

Introduction to the *PRISMA* package

Tammo Krueger

May 26, 2018

<https://github.com/tammok/PRISMA>

Introduction

This vignette gives you a first tour to the features of the *PRISMA* package. We will give an overview of the application of the algorithm, yet, the full story is available in the papers [3, 4]. If you use the *PRISMA* package in your research, please cite at least one of these references.

The *PRISMA* package consists essentially out of three parts:

1. Efficiently reading `sally` output, an extremely fast n-gram processor available at <http://www.mlsec.org/sally/>
2. Testing-based feature dimension reduction
3. Optimized matrix factorization of the reduced data exploiting the replicate structure of the data

For the theory behind these parts please consult [3, 4]. We will start this walk-through with the reading of `sally` data, then showing the inner structure of the resulting data object on which the replicate-aware non-negative matrix factorization can be applied.

Loading the Data

This section serves just as a reference how to apply the processing chain to new data, to get a usable *PRISMA* data set. The generated data set is already prepackaged inside the *PRISMA* package and can be loaded via `data(asap)`.

Before executing the examples please extract `asap.tar.gz` located in the `extdata` path of the *PRISMA* package to find all data necessary to understand the processing chain from the raw data (`asap.raw`) to the `sally` file (`asap.sally`) and the optimized file (`asap.fsally`). The `asap.sally` file can be produced as follows:

```
sally -c asap.cfg asap.raw asap.sally
```

this call generates `asap.sally` from the raw data found in `asap.raw`. To speed up the loading of the data in R, one should apply the `sallyPreprocessing.py` Python script as follows:

```
python sallyPreprocessing.py asap.sally asap.fsally
```

Now the data is ready to be efficiently loaded and processed in R via `loadPrismaData("asap")` which also executes the feature dimension reduction step.

The *PRISMA* Data Set

As an example we use the prepackages ASAP toy data set as described in [4]:

```
> data(asap)
> asap
```

```
PRISMA data asap
Unprocessed data: # features: 10034 # entries: 10000
Processed data: # features: 12 # entries: 24
```

We see that the feature reduction step worked quite well. Let's have a look behind the scenes:

```
> asap$data

12 x 24 sparse Matrix of class "dgCMatrix"
rv Gecko 1.8.1.3 Mozilla Firefox 2.0.0.3 5.0 20070309 1 1 1 1 1 1 1 1 1 1 1 .
admin.php par action 1 1 1 1 1 1 1 1 . . . . 1
show 1 1 . . . . . . . . . . 1
s search.php . . . . . . . . . . 1 1 . . .
move . . 1 1 . . . . . . . . . .
static . . . . . . . . . . 1 1 .
6.0 1 . 1 . 1 1 . . 1 . 1 . 1
9.20 Opera . . . . . . . . . . . 1
delete . . . . . 1 1 . . . . .
5.1 . 1 . 1 . . 1 1 . 1 . 1 .
cgi 1 1 1 1 1 1 1 1 1 1 . . 1
rename . . . . 1 . . 1 . . . . .

rv Gecko 1.8.1.3 Mozilla Firefox 2.0.0.3 5.0 20070309 . . . . . . . . . .
admin.php par action 1 1 1 1 1 1 1 . . . .
show 1 . . . . . . . . . .
s search.php . . . . . . . . 1 1 . .
move . 1 1 . . . . . . . . . .
static . . . . . . . . . . 1 1
6.0 . 1 . 1 1 . . 1 . 1 .
9.20 Opera 1 1 1 1 1 1 1 1 1 1 1 1
delete . . . . 1 1 . . . . .
5.1 1 . 1 . . 1 1 . 1 . 1 .
cgi 1 1 1 1 1 1 1 1 1 1 . .
rename . . . 1 . . 1 . . . . .
```

This shows us the reduced form of the initial data matrix in a features \times documents representation, i.e. this is a replicate-free version of it. We can see that the features partly consists of grouped tokens (for instance `admin.php par action` contains 3 tokens, which always co-occurred in the data) and how these tokens are present in the different documents. We can see the initial tokens before the grouping and their corresponding group assignment in the `group` variable:

```
> asap$group

      rv  admin.php      show      s search.php      par      Gecko
      1         2         3         4         4         2         1
1.8.1.3      move      static      6.0      action      9.20      Opera
      1         5         6         7         2         8         8
Mozilla      delete      Firefox      2.0.0.3      5.0         5.1      20070309
      1         9         1         1         1         10        1
      cgi      rename
      11        12
```

The member variable `unprocessed` contains the initial data matrix before the feature selection and grouping step. If we want to reconstruct all replicates in the reduced feature space, we need the `getDuplicateData` function:

```
> dim(getDuplicateData(asap))

[1] 12 10000

> dim(asap$unprocessed)

[1] 10034 10000
```

This will blow up the reduced matrix to the full 10.000 initial data points in the reduced feature space. To see, how often a specific entry in the reduced data matrix was present, we can have a look at the duplicate count:

```

> asap$duplicatecount
[1] 216 227 199 202 196 245 200 200 803 790 814 842 214 219 209 212 192 213 194
[20] 210 877 855 817 854
> sum(asap$duplicatecount)
[1] 10000

```

The Replicate-Aware Non-Negative Matrix Factorization (NMF)

The replicate-aware NMF is a matrix factorization method which describes the data according to a new base vector system, i.e. each data point is described as a weighted sum of these base vectors. Thus, the base vectors can be seen as the parts of which a document is constructed. Furthermore, the new coordinates of a document (the base weights) can also be interpreted as a soft clustering. But before we can apply the NMF we need to specify the inner dimension of the factorization. This could either be supplied by a number (which should be even, if `pca.init` is `TRUE`), or a `prismaDimension` object generated by the fully automatized dimension estimation method:

```

> asapDim = estimateDimension(asap)
> asapDim

```

Estimated data dimension for positive matrix factorization via simulated noise level: 8

Equipped with this object, we can now apply the NMF to the data:

```

> asapNMF = prismaNMF(asap, asapDim, time=60)
Error: 3771.392
Error: 3113.138
Error: 2855.863
Error: 2810.286
Error: 2765.763
Error: 2755.29
Error: 2752.505
> asapLabels = getMatrixFactorizationLabels(asapNMF)
> table(asapLabels)
asapLabels
 1  2  3  4  5  6  7  8
623 607 602 660 1696 2473 817 2522

```

We can look at the results via `plot(asapNMF)` which is shown in Figure 1. We can see that the NMF extracts a `search` template, then the four `admin.php-action` templates, a Firefox template and two `static` templates, which reproduces the results in [4], Section 3.1., with added user agents as “noise”.

Interface to the *tm* Package

To allow the application of the replicate-aware NMF to corpora generated by the *tm* package [1], the *PRISMA* package contains a converter function which maps a *tm* corpus object to a *PRISMA* data object. We exemplify this procedure with an already stemmed and cleansed version of the 15 subsections of [2]:

```

> data(thesis)
> thesis
A corpus with 15 text documents
> thesis = corpusToPrisma(thesis, NULL, TRUE)
> thesis
PRISMA data tm-Corpus
Unprocessed data: # features: 2002 # entries: 15
Processed data: # features: 2002 # entries: 15
> thesisNMF = prismaNMF(thesis, 3, pca.init=FALSE)
Error: 1329.73
Error: 1310.481
Error: 1295.959
Error: 1295.509

```

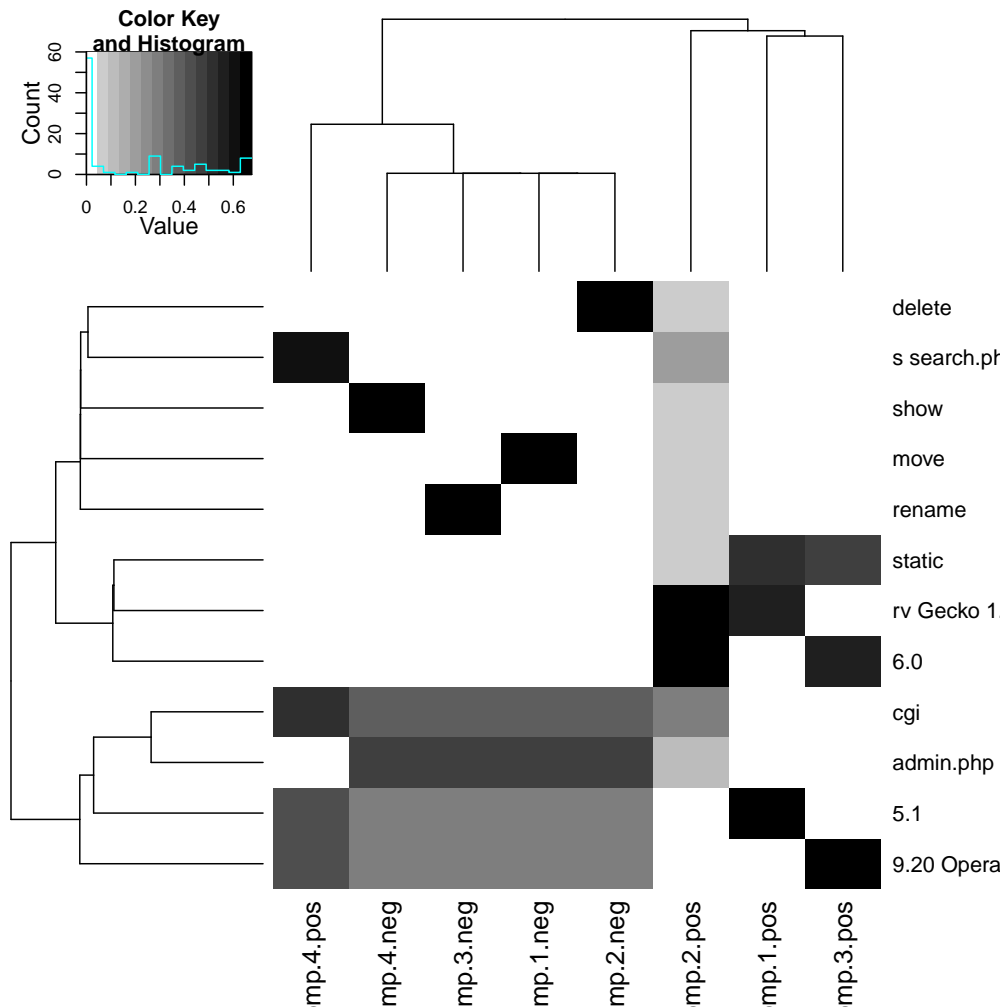


Figure 1: Result of the replicate-aware NMF on the `asap` data set.

Since we have just 15 documents, the application of the feature reduction step and the correlation analysis suffers from too less data, which also holds true for the PCA-based initialization scheme. Thus, we ignore all these processings and apply the NMF directly on the data with three components as a sophisticated guess. To analyze the result we look at the top 20 words of the resulting base matrix:

```
> isQuantile = (t(thesisNMF$B) > apply(thesisNMF$B, 2, quantile, prob=.99))
> maxFeatures = apply(isQuantile, 1, function(r) which(r == 1))
> rownames(thesis$data)[maxFeatures[, 1]]
 [1] "add"      "align"    "associ"   "cluster"  "communic" "correct"
 [7] "extract"  "fill"     "format"   "inner"    "machin"   "messag"
[13] "obvious"  "preserv"  "reflect"  "return"   "simul"    "templat"
[19] "trace"    "transit"  "tri"
> rownames(thesis$data)[maxFeatures[, 2]]
 [1] "behavior" "chang"    "configur" "crossvalid" "drop"
 [6] "fast"     "figur"    "follow"    "lead"       "learn"
[11] "lower"    "observ"   "optim"     "overall"    "procedur"
[16] "process"  "relat"    "shown"     "speed"      "statist"
[21] "use"
> rownames(thesis$data)[maxFeatures[, 3]]
 [1] "addit"    "applic"   "approach" "attack"    "base"     "construct"
 [7] "content"  "exploit"  "method"   "model"     "network"  "normal"
[13] "protocol" "server"   "similar"  "simpl"     "structur" "techniqu"
[19] "token"    "traffic"  "use"
```

These word stems accurately describe the contents of the three chapters of [2] which concludes the analysis of this section.

References

- [1] Ingo Feinerer, Kurt Hornik, and David Meyer. Text mining infrastructure in R. *Journal of Statistical Software*, 25(5):1–54, March 2008.
- [2] Tammo Krueger. *Probabilistic Methods for Network Security. From Analysis to Response*. PhD thesis, TU Berlin, 2013. <http://opus.kobv.de/tuberlin/volltexte/2013/3881/>.
- [3] Tammo Krueger, Hugo Gascon, Nicole Krämer, and Konrad Rieck. Learning stateful models for network honeypots. In *Proceedings of the 5th ACM workshop on Security and artificial intelligence*, AISEC '12, pages 37–48. ACM, 2012. <http://doi.acm.org/10.1145/2381896.2381904>.
- [4] Tammo Krueger, Nicole Krämer, and Konrad Rieck. ASAP: Automatic semantics-aware analysis of network payloads. In Christos Dimitrakakis, Aris Gkoulalas-Divanis, Aikaterini Mitrokotsa, VassiliosS. Verykios, and Yücel Saygin, editors, *Privacy and Security Issues in Data Mining and Machine Learning*, volume 6549 of *Lecture Notes in Computer Science*, pages 50–63. Springer Berlin Heidelberg, 2011. http://dx.doi.org/10.1007/978-3-642-19896-0_5.