

March 07 tensor clustering

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March 2019

1 The bottleneck of the `sparse.choosekrl()`

Listed the trace in the appendix A, what we can see is that the long running time of this function comes from the complex iterations. Therefore, what we can do to speed up this function is:

- using Rcpp to improve the speed of each iteration;
- change the for loop into `apply()`.

2 Two problems with `chooseLambda()`

2.1 Problem 1: the range of lambda

Sometimes I found it is pretty hard to find a suitable range for lambda. Instead, we have to try many times to find a suitable range for us to find the best lambda. Therefore, we may delete the parameter to input the range of lambda into this function, instead, we can use `optimize()` to find the best lambda which is different with `sparse.choosekrl()`. (I already tried this method, and it would super slow:(the result looks better but it may depends on the initial value we take.) The new result was listed in the appendices.

2.2 Problem 2: the penalty of non-zeros parameters

I tries many cases, I found that the lambda with the lowest BIC is always 0. I don't know whether it is because of the range I select is not good or the penalty is too small.

3 New problem about the definition of `plot_tensor()`

Now we already can get the same plot if the input `k,r,l` are totally the same with the true `k,r,l` by using a good definition of quantile. But what if the input `k,r,l` is different with the true `k,r,l`. Will the ouput color be totally different from the color of true mus?

4 A reminder for me to change the way to calculate the CER in sparse clustering

5 The results of clustering `dnations.mat`

The code has been put into appendices. My result is listed as follows. First I tried `sparse.choosekrl()`, the range is 2:10, 2:10, 2:10, and the result is 5,5,5. The result below is obtained by using `k,r,l=5`. To avoid the

estimated k, r, l is bounded by 5, then I enlarged the range, but then the program is too slow. And I still have not got the updated k, r, l .

5.1 Clusters of countries

```
cluster 1 :
[1] "Egypt" "India" "Israel"
cluster 2 :
[1] "UK" "USA"
cluster 3 :
[1] "Burma" "Indonesia" "Jordan"
cluster 4 :
[1] "Brazil" "Netherlands"
cluster 5 :
[1] "China" "Cuba" "Poland" "USSR"
```

5.2 Clusters of relationship

```
cluster 1 :
[1] "economicaid" "releconomicaid" "officialvisits" "warning"
      "violentactions"
[6] "militaryactions" "duration" "negativebehavior" "severdiplomatic"
      "expeldiplomats"
[11] "boycottembargo" "aidenemy" "negativecomm" "accusation"
      "protests"
[16] "unofficialacts" "attackembassy" "nonviolentbehavior" "timesincewar"
      "lostterritory"
[21] "dependent" "commonbloc0"
cluster 2 :
[1] "treaties" "conferences" "weightedunvote" "unweightedunvote"
      "intergovorgs"
[6] "ngo" "timesinceally" "independence" "
      blockpositionindex"
cluster 3 :
[1] "relintergovorgs" "relngo" "intergovorgs3" "ngoorgs3"
cluster 4 :
[1] "embassy" "reldiplomacy" "commonbloc1"
cluster 5 :
[1] "reltreaties" "exportbooks" "relexportbooks" "
      booktranslations"
[5] "relbooktranslations" "tourism" "reltourism" "tourism3"
[9] "emigrants" "relemigrants" "emigrants3" "students"
[13] "relstudents" "exports" "relexports" "exports3"
[17] "militaryalliance" "commonbloc2"
```

A Rprofile of sparse.choosekrl()

```
$by.self
      self.time self.pct total.time total.pct
tensorsparse.R#196 393.28 43.17 762.68 83.72
tensorsparse.R#87 269.92 29.63 269.92 29.63
tensorsparse.R#90 72.06 7.91 72.06 7.91
tensorsparse.R#186 54.16 5.94 54.16 5.94
tensorsparse.R#82 32.94 3.62 32.94 3.62
tensorsparse.R#148 27.46 3.01 27.46 3.01
tensorsparse.R#89 25.20 2.77 25.20 2.77
tensorsparse.R#99 19.26 2.11 19.26 2.11
tensorsparse.R#128 6.08 0.67 6.08 0.67
```

tensorsparse.R#86	2.22	0.24	2.22	0.24
tensorsparse.R#79	1.78	0.20	1.78	0.20
tensorsparse.R#160	1.38	0.15	1.38	0.15
tensorsparse.R#80	1.28	0.14	1.28	0.14
tensorsparse.R#225	0.82	0.09	0.82	0.09
tensorsparse.R#151	0.80	0.09	0.80	0.09
tensorsparse.R#121	0.44	0.05	0.44	0.05
tensorsparse.R#123	0.36	0.04	0.36	0.04
tensorsparse.R#122	0.34	0.04	0.36	0.04
tensorsparse.R#142	0.30	0.03	0.30	0.03
tensorsparse.R#145	0.10	0.01	0.10	0.01
tensorsparse.R#143	0.08	0.01	34.80	3.82
tensorsparse.R#206	0.08	0.01	23.36	2.56
tensorsparse.R#211	0.08	0.01	22.06	2.42
simulation.R#46	0.06	0.01	911.02	100.00
tensorsparse.R#201	0.06	0.01	19.58	2.15
tensorsparse.R#129	0.06	0.01	0.06	0.01
tensorsparse.R#204	0.04	0.00	2.56	0.28
tensorsparse.R#202	0.04	0.00	2.02	0.22
tensorsparse.R#138	0.04	0.00	0.04	0.00
tensorsparse.R#293	0.04	0.00	0.04	0.00
tensorsparse.R#303	0.04	0.00	0.04	0.00
tensorsparse.R#235	0.02	0.00	910.84	99.98
tensorsparse.R#212	0.02	0.00	5.82	0.64
tensorsparse.R#215	0.02	0.00	4.52	0.50
tensorsparse.R#207	0.02	0.00	2.76	0.30
tensorsparse.R#298	0.02	0.00	0.04	0.00
tensorsparse.R#124	0.02	0.00	0.02	0.00
tensorsparse.R#125	0.02	0.00	0.02	0.00
tensorsparse.R#130	0.02	0.00	0.02	0.00
tensorsparse.R#140	0.02	0.00	0.02	0.00
tensorsparse.R#159	0.02	0.00	0.02	0.00
tensorsparse.R#162	0.02	0.00	0.02	0.00

\$by.total

	total.time	total.pct	self.time	self.pct
simulation.R#46	911.02	100.00	0.06	0.01
tensorsparse.R#235	910.84	99.98	0.02	0.00
tensorsparse.R#316	910.84	99.98	0.00	0.00
tensorsparse.R#196	762.68	83.72	393.28	43.17
tensorsparse.R#87	269.92	29.63	269.92	29.63
tensorsparse.R#90	72.06	7.91	72.06	7.91
tensorsparse.R#186	54.16	5.94	54.16	5.94
tensorsparse.R#143	34.80	3.82	0.08	0.01
tensorsparse.R#82	32.94	3.62	32.94	3.62
tensorsparse.R#148	27.46	3.01	27.46	3.01
tensorsparse.R#89	25.20	2.77	25.20	2.77
tensorsparse.R#206	23.36	2.56	0.08	0.01
tensorsparse.R#211	22.06	2.42	0.08	0.01
tensorsparse.R#201	19.58	2.15	0.06	0.01
tensorsparse.R#99	19.26	2.11	19.26	2.11
tensorsparse.R#128	6.08	0.67	6.08	0.67
tensorsparse.R#212	5.82	0.64	0.02	0.00
tensorsparse.R#215	4.52	0.50	0.02	0.00
tensorsparse.R#210	2.90	0.32	0.00	0.00
tensorsparse.R#207	2.76	0.30	0.02	0.00
tensorsparse.R#204	2.56	0.28	0.04	0.00
tensorsparse.R#86	2.22	0.24	2.22	0.24
tensorsparse.R#209	2.10	0.23	0.00	0.00
tensorsparse.R#202	2.02	0.22	0.04	0.00
tensorsparse.R#79	1.78	0.20	1.78	0.20

tensorsparse.R#214	1.52	0.17	0.00	0.00
tensorsparse.R#160	1.38	0.15	1.38	0.15
tensorsparse.R#205	1.34	0.15	0.00	0.00
tensorsparse.R#80	1.28	0.14	1.28	0.14
tensorsparse.R#193	1.20	0.13	0.00	0.00
tensorsparse.R#225	0.82	0.09	0.82	0.09
tensorsparse.R#203	0.82	0.09	0.00	0.00
tensorsparse.R#151	0.80	0.09	0.80	0.09
tensorsparse.R#208	0.48	0.05	0.00	0.00
tensorsparse.R#121	0.44	0.05	0.44	0.05
tensorsparse.R#123	0.36	0.04	0.36	0.04
tensorsparse.R#122	0.36	0.04	0.34	0.04
tensorsparse.R#142	0.30	0.03	0.30	0.03
tensorsparse.R#213	0.12	0.01	0.00	0.00
tensorsparse.R#145	0.10	0.01	0.10	0.01
tensorsparse.R#129	0.06	0.01	0.06	0.01
tensorsparse.R#138	0.04	0.00	0.04	0.00
tensorsparse.R#293	0.04	0.00	0.04	0.00
tensorsparse.R#303	0.04	0.00	0.04	0.00
tensorsparse.R#298	0.04	0.00	0.02	0.00
tensorsparse.R#124	0.02	0.00	0.02	0.00
tensorsparse.R#125	0.02	0.00	0.02	0.00
tensorsparse.R#130	0.02	0.00	0.02	0.00
tensorsparse.R#140	0.02	0.00	0.02	0.00
tensorsparse.R#159	0.02	0.00	0.02	0.00
tensorsparse.R#162	0.02	0.00	0.02	0.00

\$by.line

	self.time	self.pct	total.time	total.pct
simulation.R#46	0.06	0.01	911.02	100.00
tensorsparse.R#79	1.78	0.20	1.78	0.20
tensorsparse.R#80	1.28	0.14	1.28	0.14
tensorsparse.R#82	32.94	3.62	32.94	3.62
tensorsparse.R#86	2.22	0.24	2.22	0.24
tensorsparse.R#87	269.92	29.63	269.92	29.63
tensorsparse.R#89	25.20	2.77	25.20	2.77
tensorsparse.R#90	72.06	7.91	72.06	7.91
tensorsparse.R#99	19.26	2.11	19.26	2.11
tensorsparse.R#121	0.44	0.05	0.44	0.05
tensorsparse.R#122	0.34	0.04	0.36	0.04
tensorsparse.R#123	0.36	0.04	0.36	0.04
tensorsparse.R#124	0.02	0.00	0.02	0.00
tensorsparse.R#125	0.02	0.00	0.02	0.00
tensorsparse.R#128	6.08	0.67	6.08	0.67
tensorsparse.R#129	0.06	0.01	0.06	0.01
tensorsparse.R#130	0.02	0.00	0.02	0.00
tensorsparse.R#138	0.04	0.00	0.04	0.00
tensorsparse.R#140	0.02	0.00	0.02	0.00
tensorsparse.R#142	0.30	0.03	0.30	0.03
tensorsparse.R#143	0.08	0.01	34.80	3.82
tensorsparse.R#145	0.10	0.01	0.10	0.01
tensorsparse.R#148	27.46	3.01	27.46	3.01
tensorsparse.R#151	0.80	0.09	0.80	0.09
tensorsparse.R#159	0.02	0.00	0.02	0.00
tensorsparse.R#160	1.38	0.15	1.38	0.15
tensorsparse.R#162	0.02	0.00	0.02	0.00
tensorsparse.R#186	54.16	5.94	54.16	5.94
tensorsparse.R#193	0.00	0.00	1.20	0.13
tensorsparse.R#196	393.28	43.17	762.68	83.72
tensorsparse.R#201	0.06	0.01	19.58	2.15
tensorsparse.R#202	0.04	0.00	2.02	0.22

tensorsparse.R#203	0.00	0.00	0.82	0.09
tensorsparse.R#204	0.04	0.00	2.56	0.28
tensorsparse.R#205	0.00	0.00	1.34	0.15
tensorsparse.R#206	0.08	0.01	23.36	2.56
tensorsparse.R#207	0.02	0.00	2.76	0.30
tensorsparse.R#208	0.00	0.00	0.48	0.05
tensorsparse.R#209	0.00	0.00	2.10	0.23
tensorsparse.R#210	0.00	0.00	2.90	0.32
tensorsparse.R#211	0.08	0.01	22.06	2.42
tensorsparse.R#212	0.02	0.00	5.82	0.64
tensorsparse.R#213	0.00	0.00	0.12	0.01
tensorsparse.R#214	0.00	0.00	1.52	0.17
tensorsparse.R#215	0.02	0.00	4.52	0.50
tensorsparse.R#225	0.82	0.09	0.82	0.09
tensorsparse.R#235	0.02	0.00	910.84	99.98
tensorsparse.R#293	0.04	0.00	0.04	0.00
tensorsparse.R#298	0.02	0.00	0.04	0.00
tensorsparse.R#303	0.04	0.00	0.04	0.00
tensorsparse.R#316	0.00	0.00	910.84	99.98

```
$sample.interval
[1] 0.02
```

```
$sampling.time
[1] 911.02
```

B The R code to cluster dnations.mat

```
if(!require("rmatio")){
  install.packages("rmatio")
  stopifnot(require("rmatio"))
}
source('tensorsparse.R')

dnations = read.mat("dnations.mat")
country = unlist(dnations$countrynames)
relationship = unlist(dnations$relnnames)
att = unlist(dnations$attnames)
dnation_arr = (2*dnations$R-1)*10
dnation_arr[is.nan(dnation_arr)] = 0

krl = sparse.choosekrl(dnation_arr,2:5,2:5,2:5)
#our result in sparse.choosekrl() is 5,5,5
relationship_label = label2(dnation_arr,5,5,5)
relationship_label$Cs
relationship_label$Ds
relationship_label$Es
for (i in 1:5){
  cat("cluster_",i,":\n")
  print(country[relationship_label$Cs==i])
}
for (i in 1:5){
  cat("cluster_",i,":\n")
  print(relationship[relationship_label$Es==i])
}

$estimated_kr
[,1] [,2] [,3]
```

```
[1,]      5      5      5
```

```
$results.se
```

```
, , L = 5
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5933.435	5552.789	5296.343	5239.945	5028.949	4997.151
K = 6	5949.399	5561.578	5451.368	5387.178	5076.400	5053.245
K = 7	6063.003	5682.731	5589.186	5381.293	5167.628	5082.386
K = 8	5742.482	5437.832	5518.353	5136.984	4956.522	4992.278
K = 9	5639.228	5157.166	5282.963	5121.966	4776.031	4712.576
K = 10	5594.872	5159.248	5240.639	4707.893	4612.308	4206.844

```
, , L = 6
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5828.189	5473.479	5334.921	5227.326	4973.818	5044.779
K = 6	5726.943	5647.883	5462.790	5387.830	5010.194	5115.050
K = 7	5768.731	5563.020	5581.316	5350.648	5050.824	5140.676
K = 8	5723.458	5391.735	5623.999	5232.224	5044.535	5169.820
K = 9	5558.866	5062.512	5344.152	5208.000	4892.373	4911.731
K = 10	5457.989	5073.254	5266.877	4836.138	4866.966	4547.622

```
, , L = 7
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5810.854	5471.269	5283.968	5144.203	4866.545	4943.979
K = 6	5838.357	5466.073	5281.825	5094.621	4808.000	5018.790
K = 7	5762.995	5426.509	5622.587	5506.223	5209.475	5385.598
K = 8	5463.880	5111.444	5420.685	5347.818	5184.629	5295.328
K = 9	5390.141	4865.092	5120.806	4919.150	4594.657	4629.506
K = 10	5283.692	4900.644	5082.770	4968.200	4621.289	4653.673

```
, , L = 8
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5512.850	5226.016	5170.784	5256.532	4896.963	4856.711
K = 6	5662.549	5408.524	5120.544	5292.055	4805.103	4929.998
K = 7	5482.461	5162.246	5139.782	5507.892	5378.398	5293.933
K = 8	4996.948	4832.955	4891.994	5094.060	5166.374	5103.209
K = 9	5029.056	4751.835	4652.263	4683.257	4355.256	4188.731
K = 10	5184.933	4761.462	4847.815	4864.643	4751.329	4585.901

```
, , L = 9
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5092.393	4916.785	5068.483	5194.838	5047.737	4848.045
K = 6	5215.378	5059.897	4890.586	5100.640	4822.050	4816.145
K = 7	5117.740	4956.342	5195.852	5595.416	5425.984	5175.471
K = 8	4584.519	4487.400	4849.573	5023.491	5179.372	4931.752
K = 9	4602.946	4211.446	4389.301	4535.432	4390.707	4058.499
K = 10	4720.300	4236.758	4668.369	4770.880	4782.131	4351.787

```
, , L = 10
```

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	5380.532	5204.565	5007.741	4794.561	4751.250	4765.771
K = 6	5721.548	5310.215	5074.755	4969.275	4523.610	4698.753
K = 7	5430.110	5045.681	4870.134	4780.291	4709.825	4785.550
K = 8	5057.639	4789.875	4722.049	4512.756	4590.281	4724.512
K = 9	5211.760	4679.333	4779.904	4492.020	4322.838	4312.883

K = 10 5036.333 4629.174 4550.536 4450.234 4173.690 4148.455

\$results.mean

, , L = 5

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	91316.56	90666.84	91007.17	90506.33	90560.17	90811.23
K = 6	91134.08	90157.61	90300.61	89968.64	89965.23	90055.84
K = 7	91426.30	90391.26	90823.57	90444.13	90089.88	90132.16
K = 8	91995.75	90910.09	90781.99	90597.28	90261.71	90455.54
K = 9	91285.82	90386.53	90315.76	90302.44	90454.84	90276.06
K = 10	91622.14	90551.01	90761.86	90521.31	90130.42	89732.69

, , L = 6

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	89246.44	88640.09	88880.74	88491.18	88263.54	88412.17
K = 6	88960.24	88061.17	88306.74	87972.72	87629.68	87729.48
K = 7	89433.58	88451.49	88968.78	88529.74	87617.66	87653.90
K = 8	89867.22	88806.69	88765.84	88345.07	87746.58	88087.84
K = 9	89244.91	88252.22	88331.16	88358.05	88107.40	88164.43
K = 10	89459.62	88283.11	88663.97	88378.67	87758.58	87521.30

, , L = 7

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	87469.56	86940.52	87227.04	86891.31	86754.25	86850.31
K = 6	87368.42	86452.15	86713.71	86527.74	86193.92	86104.30
K = 7	87970.76	86880.88	87435.06	87279.84	86447.41	86419.24
K = 8	88241.20	87180.46	87193.66	87161.24	86680.75	86884.03
K = 9	87334.72	86449.21	86632.21	86708.73	86750.90	86680.85
K = 10	87779.51	86519.68	86997.72	87151.32	86465.66	86276.95

, , L = 8

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	86422.09	86206.14	86438.25	86110.52	85629.39	85552.58
K = 6	86332.71	85416.49	85792.98	85573.32	84913.31	84676.26
K = 7	86880.36	85707.67	86238.97	85915.00	84863.54	84813.55
K = 8	87200.41	86089.49	85923.00	85966.07	85054.55	85194.36
K = 9	85940.44	85111.48	85133.54	85283.64	85116.78	84996.34
K = 10	86105.45	85222.57	85291.23	85723.66	84669.57	84415.23

, , L = 9

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	85841.37	85611.99	85852.10	85399.25	84934.12	85056.68
K = 6	85716.25	84737.80	84945.76	84584.84	84001.23	84012.00
K = 7	86363.89	85110.12	85590.97	85198.99	84043.05	84297.62
K = 8	86718.44	85476.28	85227.70	85372.00	84439.88	84870.34
K = 9	85325.82	84318.67	84585.79	84677.73	84404.44	84471.26
K = 10	85483.51	84398.69	84772.31	85061.83	84019.74	83971.74

, , L = 10

	R = 5	R = 6	R = 7	R = 8	R = 9	R = 10
K = 5	84106.95	83617.89	83885.61	83891.03	83000.10	83113.09
K = 6	83734.25	82784.06	83200.32	83144.59	82530.81	82586.39
K = 7	84381.33	83166.93	83860.84	83857.90	82676.44	82943.25
K = 8	84729.02	83675.82	83679.58	83957.34	83079.35	83646.69

K = 9 83415.21 82587.72 82719.32 83231.43 82858.03 82939.46
K = 10 83952.36 82996.90 83421.94 83931.18 82970.53 82946.14

C The simulation result of chooseLambda2()

The result I got by using chooseLambda() is always 0 (may because the range I selected is always bad). And here is the result I got from chooseLambda2():

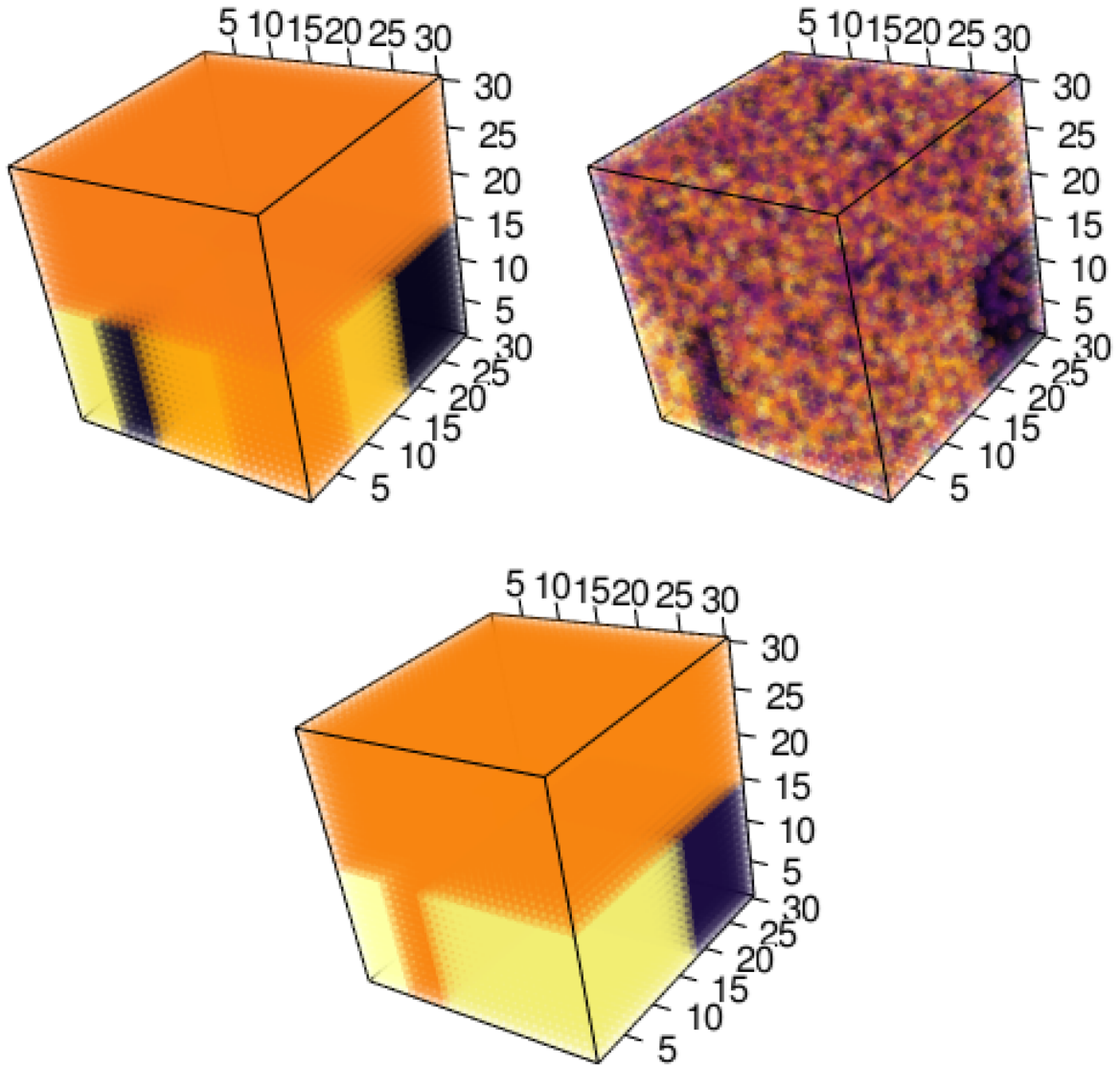


Figure 1: truth,input,output