fcaR, an R package to handle fuzzy implications: design of a recommendation system for medical diagnosis

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Table of contents

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R Packages for Implications and Rules

- **arules**: Provides the infrastructure for representing, manipulating and analyzing transaction data and patterns (frequent itemsets and association rules). Also provides C implementations of the association mining algorithms Apriori and Eclat.
- **frbs**: An implementation of various learning algorithms based on fuzzy rule-based systems (FRBSs) for dealing with classification and regression tasks.
- **RKEEL**: `KEEL` is a popular Java software for a large number of different knowledge data discovery tasks. This package takes the advantages of `KEEL` and R, allowing to use `KEEL` algorithms in simple R code.

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Objective

The main objective is to create an R package able to:

- Manage formal contexts and find concepts.
- Extract implications from a context.
- Provide tools to visualize the extracted knowledge.
- Compute closures and recommendations.
- Integrate with **arules**.

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Table of contents

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Class Structure

- `FormalContext` encapsulates the definition of a formal context (G, M, I), being G the set of objects, M the set of attributes and I the (fuzzy) relationship matrix, and provides methods to operate on the context using FCA tools.
- `ImplicationSet` represents a set of implications over a specific formal context.
- `SparseSet` is a class solely used for visualization purposes, since it encapsulates in sparse format a (fuzzy) set.
- `SparseConcept` encapsulates internally both *extent* and *intent* of a formal concept as `SparseSet`.

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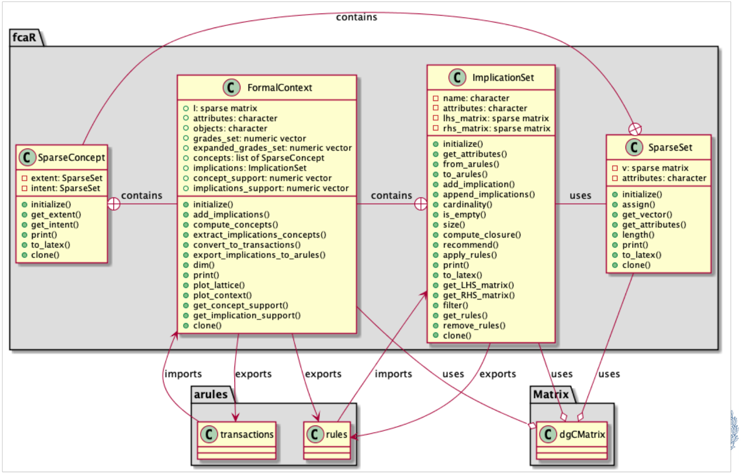
UML Diagram



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Use of Formal Contexts

Table: A sample formal context. Attributes are P1 to P6 and objects are named O1 to O6.

	P1	P2	P3	P4	P5	P6
O1	0.0	1.0	0.5	0.5	1.0	0
O2	1.0	1.0	1.0	0.0	0.0	0
O3	0.5	0.5	0.0	0.0	0.0	1
O4	0.0	0.0	0.0	1.0	0.5	0
O5	0.0	0.0	1.0	0.5	0.0	0
O6	0.5	0.0	0.0	0.0	0.0	0

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Use of Formal Contexts

```
R> fc <- formal_context$new(I)
R> print(fc)
FormalContext with 6 objects and 6 attributes.
Attributes' names are: P1, P2, P3, P4, P5, P6
Matrix:
    P1  P2  P3  P4  P5 P6
O1 0.0 1.0 0.5 0.5 1.0  0
O2 1.0 1.0 1.0 0.0 0.0  0
O3 0.5 0.5 0.0 0.0 0.0  1
O4 0.0 0.0 0.0 1.0 0.5  0
O5 0.0 0.0 1.0 0.5 0.0  0
O6 0.5 0.0 0.0 0.0 0.0  0
```

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Importing from arules

```
R> fc_mushroom <- formal_context$new(Mushroom)
R> fc_mushroom
Warning: Too many attributes, output will be truncated.
FormalContext with 8124 objects and 114 attributes.
Attributes' names are: Class=edible, Class=poisonous, CapShape=bell,
  CapShape=conical, CapShape=flat, CapShape=knobbed, ...
Matrix:
        Class=edible Class=poisonous CapShape=bell CapShape=conical
1                0               1             0                0
2                1               0             0                0
3                1               0             1                0
4                0               1             0                0
5                1               0             0                0
6                1               0             0                0
        CapShape=flat CapShape=knobbed CapShape=sunken
1                 0                0               0
2                 0                0               0
3                 0                0               0
4                 0                0               0
5                 0                0               0
6                 0                0               0
```

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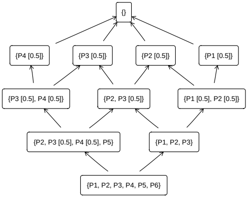
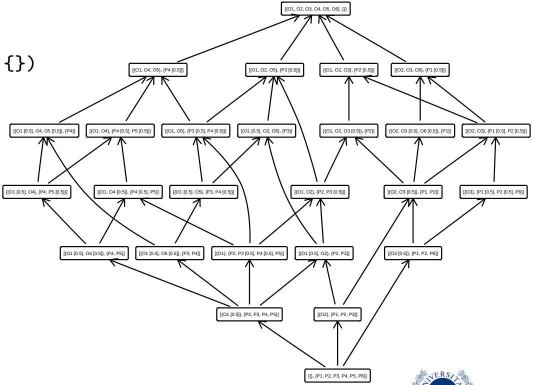
Finding and Plotting Concepts

```
R> concepts <- fc$compute_concepts()
R> length(concepts)
[1] 26
R> concepts[[1]]
({O1, O2, O3, O4, O5, O6}, {})
```





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Managing Implications

In order to build the Duquenne-Guigues basis of implications, by using NextClosure, the `extract_implications_concepts()` method is called from a `FormalContext` object, and the result is stored in `fc$implications`.

```
R> fc$extract_implications_concepts()
```

```
R> fc$implications
```

```
Implication set with 12 implications.
Rule 1: {P6 [0.5]} -> {P1 [0.5], P2 [0.5], P6}
Rule 2: {P5 [0.5]} -> {P4 [0.5]}
Rule 3: {P3 [0.5], P4 [0.5], P5 [0.5]} -> {P2, P5}
Rule 4: {P3 [0.5], P4} -> {P3}
Rule 5: {P2 [0.5], P4 [0.5]} -> {P2, P3 [0.5], P5}
Rule 6: {P2 [0.5], P3 [0.5]} -> {P2}
Rule 7: {P2, P3, P4 [0.5], P5} -> {P4}
Rule 8: {P1 [0.5], P4 [0.5]} -> {P1, P2, P3, P4, P5, P6}
Rule 9: {P1 [0.5], P3 [0.5]} -> {P1, P2, P3}
Rule 10: {P1 [0.5], P2} -> {P1}
Rule 11: {P1, P2 [0.5]} -> {P2}
Rule 12: {P1, P2, P3, P6} -> {P4, P5}
```

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Importing/Exporting Binary Rules

The `ImplicationSet` can interface with **arules**, importing and exporting sets of rules in **arules** format.

```
R> fc_mushroom$add_implications(mush_rules)
R> fc_mushroom$implications$cardinality()
[1] 2002
R> my_rules <- fc_mushroom$export_implications_to_arules(
                                             quality = TRUE)
R> class(my_rules)
[1] "rules"
attr(,"package")
[1] "arules"
```

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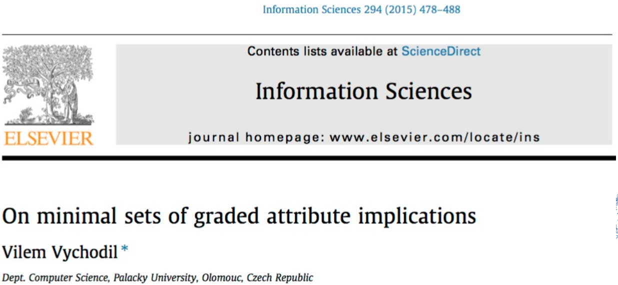
Removing redundancy in graded attribute implications

- To obtain equivalent implicational sets with lower size (small number of implications) or with less attributes in the LHS or RHS.
- Widely studied in the classical setting.
- Approached by Vilem Vychodil in [IS2015].



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journal homepage: www.elsevier.com/locate/ins

ELSEVIER

On minimal sets of graded attribute implications

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Removing redundancy in graded attribute implications

- We tackle this problem using the so-called *Fuzzy Attribute Simplification Logic*, **FASL**, which has been introduced in [Belohlavek 2016].
- This logic leads to the design of automatic reasoning methods for implications in data with grades.

International Journal of Approximate Reasoning 70 (2016) 51–67

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Automated prover for attribute dependencies in data with grades

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FASL

Axiomatic system

- Firstly, we proposed a new Simplification Rule adequate to remove redundancy in an automatic way.
- Simplification Rule turned into the *heart* of a novel logic: FASL - Fuzzy Attributes Simplification Logic.
- FASL becomes the *engine* of automated methods: redundancy removal, closure algorithm, etc.

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FASL

Axiomatic system

The axiomatic system in FASL is defined as follows: for all $A, B, C, D \in L^\Omega$ and $c \in L$,

[Ax] infer $A \cup B \Rightarrow A$ (*Axiom*)

[Mul] from $A \Rightarrow B$ infer $c^* \otimes A \Rightarrow c^* \otimes B$ (*Multiplication*)

[Sim] from $A \Rightarrow B$ and $C \Rightarrow D$ infer $A \cup (C \smallsetminus B) \Rightarrow D$ (*Simplification*)

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Removal of Redundancies with FASL

The axiomatic system is equivalent to the following, which are implemented in **fcaR**:

- **Reduction** rule: from $A \Rightarrow B$, deduce $A \Rightarrow B \smallsetminus A$, being $B \smallsetminus A$ the fuzzy set difference B minus A.
- **Generalization** rule: from $A \Rightarrow B$ and $C \Rightarrow D$, if $A \subseteq C$ and $D \subseteq B$, remove $C \Rightarrow D$.
- **Composition** rule: if $A \Rightarrow B$ and $A \Rightarrow C$, substitute both implications by this $A \Rightarrow B \cup C$.
- **Simplification** rule: if $A \Rightarrow B$ and $C \Rightarrow D$, with $A \subset C$ and $A \cap B = \emptyset$, substitute $C \Rightarrow D$ by $C \smallsetminus B \Rightarrow D \smallsetminus B$.

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Removal of Redundancies

```
R> fc_mushroom$implications$apply_rules(c("reduction",
R+                                         "composition",
R+                                         "generalization",
R+                                         "simplification"))
Using parallel execution
Processing batch
--> reduction : from 2002 to 2002 in 0.199 secs.
--> composition : from 2002 to 961 in 2.719 secs.
--> generalization : from 961 to 961 in 0.07 secs.
--> simplification : from 961 to 961 in 18.788 secs.
Batch took 21.781 secs.
```

These set operations have been implemented in C.
If a parallel backend is available (via package **parallel**, for instance), the `ImplicationSet` is split into batches of a specific cardinality (defined by the `batch_size` parameter), and the `apply_rules` method distributes batches across workers, allowing to process all batches in parallel.

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FASL for Computing Closures

```
R> # Generate a fuzzy set with attribute "CapColor=white"
R> A <- sparse_set$new(attributes = fc_mushroom$attributes)
R> A$assign(attributes = "CapColor=white", values = 1)
R>
R> closure <- fc_mushroom$implications$compute_closure(A,
R+                                                      reduce = TRUE)
R> closure$closure
```

```
{CapColor=white, GillAttached=free, ColorAboveRing=white,
        ColorBelowRing=white, VeilType=partial, VeilColor=white}
```

```
R> closure$implications$get_rules(1:4)
```

```
Implication set with 4 implications.
Rule 1: {Habitat=woods} -> {RingNumber=one}
Rule 2: {Habitat=woods} -> {RingNumber=one}
Rule 3: {StalkRoot=bulbous} -> {RingType=pendant}
Rule 4: {CapColor=yellow, StalkShape=enlarging} -> {GillSpace=close}
```

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Table of contents

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Included Datasets

Two complete examples of the use of **fcaR** on real-world problems:

`cobre32`: Designing a diagnostic system from a formal context with (fuzzy) medical data.

`vegas`: Extracting knowledge about the features of tourist destinations given an user profile.

The datasets for this section are provided and documented in the package.

Medical Context

```
R> colnames(cobre32)
 [1] "COSAS_1"   "COSAS_2"   "COSAS_3"   "COSAS_4"
 [5] "COSAS_5"   "COSAS_6"   "COSAS_7"   "FICAL_1"
 [9] "FICAL_2"   "FICAL_3"   "FICAL_4"   "FICAL_5"
[13] "FICAL_6"   "FICAL_7"   "FICAL_8"   "FICAL_9"
[17] "SCIDII_10" "SCIDII_11" "SCIDII_12" "SCIDII_13"
[21] "SCIDII_14" "SCIDII_15" "SCIDII_16" "SCIDII_17"
[25] "SCIDII_18" "SCIDII_19" "SCIDII_20" "SCIDII_21"
[29] "SCIDII_22" "SCIDII_23" "dx_ss"     "dx_other"
```

- The *Simpson-Angus Scale*, 6 items to evaluate Parkinsonism-like alterations.
- *Calgary Depression Scale for Schizophrenia*, 9 items (attributes) assessing the level of depression in schizophrenia.
- The *Structured Clinical Interview for DSM-III-R Personality Disorders*, with 9 variables related to the presence of signs affecting personality.
- The diagnosis for each individual: it can be *schizophrenia strict* or *other diagnosis* (which includes schizoaffective and bipolar disorders).

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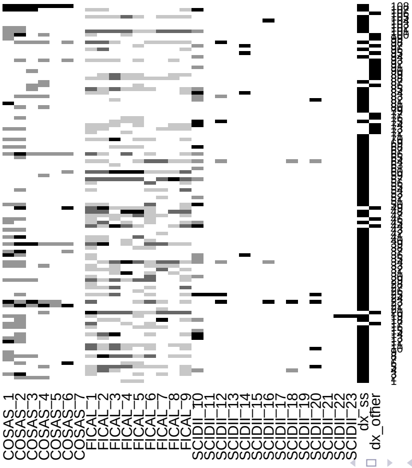
Medical Context

In summary, the dataset consists in the previous 30 attributes related to signs or symptoms, and 2 attributes related to diagnosis. This makes a dataset with 105 objects (patients) and 32 attributes to explore. For a given attribute (symptom), the available grades range from *absent* to *extreme*, with *minimal*, *mild*, *moderate*, *moderate severe* and *severe* in between. These fuzzy attributes are mapped to values in the interval $[0, 1]$.

Medical Context

```
R> fc <- formal_context$new(cobre32)
```



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Implications and Simplification

```
R> fc$extract_implications_concepts()
R> length(fc$concepts)

[1] 14686

R> fc$implications$cardinality()

[1] 985

R> fc$implications$apply_rules(rules = c("simplification"))

Using parallel execution
Processing batch
--> simplification : from 985 to 985 in 3.847 secs.
Batch took 3.849 secs.
```

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Simple Diagnostic System

```
R> diagnose <- function(S) {
R+
R+   fc$implications$recommend(S = S,
R+                             attribute_filter = c("dx_ss",
R+                                                  "dx_other"))
R+
R+ }
```

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Diagnosis Example

```
R> S1 <- sparse_set$new(attributes = fc$attributes)
R> S1$assign(attributes = c("COSAS_1", "COSAS_2", "COSAS_3", "COSAS_4",
R+                          "COSAS_5", "COSAS_6"),
R+           values = c(0.5, 1, 0.5, 0.166667, 0.5, 1))
R>
R> diagnose(S1) # Schizophrenia strict

dx_ss dx_other
    1        0

R> S2 <- sparse_set$new(attributes = fc$attributes)
R> S2$assign(attributes = c("FICAL_1", "FICAL_2", "COSAS_1"),
R+           values = c(0, 1, 0))
R>
R> diagnose(S2) # Not enough information

dx_ss dx_other
    0        0

R> S3 <- sparse_set$new(attributes = fc$attributes)
R> S3$assign(attributes = c("COSAS_4", "FICAL_3", "FICAL_5", "FICAL_8"),
R+           values = c(0.6666667, 0.5, 0.5, 0.5))
R>
R> diagnose(S3) # Other, not schizophrenia strict

dx_ss dx_other
    0        1
```

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Data and Problem

500 TripAdvisor reviews of hotels in Las Vegas Strip:

- `Period of Stay`: 4 categories are present in the original data, which produces as many binary variables: `Period of stay=Dec-Feb`, `Period of stay=Mar-May`, `Period of stay=Jun-Aug` and `Period of stay=Sep-Nov`.
- `Traveler type`: five binary categories are created from the original data: `Traveler type=Business`, `Traveler type=Couples`, `Traveler type=Families`, `Traveler type=Friends` and `Traveler type=Solo`.
- `Pool`, `Gym`, `Tennis court`, `Spa`, `Casino`, `Free internet`: binary variables for the services offered by each destination hotel.
- `Stars`: five binary variables are created, according to the number of stars of the hotel, `Stars=3`, `Stars=3.5`, `Stars=4`, `Stars=4.5` and `Stars=5`.
- `Score`, the score assigned in the review, from `Score=1` to `Score=5`, five variables are created.

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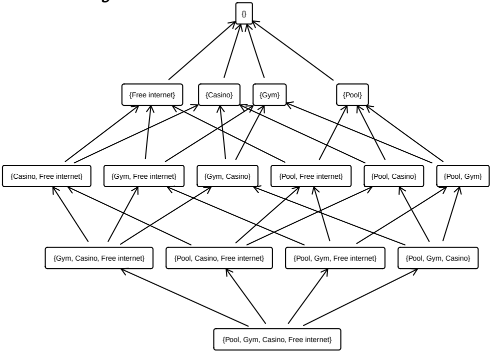
Managing Knowledge

```
R> fc <- formal_context$new(vegas)
R> fc$extract_implications_concepts()
R> fc$plot_lattice(minsupp = 0.9,
R+                 object_names = FALSE)
```



Managing Knowledge

```
R> # Remove redundancies
R> fc$implications$apply_rules(c("simplification",
R+                                "composition",
R+                                "generalization"))

Using parallel execution
Processing batch
--> simplification : from 382 to 382 in 1.173 secs.
--> composition : from 382 to 382 in 0.004 secs.
--> generalization : from 382 to 382 in 0.012 secs.
Batch took 1.191 secs.

R> # Remove implications with no support
R> supp <- fc$get_implication_support()
R> idx_zero_supp <- which(supp == 0)
R> fc$implications$remove_rules(idx_zero_supp)
```

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Desirable Services in Destination

Question:
For a given couple, searching for a hotel in Las Vegas with Spa, which are the additional services that a destination should offer to get the highest score of 5?

Applying FASL

First, filter those rules related to couples:

```
R> base_implications <- fc$implications$filter(
R+                              "Traveler type=Couples")
```

Then, specify the minimum services (Spa)

```
R> S <- sparse_set$new(fc$attributes)
R> S$assign(attributes = c("Traveler type=Couples", "Spa"),
R+          values = c(1, 1))
```

And compute the closure by using the simplification logic, since we are interested in the knowledge that can be inferred from the condition given by the set :

```
R> cl <- base_implications$compute_closure(S, reduce = TRUE)
R> specific_implications <- cl$implications
```

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Inspecting the Rules

```
R> # Filter interesting rules
R> specific_implications$filter(rhs = c("Score=5"))
Implication set with 5 implications.
Rule 1: {Period of stay=Mar-May, Stars=4.5} -> {Score=5}
Rule 2: {Period of stay=Jun-Aug, Stars=4.5} -> {Score=5}
Rule 3: {Period of stay=Jun-Aug, Tennis court, Stars=3.5} -> {Score=5}
Rule 4: {Period of stay=Dec-Feb, Tennis court, Stars=3.5} -> {Score=5}
Rule 5: {Period of stay=Dec-Feb, Tennis court, Stars=3} -> {Score=5}
```

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Table of contents

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GitHub

fcaR

lifecycle maturing | CRAN not published | build passing | codecov 92%

The goal of fcaR is to provide FCA tools inside the R environment.

Installation

The development version of this package can be installed with

```
remotes::install_github("neuroimaginador/fcaR", build_vignettes = TRUE)
```

- Installation instructions.
- Unit tests.
- Vignettes with demos.

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Table of contents

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Conclusions

Conclusions

- A package for fuzzy FCA in the R programming language has been presented.
- It is integrable with **arules**.
- Its main methods are related to the computation and plotting of the concept lattice and the calculation of implications and their management.
- The package is applicable to the creation of recommendation systems and to explore conceptual knowledge in a formal context.

Future Work

Future Work

- Include other theoretical aspects regarding computation of direct bases or positive and negative attributes.
- Implement more efficient algorithms for extracting concepts and implications.
- Make it available in CRAN.

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