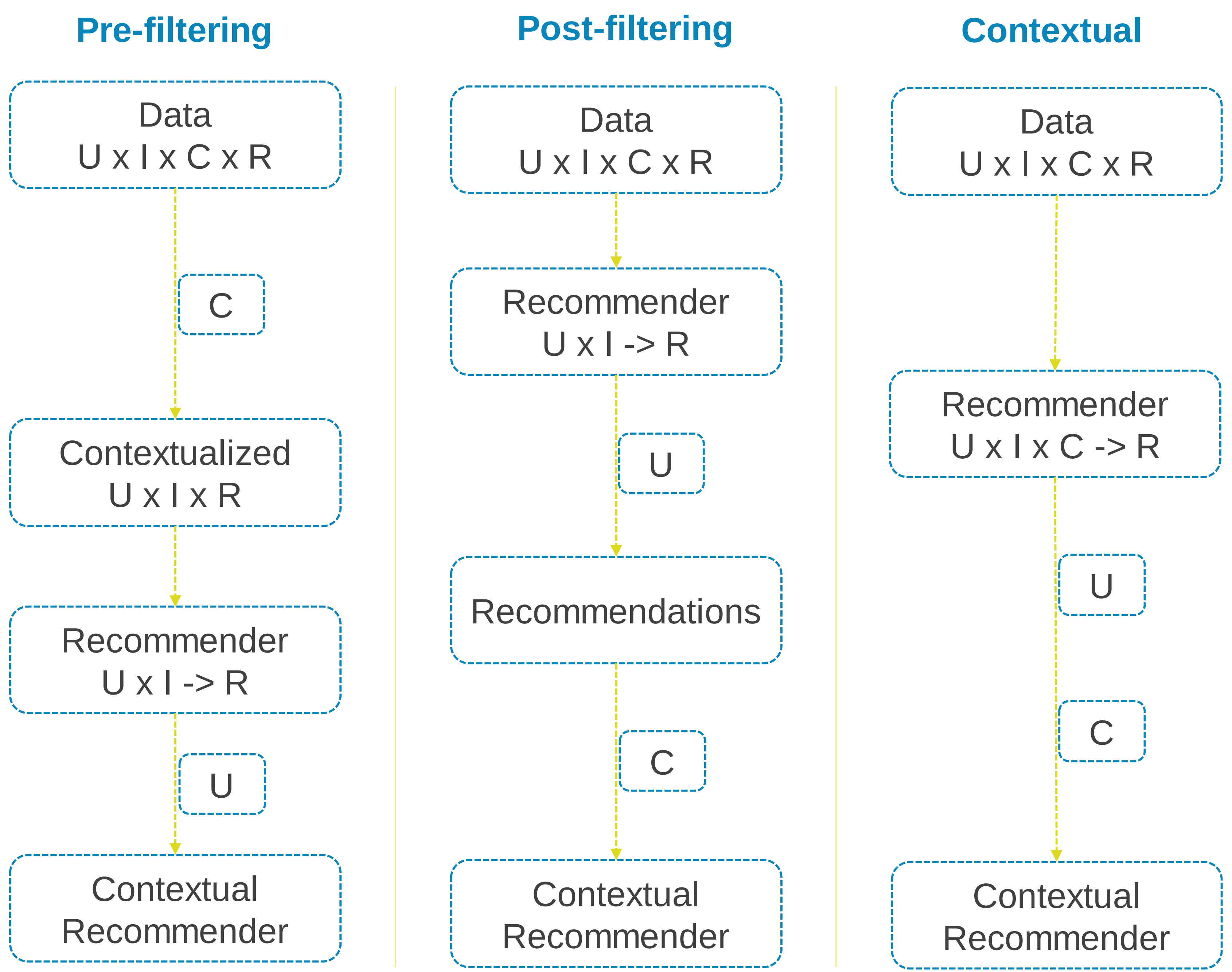
1 Create
similar categories

2 Know hierarchy

ALS and
context funnel

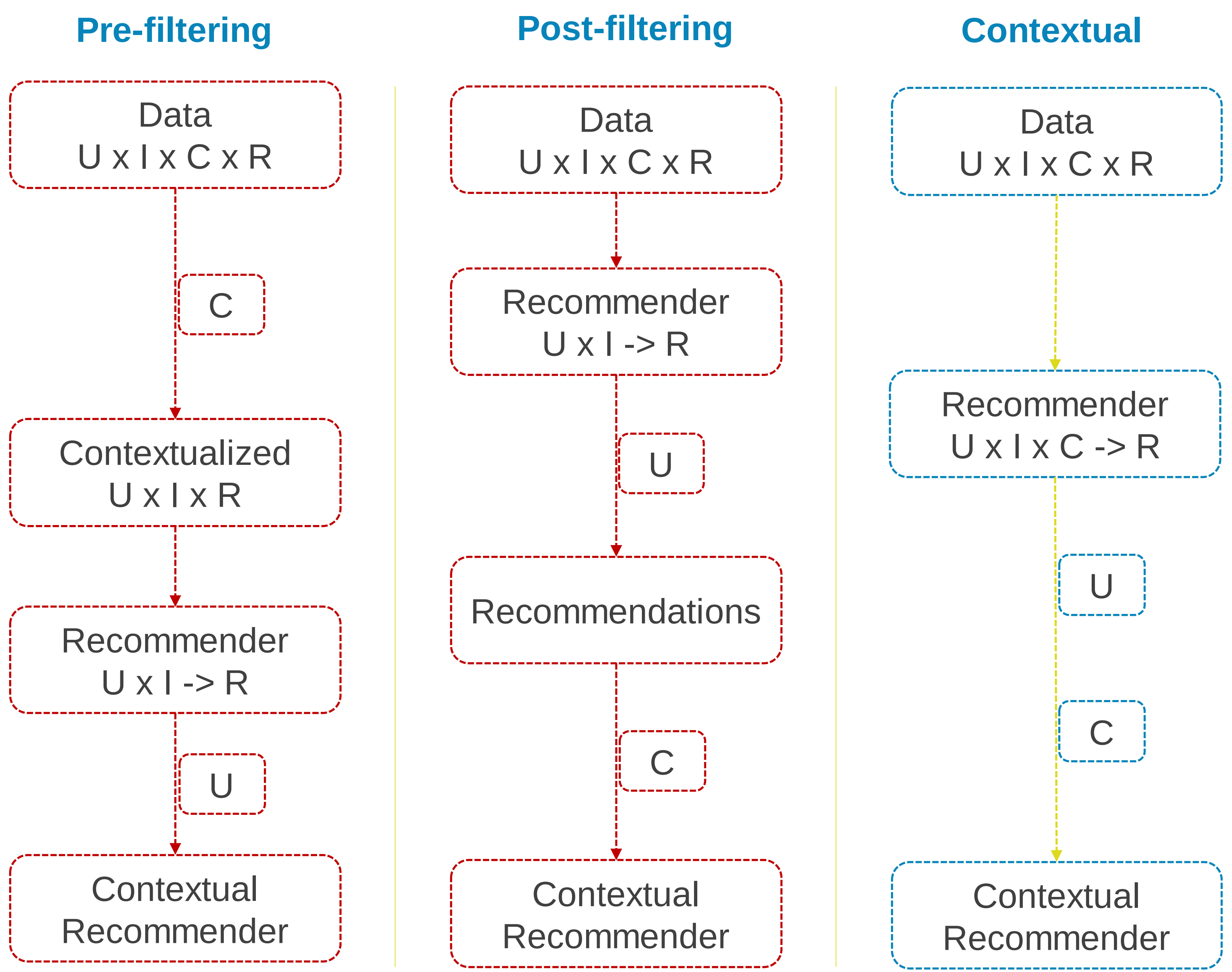
HOW TO ADD CONTEXT

1 Choose paradigm of using context



HOW TO ADD CONTEXT

1 Choose paradigm of using context



Film	f_1	f_10	f_1010	f_102	f_104	f_1078
Wine						
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

ALS

Film	f_1	f_10	f_1010	f_102	f_104	f_1078
Wine						
w_10	0.004354	0.001233	0.006094	0.006962	0.003187	0.002150
w_11	0.002201	0.008481	0.002728	0.008756	0.009007	0.004807
w_12	0.007575	0.009497	0.000082	0.000812	0.009892	0.006491
w_2	0.007037	0.000828	0.005426	0.004486	0.007328	0.002573
w_3	0.006890	0.002751	0.003770	0.009438	0.004094	0.004566
w_4	0.003750	0.005030	0.007132	0.007889	0.007560	0.003239
w_5	0.003616	0.000988	0.008382	0.000849	0.009921	0.008695
w_6	0.005031	0.003143	0.007940	0.002468	0.003908	0.007429
w_7	0.001434	0.001843	0.009584	0.001796	0.006374	0.005471
w_8	0.000660	0.003330	0.000656	0.009253	0.001410	0.009041

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual funnel

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual funnel

ALS

Film / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

Film / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.004354	0.001233	0.006094	0.006962	0.003187	0.002150
w_11	0.002201	0.008481	0.002728	0.008756	0.009007	0.004807
w_12	0.007575	0.009497	0.000082	0.000812	0.009892	0.006491
w_2	0.007037	0.000828	0.005426	0.004486	0.007328	0.002573
w_3	0.006890	0.002751	0.003770	0.009438	0.004094	0.004566
w_4	0.003750	0.005030	0.007132	0.007889	0.007560	0.003239
w_5	0.003616	0.000988	0.008382	0.000849	0.009921	0.008695
w_6	0.005031	0.003143	0.007940	0.002468	0.003908	0.007429
w_7	0.001434	0.001843	0.009584	0.001796	0.006374	0.005471
w_8	0.000660	0.003330	0.000656	0.009253	0.001410	0.009041

Gener / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

Gener / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.009808	0.003580	0.001264	0.000377	0.006196	0.006116
w_11	0.000644	0.000140	0.009966	0.008271	0.007089	0.004144
w_12	0.006116	0.003331	0.007042	0.000930	0.006767	0.007332
w_2	0.006918	0.000382	0.009091	0.005865	0.004201	0.009829
w_3	0.001293	0.003970	0.004345	0.004472	0.002541	0.007995
w_4	0.004228	0.003426	0.001352	0.006517	0.008969	0.003160
w_5	0.003782	0.001038	0.003337	0.000139	0.000559	0.009376
w_6	0.008357	0.009565	0.002437	0.007114	0.004331	0.002473
w_7	0.005026	0.009302	0.006770	0.006522	0.007388	0.007674
w_8	0.002310	0.007918	0.005483	0.003999	0.004173	0.009916

Film Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

ALS

Film Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.004354	0.001233	0.006094	0.006962	0.003187	0.002150
w_11	0.002201	0.008481	0.002728	0.008756	0.009007	0.004807
w_12	0.007575	0.009497	0.000082	0.000812	0.009892	0.006491
w_2	0.007037	0.000828	0.005426	0.004486	0.007328	0.002573
w_3	0.006890	0.002751	0.003770	0.009438	0.004094	0.004566
w_4	0.003750	0.005030	0.007132	0.007889	0.007560	0.003239
w_5	0.003616	0.000988	0.008382	0.000849	0.009921	0.008695
w_6	0.005031	0.003143	0.007940	0.002468	0.003908	0.007429
w_7	0.001434	0.001843	0.009584	0.001796	0.006374	0.005471
w_8	0.000660	0.003330	0.000656	0.009253	0.001410	0.009041

Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.009808	0.003580	0.001264	0.000377	0.006196	0.006116
w_11	0.000644	0.000140	0.009966	0.008271	0.007089	0.004144
w_12	0.006116	0.003331	0.007042	0.000930	0.006767	0.007332
w_2	0.006918	0.000382	0.009091	0.005865	0.004201	0.009829
w_3	0.001293	0.003970	0.004345	0.004472	0.002541	0.007995
w_4	0.004228	0.003426	0.001352	0.006517	0.008969	0.003160
w_5	0.003782	0.001038	0.003337	0.000139	0.000559	0.009376
w_6	0.008357	0.009565	0.002437	0.007114	0.004331	0.002473
w_7	0.005026	0.009302	0.006770	0.006522	0.007388	0.007674
w_8	0.002310	0.007918	0.005483	0.003999	0.004173	0.009916

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual funnel

HOW TO ADD CONTEXT

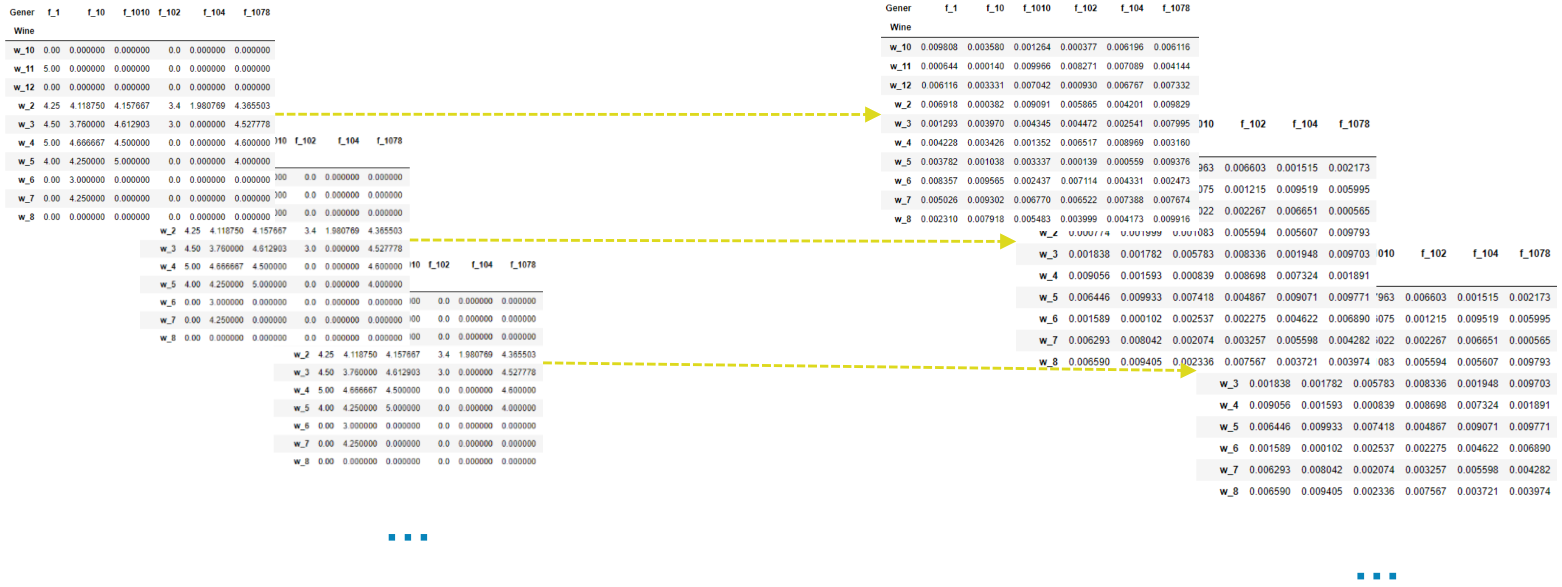
1 Choose paradigm of using context

2 Create contextual funnel

Film Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

ALS

Film Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.004354	0.001233	0.006094	0.006962	0.003187	0.002150
w_11	0.002201	0.008481	0.002728	0.008756	0.009007	0.004807
w_12	0.007575	0.009497	0.000082	0.000812	0.009892	0.006491
w_2	0.007037	0.000828	0.005426	0.004486	0.007328	0.002573
w_3	0.006890	0.002751	0.003770	0.000438	0.004094	0.004566
w_4	0.003750	0.005030	0.007732	0.007389	0.007560	0.003239
w_5	0.003616	0.000988	0.008382	0.000849	0.009921	0.008695
w_6	0.005031	0.003143	0.007940	0.002468	0.003908	0.007429
w_7	0.001434	0.001843	0.009584	0.001796	0.006374	0.005471
w_8	0.000660	0.003330	0.000656	0.009253	0.001410	0.009041



HOW TO ADD CONTEXT

Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

...

Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.009808	0.003580	0.001264	0.000377	0.006196	0.006116
w_11	0.000644	0.000140	0.009966	0.008271	0.007089	0.004144
w_12	0.006116	0.003331	0.007042	0.000930	0.006767	0.007332
w_2	0.006918	0.000382	0.009091	0.005865	0.004201	0.009829
w_3	0.001293	0.003970	0.004345	0.004472	0.002541	0.007995
w_4	0.004228	0.003426	0.001352	0.006517	0.008969	0.003160
w_5	0.003782	0.001038	0.003337	0.000139	0.000559	0.009376
w_6	0.008357	0.009565	0.002437	0.007114	0.004331	0.002473
w_7	0.005026	0.009302	0.006770	0.006522	0.007388	0.007674
w_8	0.002310	0.007918	0.005483	0.003999	0.004173	0.009916

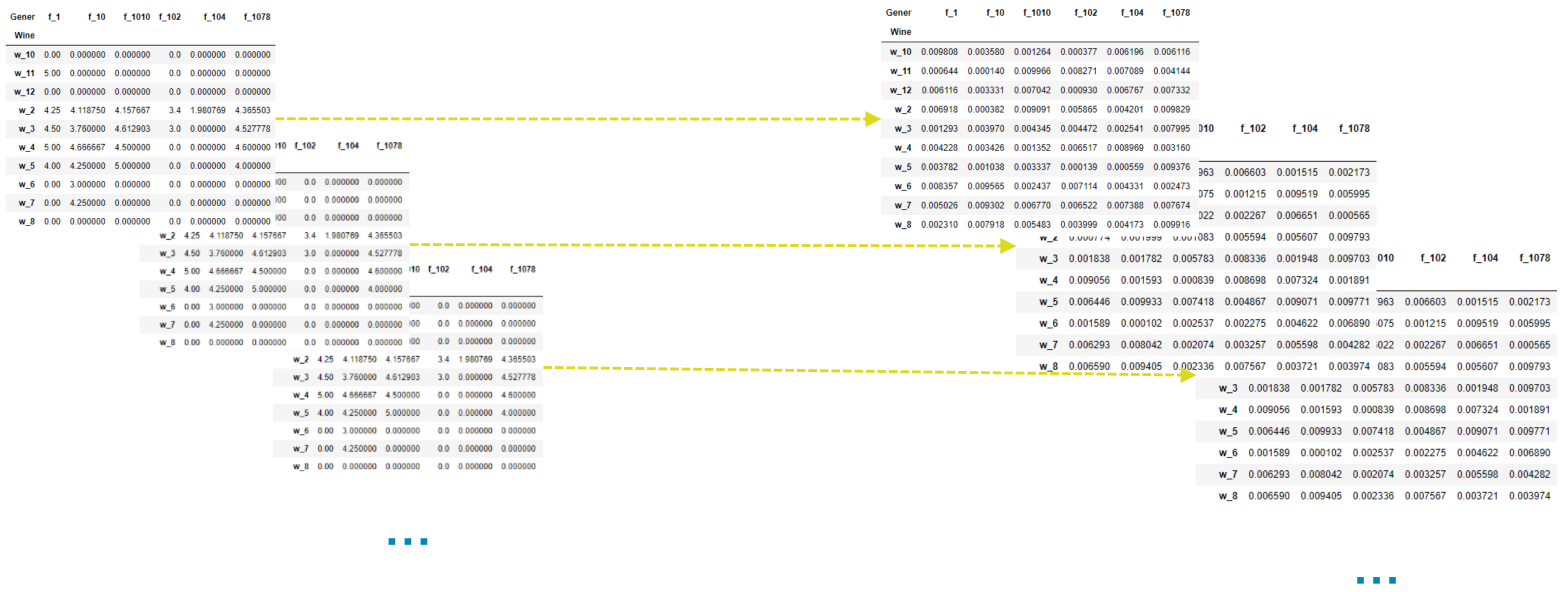
...

score(u, i) = avg(R1 + R2 + R3 + RN)

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate



score(u, i) = avg(R1 + R2 + R3 + RN)

score(u, i) = avg(wR1 + wR2 + wR3 + wRN)

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

Gener / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

...

Gener / Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.009808	0.003580	0.001264	0.000377	0.006196	0.006116
w_11	0.000644	0.000140	0.009966	0.008271	0.007089	0.004144
w_12	0.006116	0.003331	0.007042	0.000930	0.006767	0.007332
w_2	0.006918	0.000382	0.009091	0.005865	0.004201	0.009829
w_3	0.001293	0.003970	0.004345	0.004472	0.002541	0.007995
w_4	0.004228	0.003426	0.001352	0.006517	0.008969	0.003160
w_5	0.003782	0.001038	0.003337	0.000139	0.000559	0.009376
w_6	0.008357	0.009565	0.002437	0.007114	0.004331	0.002473
w_7	0.005026	0.009302	0.006770	0.006522	0.007388	0.007674
w_8	0.002310	0.007918	0.005483	0.003999	0.004173	0.009916

...

score(u, i) = avg(R1 + R2 + R3 + RN)

score(u, i) = avg(wR1 + wR2 + wR3 + wRN)

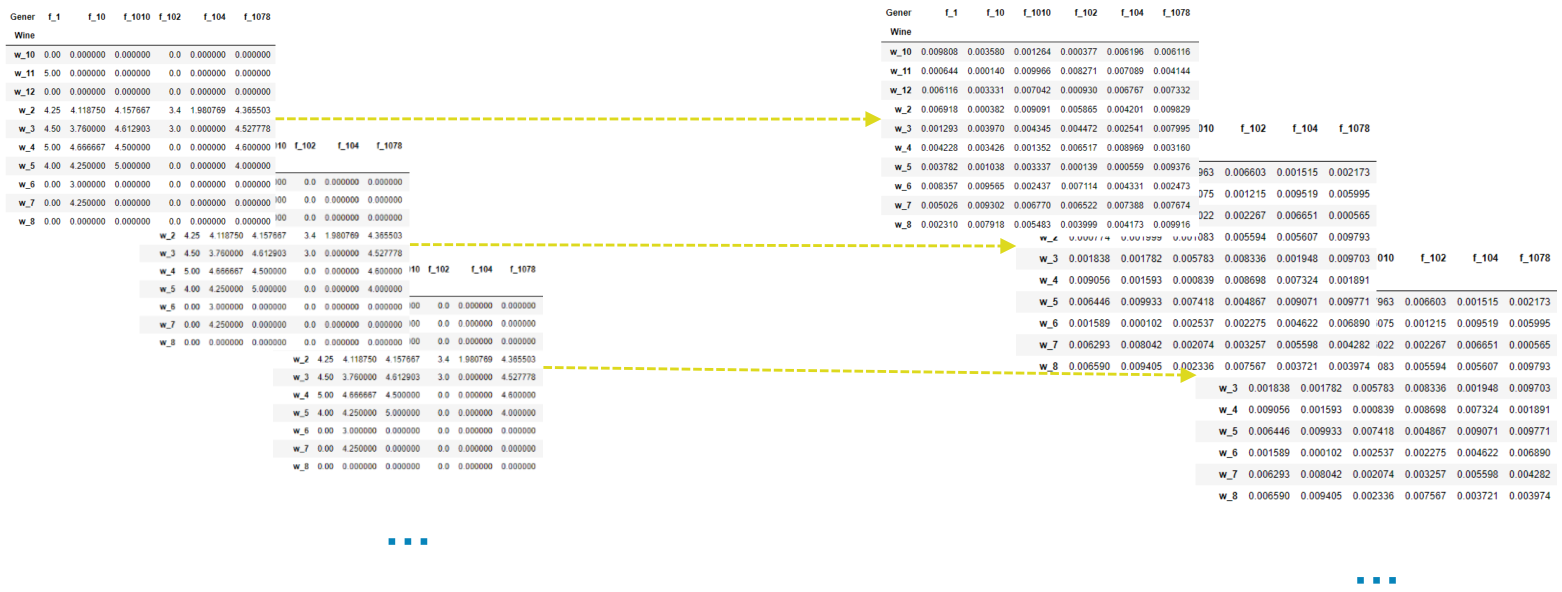
- A Classification model is a slippery slope

HOW TO ADD CONTEXT

1 Choose paradigm of using context

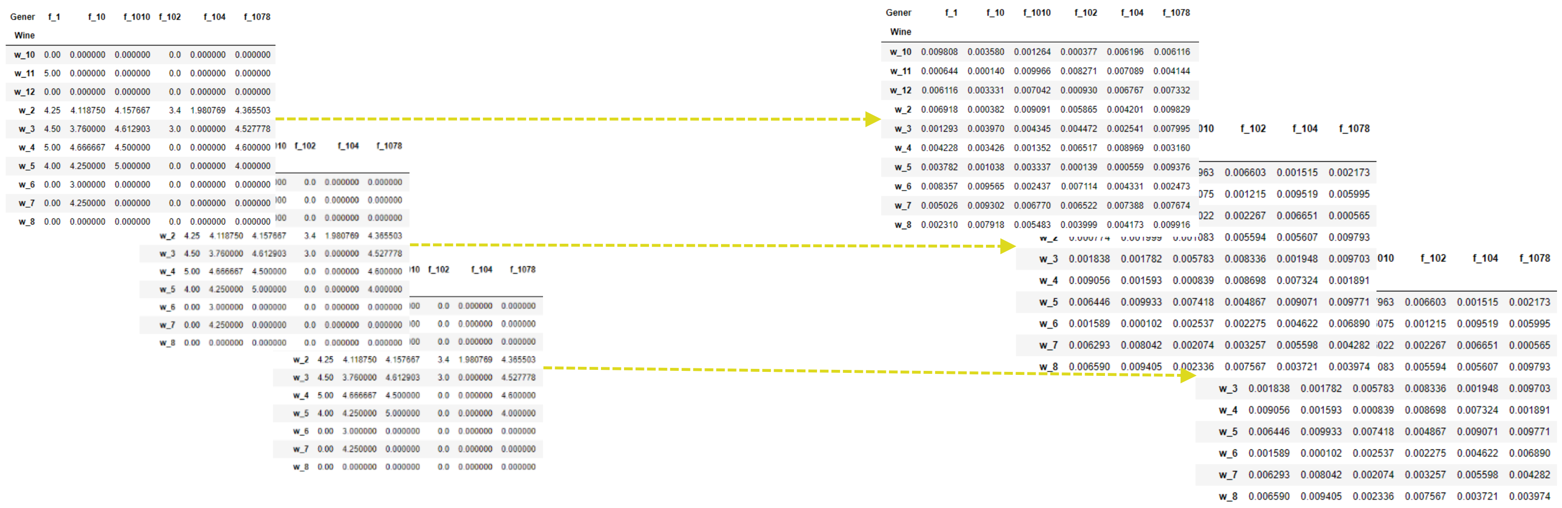
2 Create contextual Funnel

3 Calculate rate



score(u, i) = avg(R1 + R2 + R3 + RN)

score(u, i) = avg((prob*R1) + (prob* R2) + (prob* R3) + (prob* RN))



Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_11	5.00	0.000000	0.000000	0.0	0.000000	0.000000
w_12	0.00	0.000000	0.000000	0.0	0.000000	0.000000
w_2	4.25	4.118750	4.157667	3.4	1.980769	4.365503
w_3	4.50	3.760000	4.612903	3.0	0.000000	4.527778
w_4	5.00	4.666667	4.500000	0.0	0.000000	4.600000
w_5	4.00	4.250000	5.000000	0.0	0.000000	4.000000
w_6	0.00	3.000000	0.000000	0.0	0.000000	0.000000
w_7	0.00	4.250000	0.000000	0.0	0.000000	0.000000
w_8	0.00	0.000000	0.000000	0.0	0.000000	0.000000

Gener Wine	f_1	f_10	f_1010	f_102	f_104	f_1078
w_10	0.009808	0.003580	0.001264	0.000377	0.006196	0.006116
w_11	0.000644	0.000140	0.009966	0.008271	0.007089	0.004144
w_12	0.006116	0.003331	0.007042	0.000930	0.006767	0.007332
w_2	0.006918	0.000382	0.009091	0.005865	0.004201	0.009829
w_3	0.001293	0.003970	0.004345	0.004472	0.002541	0.007995
w_4	0.004228	0.003426	0.001352	0.006517	0.008969	0.003160
w_5	0.003782	0.001038	0.003337	0.000139	0.000559	0.009376
w_6	0.008357	0.009565	0.002437	0.007114	0.004331	0.002473
w_7	0.005026	0.009302	0.006770	0.006522	0.007388	0.007674
w_8	0.002310	0.007918	0.005483	0.003999	0.004173	0.009916

...

...

score(u, i) = avg(R1 + R2 + R3 + RN)

score(u, i) = avg((prob*R1) + (prob* R2) + (prob* R3) + (prob* RN))

score(u, i) = avg(R1 + R2 + R3 + RN) * prob

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

score(u, i) = avg(R1 + R2 + R3 + RN) * prob

```
def recom_context_score(user_id, context_id, s_matrix, c_current, delta):

    # calculate cf
    initial_pred = CF(user_id, contex_id, s_matrix)

    if context_id in r_df:
        ...
        # get contexts of similar users with similar context
        l_cnx = np.array(c_profile.loc[c_profile.context_id==context_id,['user_id','context']])

        if c_current in all_cnx:
            # find similarity of the current context and others
            cnx_scores = np.array([[uid, cs_df[c_current][cx]] for uid,cx in l_cnx])

            # filter users whose similarity bigger than delta
            filtered_scores = cnx_scores[cnx_scores[:,1].astype(float)>delta]

            # context popularity based on current
            context_prob = len(filtered_scores) / len(cnx_scores)

        else:
            context_prob = 1

        return initial_pred * context_prob

    else:
        return initial_pred
```

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

score(u, i) = avg(R1 + R2 + R3 + RN) * prob

```python
def recom_context_score(user_id, context_id, s_matrix, c_current, delta):

    # calculate cf
    initial_pred = CF(user_id, contex_id, s_matrix)

    if context_id in r_df:
        ...
        # get contexts of similar users with similar context
        l_cnx = np.array(c_profile.loc[c_profile.context_id==context_id,['user_id','context']])

        if c_current in all_cnx:
            # find similarity of the current context and others
            cnx_scores = np.array([[uid, cs_df[c_current][cx]] for uid,cx in l_cnx])

            # filter users whose similarity bigger than delta
            filtered_scores = cnx_scores[cnx_scores[:,1].astype(float)>delta]

            # context popularity based on current
            context_prob = len(filtered_scores) / len(cnx_scores)

        else:
            context_prob = 1

        return initial_pred * context_prob

    else:
        return initial_pred
```

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

score(u, i) = avg(R1 + R2 + R3 + RN) * prob

```python
def recom_context_score(user_id, context_id, s_matrix, c_current, delta):

    # calculate cf
    initial_pred = CF(user_id, contex_id, s_matrix)

    if context_id in r_df:
        ...
        # get contexts of similar users with similar context
        l_cnx = np.array(c_profile.loc[c_profile.context_id==context_id,['user_id','context']])

        if c_current in all_cnx:
            # find similarity of the current context and others
            cnx_scores = np.array([[uid, cs_df[c_current][cx]] for uid,cx in l_cnx])

            # filter users whose similarity bigger than delta
            filtered_scores = cnx_scores[cnx_scores[:,1].astype(float)>delta]

            # context popularity based on current
            context_prob = len(filtered_scores) / len(cnx_scores)

        else:
            context_prob = 1

        return initial_pred * context_prob

    else:
        return initial_pred
```

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

HOW TO ADD CONTEXT

1 Choose paradigm of using context

2 Create contextual Funnel

3 Calculate rate

score(u, i) = avg(R1 + R2 + R3 + RN) * prob

```
def recom_context_score(user_id, context_id, s_matrix, c_current, delta):

    # calculate cf
    initial_pred = CF(user_id, contex_id, s_matrix)

    if context_id in r_df:
        ...
        # get contexts of similar users with similar context
        l_cnx = np.array(c_profile.loc[c_profile.context_id==context_id,['user_id','context']])

        if c_current in all_cnx:
            # find similarity of the current context and others
            cnx_scores = np.array([[uid, cs_df[c_current][cx]] for uid,cx in l_cnx])

            # filter users whose similarity bigger than delta
            filtered_scores = cnx_scores[cnx_scores[:,1].astype(float)>delta]

            # context popularity based on current
            context_prob = len(filtered_scores) / len(cnx_scores)

        else:
            context_prob = 1

        return initial_pred * context_prob

    else:
        return initial_pred
```

Context novelty
Context diversity

!

- **Novelty** $$\frac{1}{\#Z-1}\sum_{j\in Z_u}[1-sim(i,j)]$$

- **Diversity** $$\frac{1}{\#Z(\#Z-1)}\sum_{i\in Z_u}\sum_{j\in Z_u,j\neq i}[1-sim(i,j)]$$

!

- **Novelty**

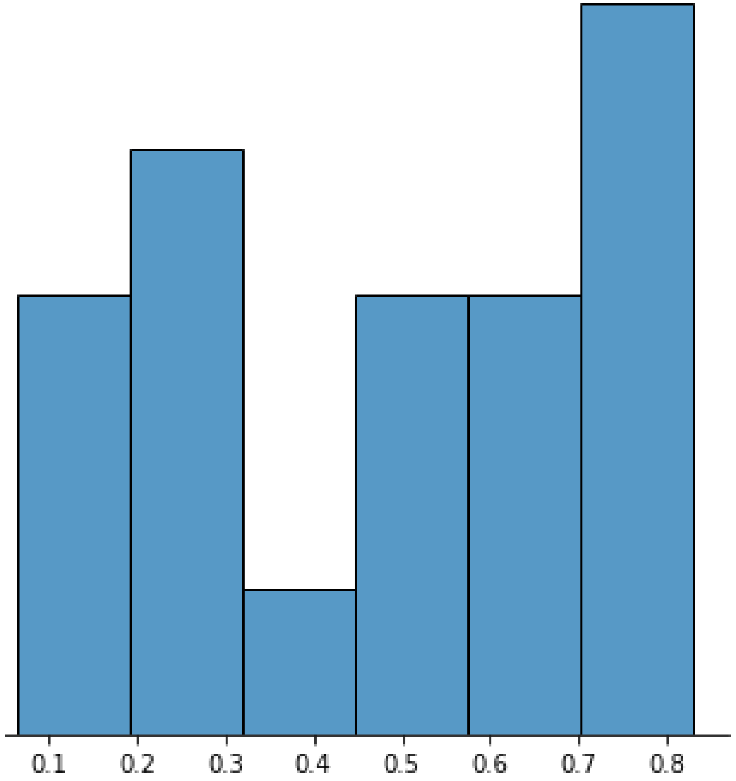
$$\frac{1}{\#Z-1}\sum_{j\in Z_u}[1-sim(i,j)]$$

Film
- Genre
- Subgenre
- Actors / Actresses
- Director
- Opinion 😱
- Country

Wine
- Aged in / Tannins
- Sugar / Taste
- Grape
- Appelcion
- Opinion 🥳
- Country / Region

- **Diversity**

$$\frac{1}{\#Z(\#Z-1)}\sum_{i\in Z_u}\sum_{j\in Z_u, j\neq i}[1-sim(i,j)]$$



- **Diversity** $$\frac{1}{\#Z(\#Z-1)} \sum_{i \in Z_u} \sum_{j \in Z_u, j \neq i} [1 - sim(i,j)]$$

See you on GitHub

@SeleznevArtem

/NameArtem

/seleznev-artem

/seleznev.artem.info

github.com/NameArtem/recom_way