SWAP researchgroup

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

DIPARTIMENTO DI INFORMATICA

ClayRS

CBRS framework written in Python

Architecture and its three main modules

Slides made by: Antonio Silletti

Infographic timeline

March 2020

Initial idea

Alpha version made by Mattia Patruno, Roberto Barile, Francesco Benedetti, Carlo Parisi

December 2020

First Refactor

Refactor of classifiers and graphs, redo of the testing pipeline made by Antonio Silletti

April 2021

Complete Redo

Major Refactor and Overhaul of the whole framework made by Antonio Silletti, Elio Musacchio, Roberta Sallustio

July 2021

User Interface

Initial UI made by Raffaele Disabato (discontinued atm)

October 2021

Load tests

Testing of algorithms and metrics by Giuseppe Sancesario and Vincenzo Maria Giulio Martemucci

Infographic timeline

April 2022

Moved to SWAP

Changed name to **ClayRS** and moved repo to SWAP organization

July 2022

v0.1.0 on pip 🎉

Initial version released on pypi with the complete documentation!

September 2022

v0.2.0 released

Implemented multiprocessing, added bootstrap partitioning, MAP and MAP@K metrics

October 2022

v0.3.0 released

Implemented Experiment class for easily compare different algorithms

2023

?

Who’s and what’s next?

This is a project entirely made by students, with the constant and maximum supervision of the **SWAP** research group:

- *Prof. Pasquale Lops*
- *Ph.D. Marco Polignano*
- *Prof. Giovanni Semeraro*
- *Prof. Cataldo Musto*
- *Prof. Pierpaolo Basile*

There’s so much to do with so small time, that’s why highly motivated people are always welcome to come on board ☺

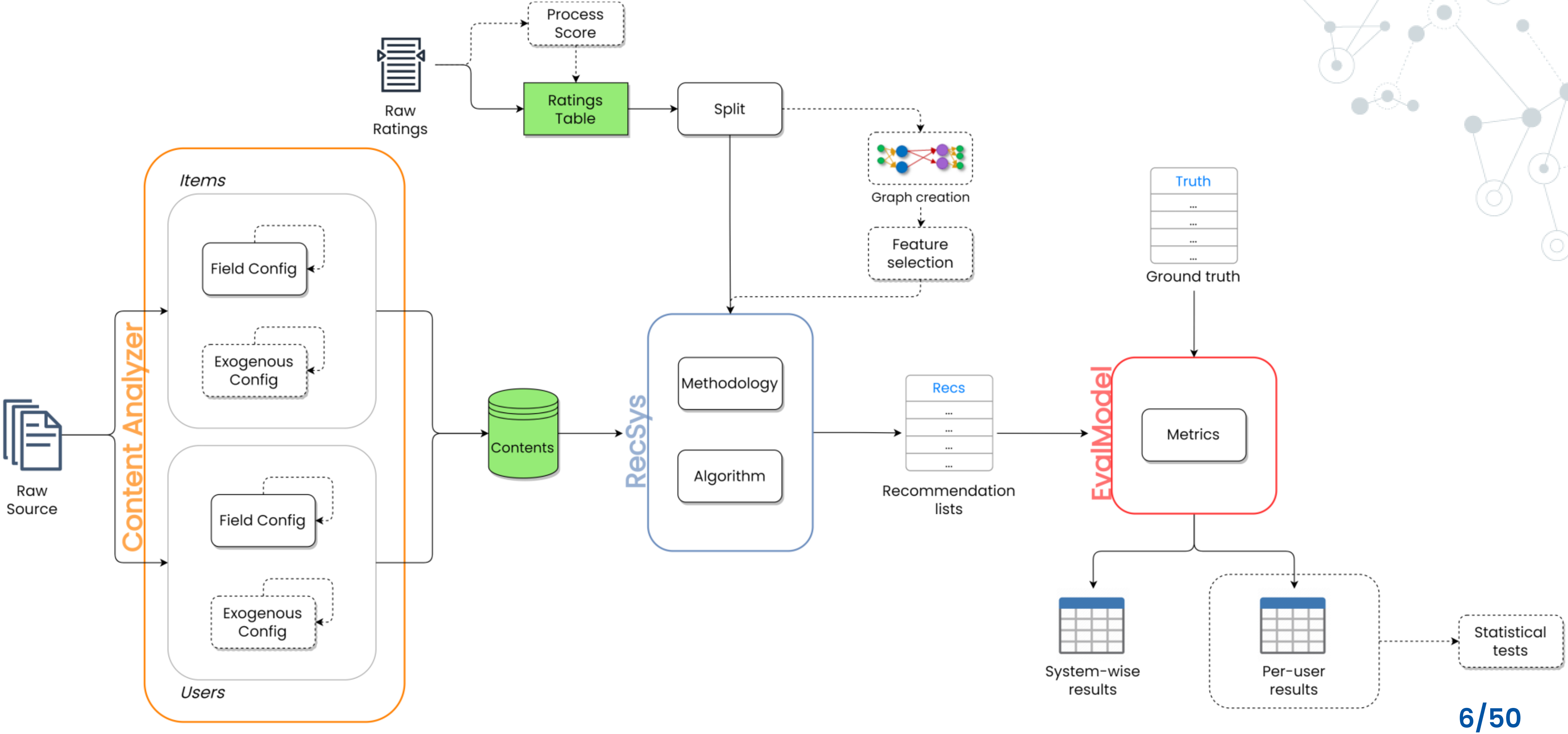
Idea

ClayRS allows you to conduct a complete experiment, starting from a raw representation of users and items to building and evaluating a recommender system.

It does so with three main modules, which you can also use individually:

Content Analyzer	*RecSys*	*EvalModel*

General pipeline

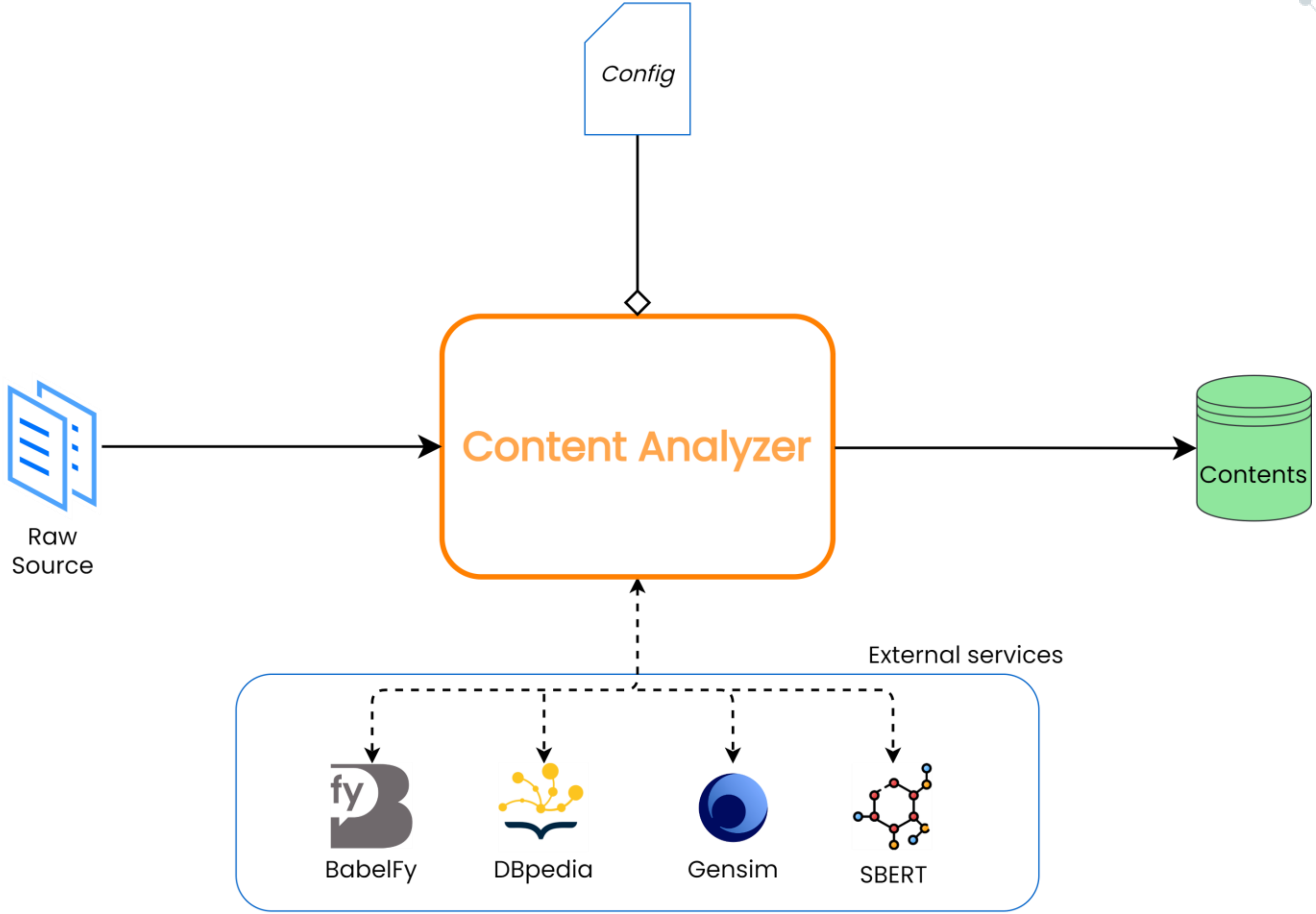


Content Analyzer

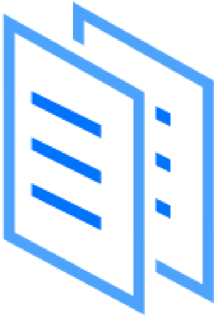
Given a raw source, the `Content Analyzer`:

- Creates and serializes content,
- Using the chosen configuration

Content Analyzer Architecture



What do we mean by Raw Source?



Raw Source

- A **Raw Source** is a file containing several information of the content to represent

  - Ex. Movies in a `JSON` file

```
{  "Title": "Jumanji",
   "IMDB_ID": "0113497"
   "Year": "1995",
   "Rated": "PG",
   "Genre": "Adventure, Family, Fantasy",
   "Released":"15 Dec 1995",
   "Runtime":"104 min",
   … }
```

  - Ex. Users in a `CSV` file (represented here as a table)

User_ID	Name	Age	Occupation
1	Antonio	24	student
2	Mario	44	lawyer

How can we represent content?

Config

You can set via configuration which fields of every raw content must be represented and how to represent them

- *Multiple representations for a single field are allowed*

```
{ "Title": "Jumanji",
  "Year": "1995",
  "Rated": "PG",
  "Genre": "Adventure, Family, Fantasy",
  "Released": "15 Dec 1995",
  "Runtime": "104 min",
  … }
```

tf-idf

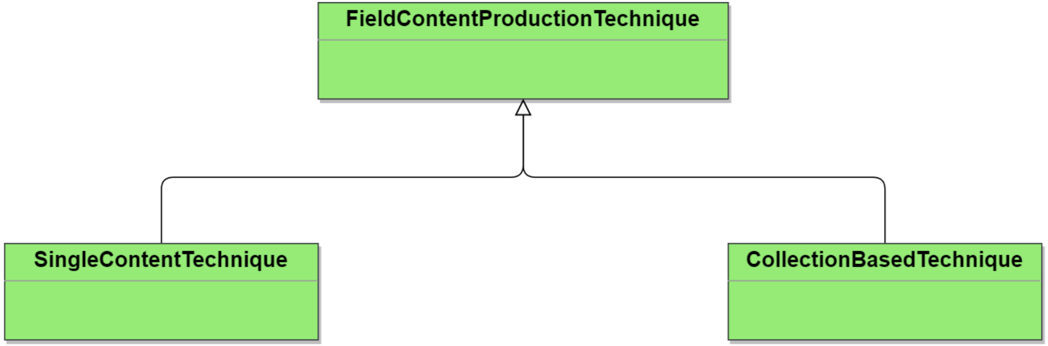
```
{ 'adventure': 0.49122938570380714,
  'family': 0.5631439252085217,
  'fantasy': 0.6645017758605305 }
```

embedding with glove-twitter-25 model

```
array([-0.01160799, -0.28532598, 0.0177138,
       -0.128398,   -0.10475059, 0.37144921,
        1.08316798,  0.63348202, 0.226706,
        …,           …,          …])
```

Which representation techniques are implemented?

Every representation technique is implemented as a `class`, in order to make use of polymorphism



There are two techniques implemented as `CollectionBased` techniques:

`tf-idf`

- `SkLearnTfIdf()`
- `WhooshTfIdf()`

`Synset Document frequency`

- PyWSDSynsetDocumentFrequency()

Which representation techniques are implemented?

There are several `SingleContent` techniques available, mainly based on embeddings:

- techniques which can store the original representation of the `raw source` *(useful for* `IndexQuery` *algorithm):*
  - `OriginalData()`

- techniques which compute the embedding representation of the content (cont.)

Embedding techniques

Embedding techniques implemented include:

- `WordEmbedding()`
- `SentenceEmbedding()`
- `DocumentEmbedding()`

They also exist in their «combined form», given a combiner (`Centroid()`, `Sum()`):

- `Word2SentenceEmbedding()`
- `Word2DocumentEmbedding()`

  …

For each *embedding* technique, a pre-trained model must be specified. It will be downloaded (optionally) from the following external sources:

- *Gensim*
- *SBERT*
- *Hugging Face models (BERT and T5 models)*
- *Local storage* (cont.)

Embedding techniques

It’s also possible to train via Framework the following Gensim models:

- `FastText`
- `Word2Vec`
- `RandomIndexing`
- `LatentSemanticAnalysis`
- `Doc2Vec`

The field(s) of every content of the *raw source* will be used as corpus

- If preprocessing operations are specified, the preprocessed corpus will be used
- The trained model will then be used (and optionally saved) to represent contents

Other available operations

Reduce the content dimensionality

By performing preprocessing operations, such as *stemming*, *lemmatization*, *stopwords removal*, etc. via the *NLTK* library, *SPACY or Ekphrasis*

```
"This is beautiful too and entertaining"

['This', 'beautiful', 'entertaining']
```

Save representations in an index

Each representation can be saved in an index, both for exporting reason or to perform a specific recommendation algorithm *(IndexQuery)*

```
...
content_id: 0113497
    Plot#0#original: After being trapped…
    Plot#1#tfidf: {trapped: 0.0185185…, …}
...
```

Content Analyzer: code example

Let’s instantiate a `config` both for `Items` and `Users`:

```python
import clayrs.content_analyzer as ca

movies_config = ca.ItemAnalyzerConfig(
        source=ca.JSONFile("items_info.json"),
        id="IMDB_ID",
        output_directory='movies_codified/'
)

users_config = ca.UserAnalyzerConfig(
        source=ca.CSVFile("users_info.csv"),
        id="User_ID",
        output_directory='users_codified/'
)
```

`items_info.json`

```
{  "Title": "Jumanji",
   "IMDB_ID": "0113497"
   "Year": "1995",
   "Rated": "PG",
   "Genre": "Adventure, Family, Fantasy",
   "Released":"15 Dec 1995",
   "Runtime":"104 min",
   … }
```

`users_info.csv`

User_ID	Name	Age	Occupation
1	Antonio	24	student
2	Mario	44	lawyer

Let’s specify how to represent items:

```
movies_config.add_single_config(
    'Plot',
    ca.FieldConfig(ca.SkLearnTfIdf())
)

movies_config.add_single_config(
    'Plot',
    ca.FieldConfig(ca.WhooshTfIdf(),
                   preprocessing=ca.NLTK(stemming=True),
                   id="whooshtfidf")
)

movies_config.add_single_config(
    'Genre',
    ca.FieldConfig(
        ca.WordEmbeddingTechnique('glove-twitter-25'),
        ca.NLTK(stopwords_removal=True, lemmatization=True)
    )
)
```

Equivalent of using `add_multiple_config(…)` and passing a list of representation

Exogenous techniques

You can also expand the content via:

- *`DBpedia`*
- *`BabelFy Entity Linking`*
- *`Local dataset`*

For the `DBpedia` mapping technique you can choose how to retrieve properties in four different ways:

- **`only_retrieved_evaluated:`** retrieve only properties in DBpedia which have a value
- **`original_retrieved:`** retrieve only local properties which have a value in DBpedia
- **`all_retrieved:`** retrieve all properties from DBpedia
- **`all:`** retrieve all properties from DBpedia + all properties in local

Let’s add an exogenous representation both for items and users:

```
movies_config.add_single_exogenous(
    ca.ExogenousConfig(
        ca.DBPediaMappingTechnique('Film', 'EN', 'dbpedia_label')
    )
)

users_config.add_single_exogenous(
    ca.ExogenousConfig(
        ca.PropertiesFromDataset(field_name_list=['gender', 'occupation'])
    )
)
```

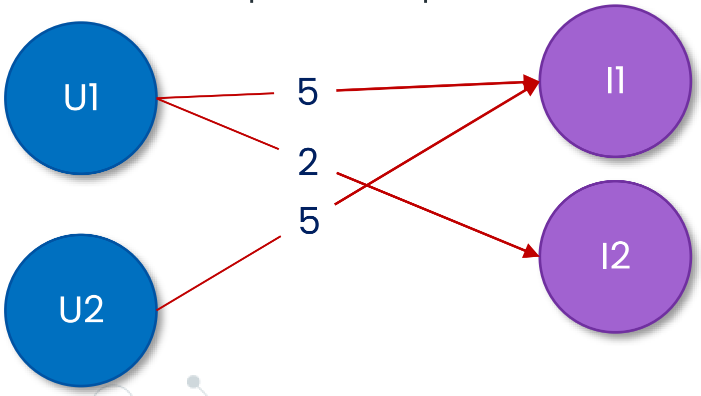
Graphs

ClayRS can represent the User-Item rating matrix as a *graph*, which can be further manipulated by adding other kinds of nodes (property nodes), by removing some others, etc.

User	Item	Rating
U1	I1	5
U1	I2	2
U2	I1	5

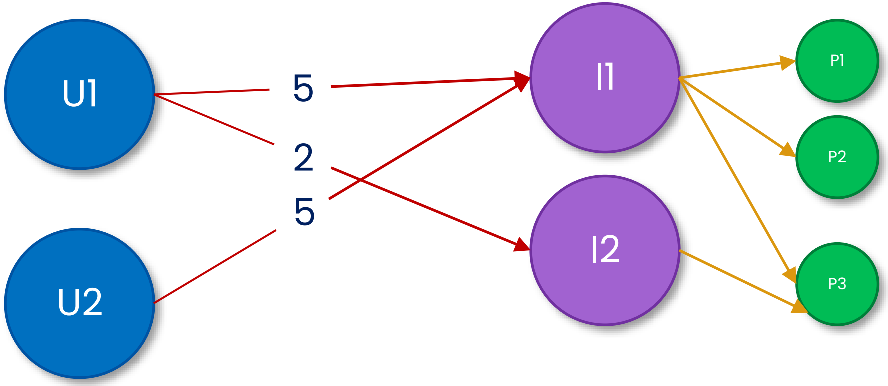
User-Item Rating Matrix

Bipartite Graph:



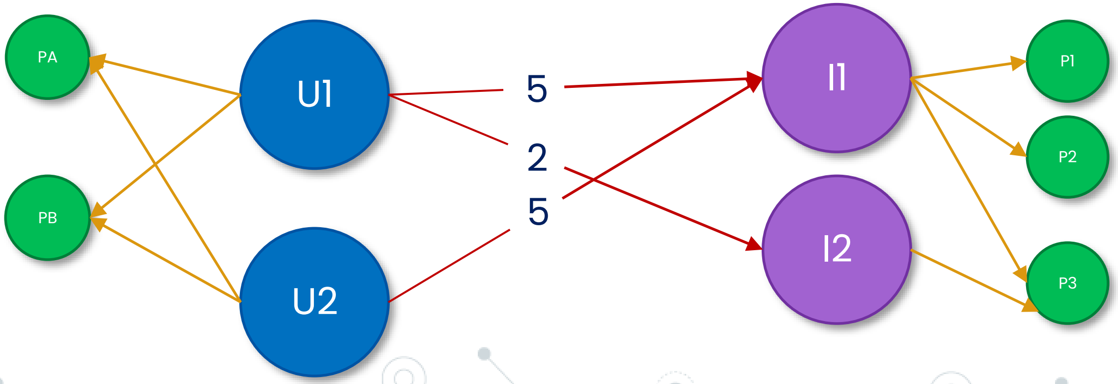
Tripartite graph:

Graph with property nodes only linked to item nodes

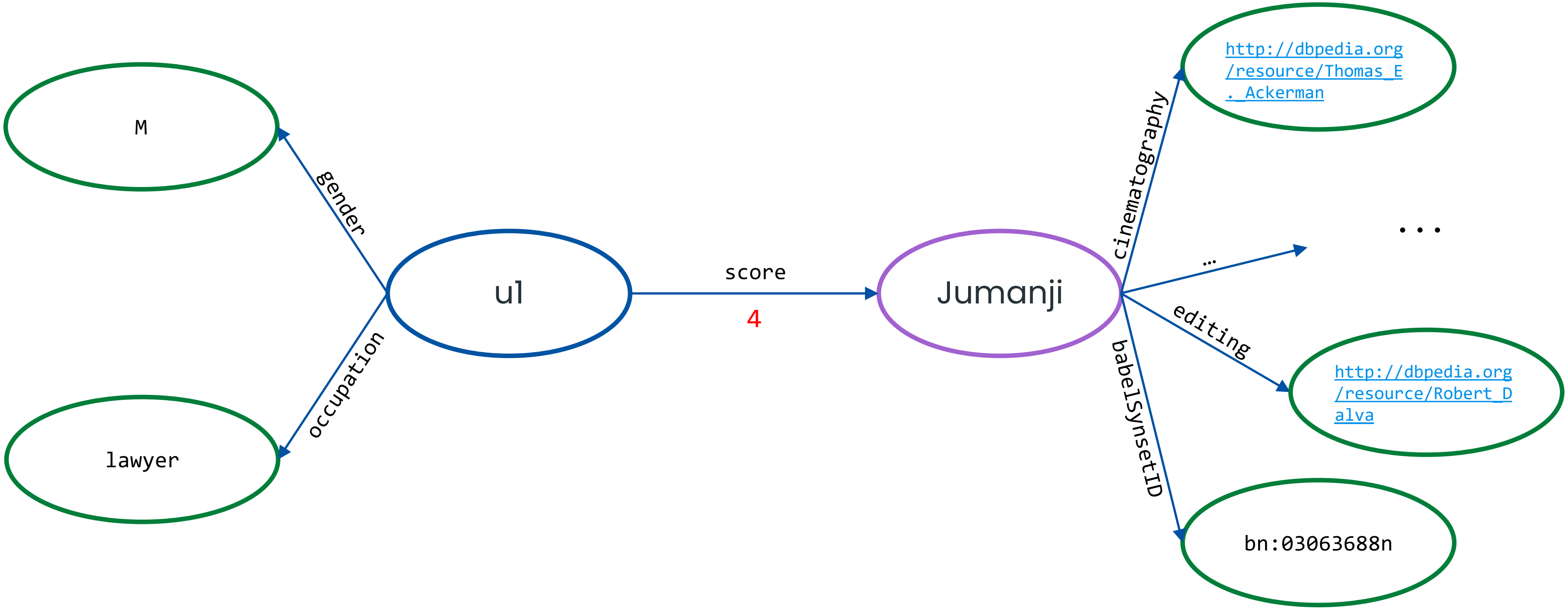


Full Graph:

Graph with no restriction



Full graph + exogenous techniques



How to export content?

- In a format recognizable by the framework (`.xz`), so that contents could be used in the recommending phase

- In `JSON` format which is readable and allows complex representations to be used in other contexts

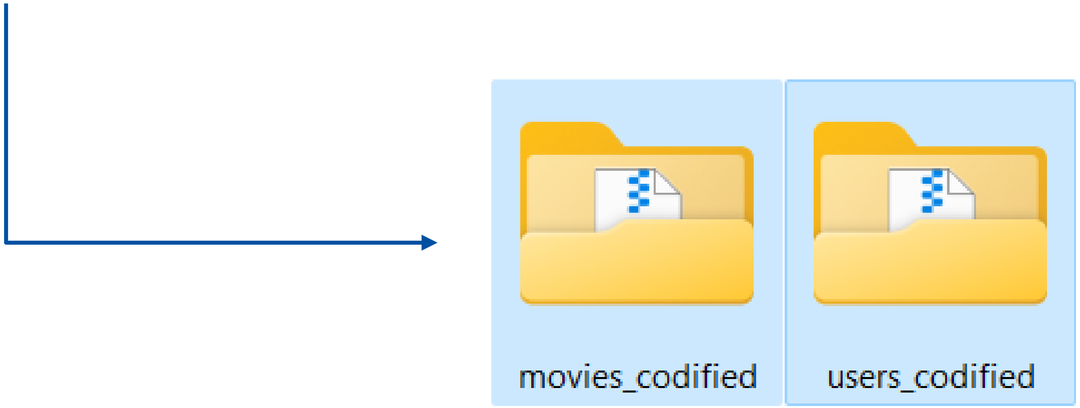

```
[
    {
        "content_id": "0113497",
        "Exo#0": "{'starring': ['http://dbpedia.org/resource/David_
        "Plot#0": "{'stop': 0.1901064866700191, 'city': 0.21627210
        "Plot#1": "[[ 0.03125608  0.11693476  0.05183702 ... -0.10
        "Plot#2": "After being trapped in a jungle board game for 2
        "Plot#3": "trapped jungle board game 26 years , Man-Child w
        "Genre#0": "[[-4.71320003e-01  2.49479994e-01 -2.35080004e-
        "Genre#1": "{',': 0.028982257714459496, 'adventur': 0.4559
        "Genre#2": "Adventure, Family, Fantasy",
        "Genre#3": "Adventure , Family , Fantasy",
        "Year#0": "1995",
        "Year#1": "1995",
```

Content Analyzer: output

Let's serialize items and users with the representations we chose:

```
ca.ContentAnalyzer(movies_config).fit()

ca.ContentAnalyzer(users_config).fit()
```



We could also check if everything went smoothly:

```python
from clayrs.utils import load_content_instance

item = load_content_instance('movies_codified', '0113497')

print(item)
```

Exogenous representations

Field representations

```
Content:   0113497

Exogenous representations:
                                                            representation
internal_id external_id
0           NaN         {'cinematography': 'http://dbpedia.org/resourc...

Field: Plot
                                                            representation
internal_id external_id
0           NaN         {'them': 0.1144577150792816, 'stop': 0.1606690...
1           whooshtfidf {'26': 1.3010299956639813, 'After': 0.82390874...

Field: Genre
                                                            representation
internal_id external_id
0           NaN         [-0.58404666  0.21438999  0.06313567 -0.39509 ...

###############################
```

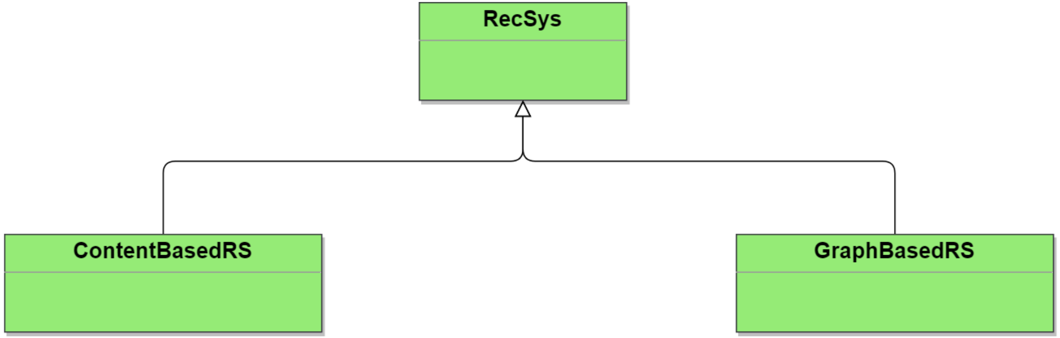
RecSys

The `RecSys` module allows to:

- Instantiate a recommender system
  - Using items and users serialized by the *`Content Analyzer`*
- Make score prediction or recommend items for the active user

Implemented Recommender Systems

Each recommender system is a specialization of the abstract class `RecSys`

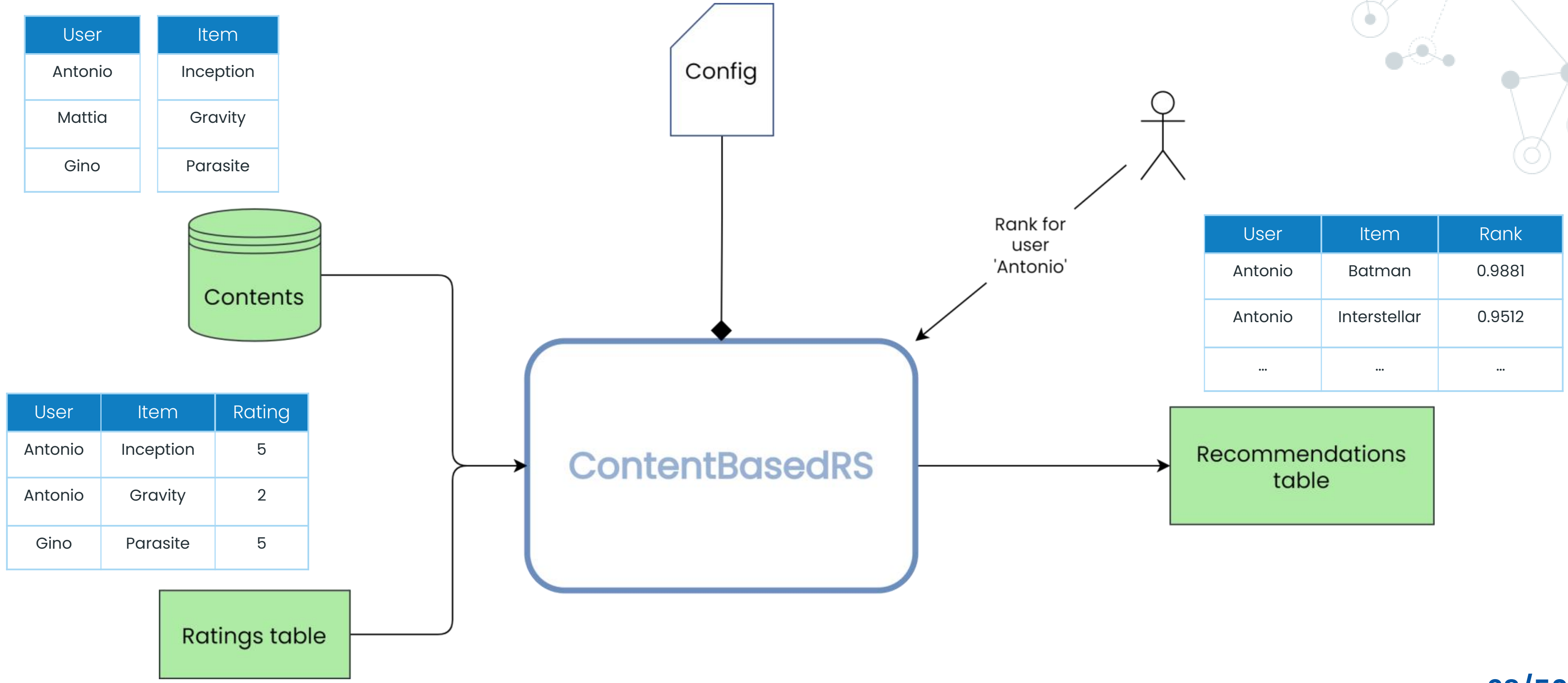


There are two available implementations:

- *Content Based RecSys* (`ContentBasedRS`)
- *Graph Based RecSys* (`GraphBasedRS`)

To implement other typologies, simply extend the `RecSys` class

Content Based RS Architecture



User	Item
Antonio	Inception
Mattia	Gravity
Gino	Parasite

User	Item	Rating
Antonio	Inception	5
Antonio	Gravity	2
Gino	Parasite	5

User	Item	Rank
Antonio	Batman	0.9881
Antonio	Interstellar	0.9512
...	...	...

Ratings Table

In order to instantiate a RecSys, the User x Item matrix must be imported. The framework can also manipulate its 'score' field if a *processor* is specified

- `NumberNormalizer()`
- `TextBlobSentimentAnalysis()`

Ratings table

`NumberNormalizer` normalizes a numeric field in the $[-1, 1]$

`TextBlobSentimentAnalysis` returns the polarity of a text field in the $[-1, 1]$ range

How to import Ratings into ClayRS

1. The columns are ordered:

```
ca.Ratings(ca.CSVFile('ratings_ordered.csv'))
```

2. The ‘score’ column isn’t next to the ‘item’ column:

```
ca.Ratings(
    ca.CSVFile('ratings.csv')),
    score_column='points'
)
```

3. The ‘score’ column needs to be processed:

```
ca.Ratings(
    ca.CSVFile('ratings.csv')),
    score_column=2,
    score_processor=ca.TextBlobSentimentAnalysis()
)
```

ratings.csv

user	item	review	points
Antonio	Inception	good	4.5
Mario	Gravity	bad	1

Splitting the dataset

```
n_split = 2
[train_split1, train_split2], [test_split1, test_split2] =
rs.KFoldPartitioning(n_split).split_all(original_ratings)
```

from_id	to_id	rating
u1	Tenet	1
u1	Gravity	-0,5
u2	Her	0,6
u2	Gravity	-0,2

1st split

train_split1

from_id	to_id	rating
u1	Tenet	1
u2	Her	0,6

test_split1

from_id	to_id	rating
u1	Gravity	-0,5
u2	Gravity	-0,2

2nd split

train_split2

from_id	to_id	rating
u1	Gravity	-0,5
u2	Gravity	-0,2

test_split2

from_id	to_id	rating
u1	Tenet	1
u2	Her	0,6

Which partitioning techniques are available?

The following are the partitioning techniques available, all using the *sklearn* library:

- `KFoldPartitioning()`
- `HoldOutPartitioning()`
- `BootstrapPartitioning()`

Choosing the CB algorithm

Representations codified

```
Field: Plot

internal_id external_id
0           NaN
1           whooshtfidf

Field: Genre

internal_id external_id
0           NaN

##########################
```

```python
import clayrs.recsys as rs

# Centroid Vector alg
alg = rs.CentroidVector(
    {
     'Plot': [0, 'whooshtfidf'],
     'Genre': 0
    }
    similarity=rs.CosineSimilarity()
    # threshold=2
)
# Classifier alg
alg = rs.ClassifierRecommender(
    {
     'Plot': [0, 'whooshtfidf'],
     'Genre': 0
    }
    classifier=rs.SkKNN(n_neighbors=4)
    # threshold=2
)
```

Computing recommendations

Regardless of the algorithm chosen, simply instantiate the cbrs:

```
cbrs = rs.ContentBasedRS(alg, train_split1, items_path)
```

And then compute the rank, given the test set (which will only be used to compute which items are eligible for ranking):

```
cbrs.fit_rank(test_split1,
              recs_number=2,
              methodology=rs.TestRatingsMethodology())
```

User	Item	Rank score
3	0113497	0.98578
3	0114709	0.97324
8	0116367	0.99734
8	0117110	0.99711

Which methodologies are available?

Methodologies available:
(L is the recommendation list, u is the active user, Te is the test set, Tr is the training set)

- [TestRatingsMethodology()]()

$$L_u = Te_u$$

- TestItemsMethodology()

$$L_u = \bigcup_v Te_v \setminus Tr_u$$

Where:
- v is the generic user of the Te

- TrainingItemsMethodology()

$$L_u = \bigcup_{v \neq u} Tr_v$$

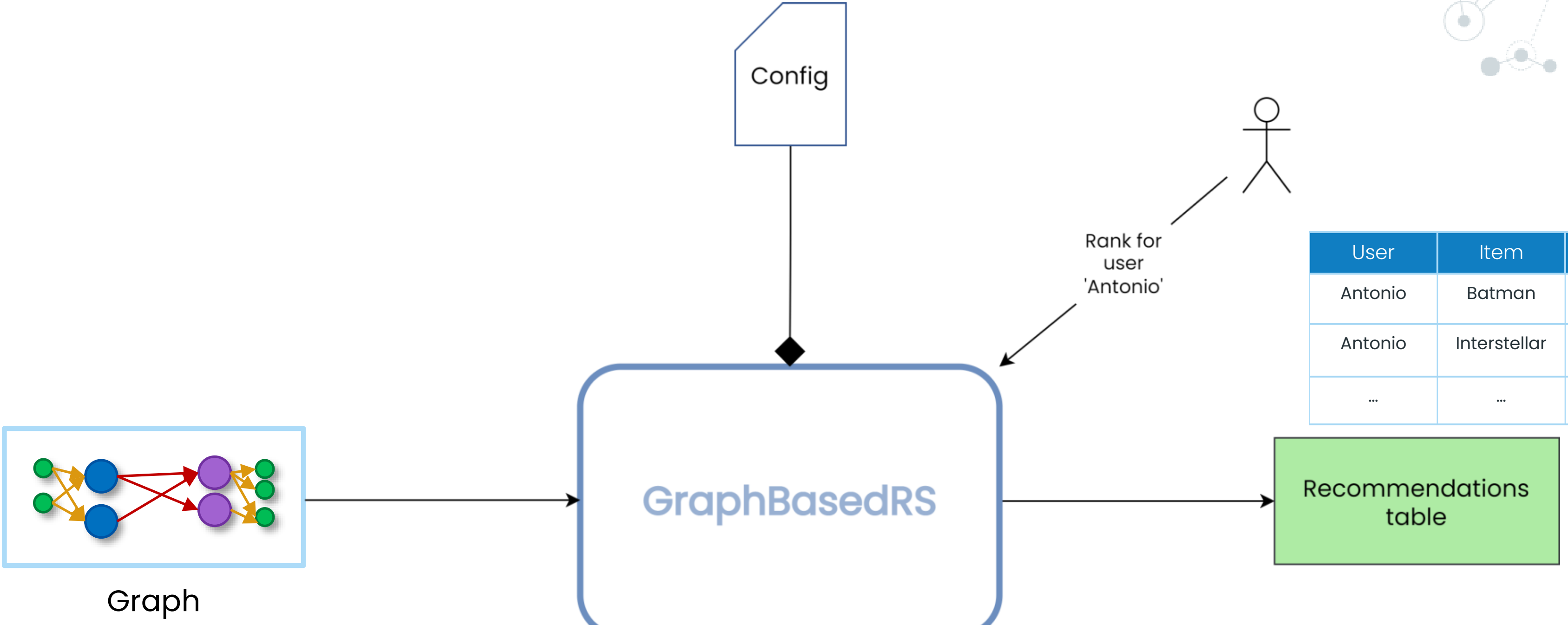
Where:
- v is the generic user of the Tr

- AllItemsMethodology()

$$L_u = I \setminus Tr_u$$

Where:
- I is the set which contains all items of the catalog

Graph Based RS Architecture



User	Item	Rank
Antonio	Batman	0.9881
Antonio	Interstellar	0.9512
...	...	...

GBRS: code example

Graph creation:

```
full_graph = rs.NXFullGraph(train_set1,
                             user_contents_dir='users_codified/',
                             item_contents_dir='movies_codified/',
                             user_exo_representation=0,
                             item_exo_representation=0)
```

GBRS definition:

```
alg = rs.NXPageRank(personalized=True)

gbrs = rs.GraphBasedRS(alg, full_graph)
```

And then, just like for `ContentBasedRS`, you can compute the rank given the test set:

```
gbrs.rank(test_set1, …)
```

Which recommendation algorithms are available?

GraphBasedRS:

- `PageRank()` *rank*
- `PageRank(personalized=True)` *rank*

ContentBasedRS:

- `CentroidVector()` *rank*
    - `CosineSimilarity()`
- `ClassifierRecommender()` *rank*
    - `SkSVC()`
    - `SkKNN()`
    - `SkLogisticRegression()`
    - `SkDecisionTree()`
    - `SkGaussianProcess()`
- `LinearPredictor()` *rank* *pred*
    - `SkLinearRegression()`
    - `SkRidge()`
    - `SkBayesianRidge()`
    - `SkSGDRegressor()`
    - `SkARDRegression()`
    - `SkHuberRegressor()`
    - `SkPassiveAggressiveRegressor()`
- `IndexQuery()` *rank*

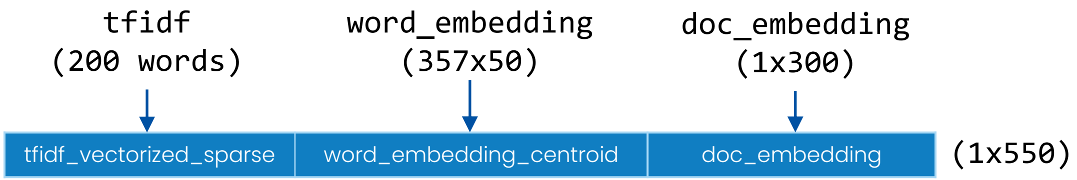
Flexibility of CB algorithms: a technical hint

Each content-based algorithm can work on multiple representations of a field, or even multiple representations of multiple fields

- e. g. You could train a classifier using a `tfidf` representation, a `WordEmbedding` representation and a `DocumentEmbedding` representation

Every representation specified will be vectorized (if necessary) and added as a column to the representation matrix that will be used in the *training phase*

- If vectors have different dimensions, they will be transformed into row vectors by using a chosen combiner from those implemented for the Content Analyzer (`Centroid(), Sum()`)



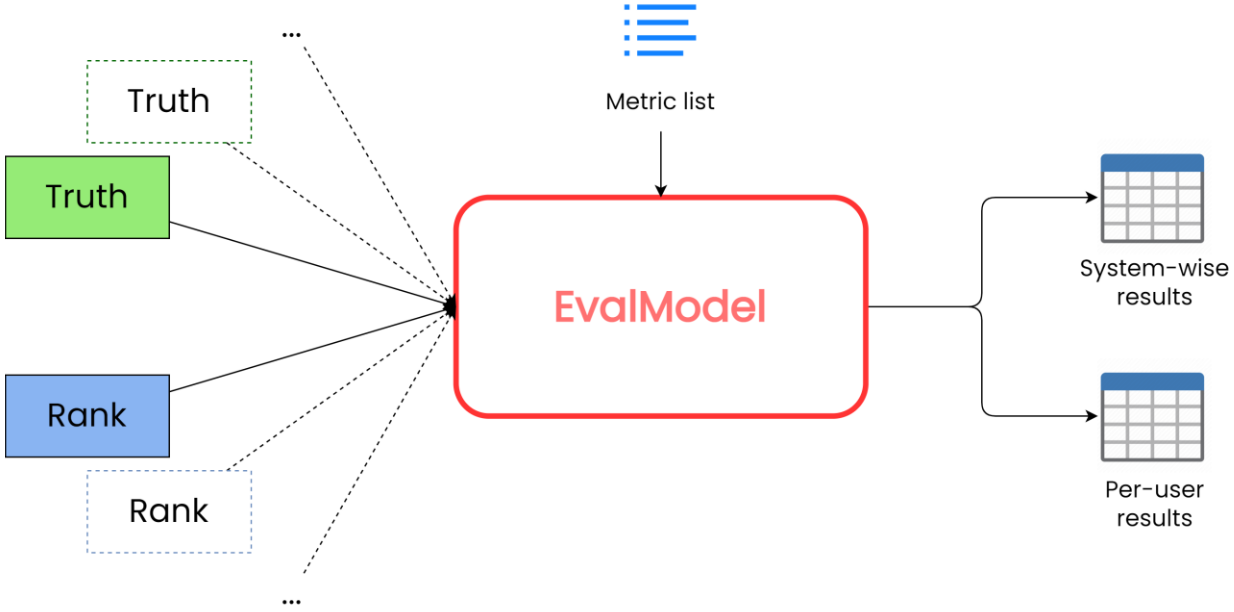
EvalModel

The `EvalModel` has the task of evaluating a recommender system, using several state-of-the-art metrics

EvalModel architecture

To evaluate a recommender, the `EvalModel` needs the rankings computed for each split, the relative ground truth, and a list of metrics

- It will return two pandas `DataFrame`, one containing metrics result for each user, the other containing metrics result of the whole system



EvalModel: code example

```python
import clayrs.evaluation as eva

em = eva.EvalModel(
    pred_list=[rank_split0, rank_split1],
    truth_list=[test_split0, test_split1],
    metric_list=[
        eva.Precision(),
        eva.PrecisionAtK(k=1),
        eva.RPrecision(sys_average='micro'),
        eva.Recall(),
        eva.RecallAtK(k=3),
        eva.FMeasure(),
        eva.FMeasureAtK(k=2),
    ],
)

sys_result, users_result = em.fit()
```

Results of each user
(avg of the two splits):

users_result

user_id	Precision - macro	Precision@1	RPrecision – micro	…
1	0.6	1.0	0.6	…
10	0.25	0.5	0.25	…
100	0.5	0.5	0.5	…
101	0.75	1.0	0.75	…
…	…	…	…	…

System wide results:

sys_result

user_id	Precision - macro	Precision@1	RPrecision – micro	…
sys - fold1	0.55662	0.55037	0.56369	…
sys - fold2	0.54644	0.55885	0.55637	…
sys - mean	0.55153	0.55461	0.56003	…

Which metrics are available?

Classification metrics (sys average computed as micro/macro):

- `Precision()`
- `PrecisionAtK()`
- `RPrecision()`
- `Recall()`
- `RecallAtK()`
- `FMeasure()`
- `FMeasureAtK()`

Ranking metrics:

- `NDCG()`
- `NDCGAtK()`
- `MRR()`
- `MRRAtK()`
- `Correlation('pearson') - Correlation('spearman') - Correlation('kendall’)`
- `MAP()`
- `MAPAtK()`

Which metrics are available?

Error metrics:

- `MSE()`
- `RMSE()`
- `MAE()`

Fairness metrics:

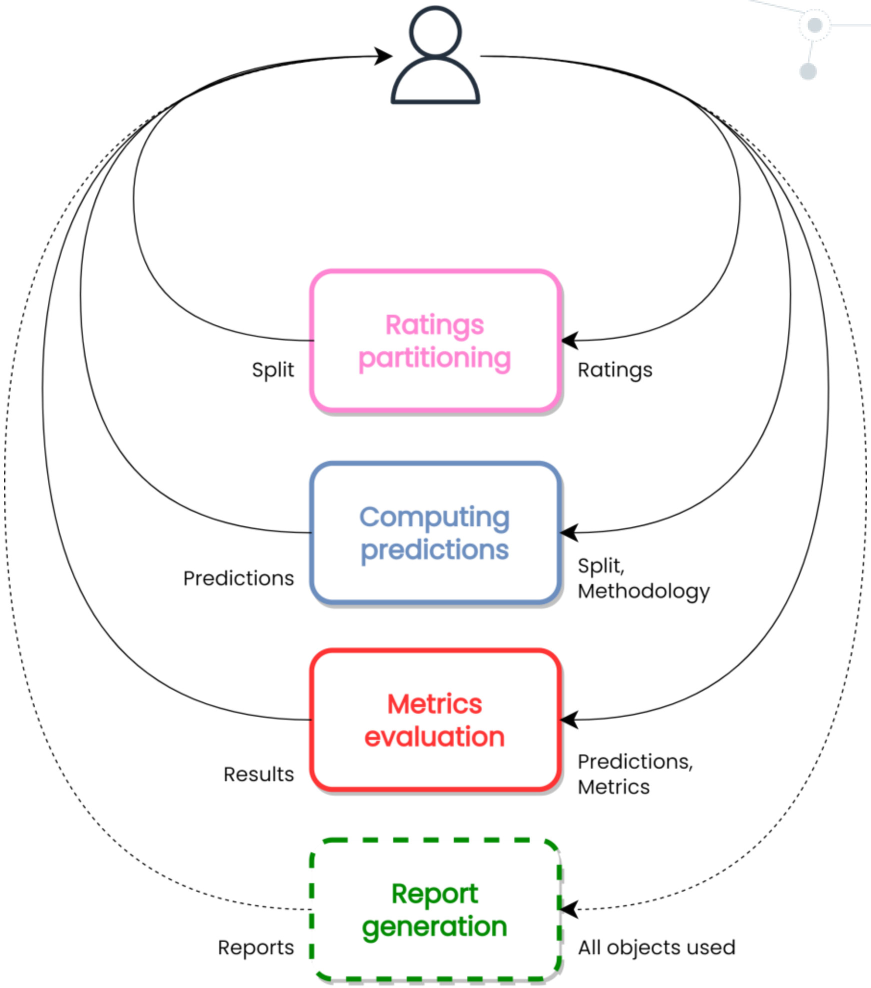
- `GiniIndex()`
- `PredictionCoverage()`
- `CatalogCoverage()`
- `DeltaGap()`

Plot metrics:

- `LongTailDistr()`
- `PopProfileVsRecs()`
- `PopRecsCorrelation()`

Pipeline of recommending and evaluating

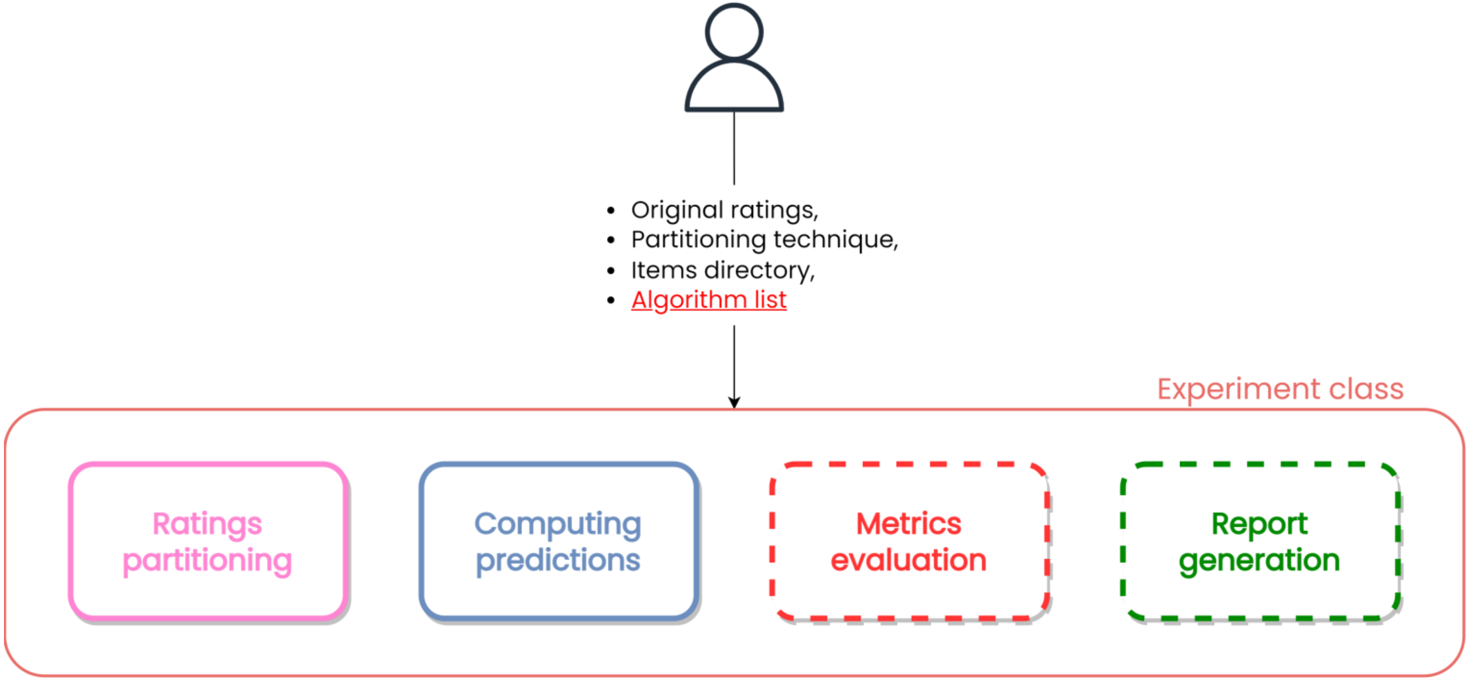
- Can this be automated?
- What about comparing different algorithms?



Experiment class

With a simple interface, the `Experiment` class lets you cover a complete experiment!

- It also makes it easy to compare different algorithms



Experiment class: code example

```
rat = ca.Ratings(ca.CSVFile('ratings.csv'))

alg1 = rs.CentroidVector({'plot': 0}, similarity=rs.CosineSimilarity())

alg2 = rs.ClassifierRecommender({'plot': 0}, classifier=rs.SkSVC())

metrics = [eva.RPrecision(sys_average='micro'), eva.RecallAtK(k=3)]

rs.ContentBasedExperiment(
        original_ratings=rat,
        partitioning_technique=rs.HoldOutPartitioning(),
        algorithm_list=[alg1, alg2],
        items_directory='movies_codified_plot',
        metric_list=metrics,
        report=True
).rank(n_recs=10)
```

Experiment class: output

experiment_result

CentroidVector_1	24/10/2022 19:35	Cartella di file	
ClassifierRecommender_1	24/10/2022 19:35	Cartella di file	
HoldOutPartitioning_test_split0.csv	24/10/2022 19:35	File con valori sep...	255 KB
HoldOutPartitioning_train_split0.csv	24/10/2022 19:35	File con valori sep...	995 KB

eva_report.yml	24/10/2022 19:35	File YML	1 KB
eva_sys_results.csv	24/10/2022 19:35	File con valori sep...	1 KB
eva_users_results.csv	24/10/2022 19:35	File con valori sep...	23 KB
rs_rank_split0.csv	24/10/2022 19:35	File con valori sep...	220 KB
rs_report.yml	24/10/2022 19:35	File YML	1 KB

ClayRS

Thank you!

Antonio Silletti