Numericware i: Identical by State Matrix Calculator

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ABSTRACT: We introduce software, Numericware i, to compute identical by state (IBS) matrix based on genotypic data. Calculating an IBS matrix with a large dataset requires large computer memory and takes lengthy processing time. Numericware i addresses these challenges with 2 algorithmic methods: multithreading and forward chopping. The multithreading allows computational routines to concurrently run on multiple central processing unit (CPU) processors. The forward chopping addresses memory limitation by dividing a dataset into appropriately sized subsets. Numericware i allows calculation of the IBS matrix for a large genotypic dataset using a laptop or a desktop computer. For comparison with different software, we calculated genetic relationship matrices using Numericware i, SPAGeDi, and TASSEL with the same genotypic dataset. Numericware i calculates IBS coefficients between 0 and 2, whereas SPAGeDi and TASSEL produce different ranges of values including negative values. The Pearson correlation coefficient between the matrices from Numericware i and TASSEL was high at .9972, whereas SPAGeDi showed low correlation with Numericware i (.0505) and TASSEL (.0587). With a high-dimensional dataset of 500 entities by 10 000 000 SNPs, Numericware i spent 382 minutes using 19 CPU threads and 64 GB memory by dividing the dataset into 3 pieces, whereas SPAGeDi and TASSEL failed with the same dataset. Numericware i is freely available for Windows and Linux under CC-BY 4.0 license at https://figshare.com/s/f100f33a8857131eb2db.

KEYWORDS: Identical by state matrix, Numericware i, Genetic relationship matrix, Forward chopping, Multithreading

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Background

The inbreeding, identical by descent (synonymous to IBD, kinship, and coancestry), and identical by state (IBS) coefficients are central parameters in population genetics. 1 By definition, (1) the inbreeding coefficient refers to a proportion that a pair of alleles in an entity is identical in origin and state,2 (2) the IBD coefficient between 2 entities equals twice the inbreeding coefficient for their virtual offspring,³ and (3) the IBS coefficient between 2 entities equals twice a proportion that a pair of alleles in their virtual offspring is identical in state. The IBD matrix is a conventional indicator to represent genetic relationship among entities in a population, for which pedigrees are available. Emik and Terrill³ suggested a systematic method for calculating a numerator relationship matrix (NRM) that displays IBD coefficients among every pair of entities in a population. Because the NRM is based on pedigrees, it represents genetic relationship from the genealogical perspective.

High-throughput genotyping technologies provide abundant DNA profile that is useful to calculate the IBS matrix as a genetic relationship matrix. Some references^{4,5} introduced a method for computing the IBS matrix. Although the concept about the IBS matrix is general and simple, the IBS matrix is not widely used. Presumably, it might be due to the notoriously heavy computing burden. In this paper, we present

software referred to as Numericware i. In order to deal with heavy workload, Numericware i supports parallelization and data management to avoid low memory.

Implementation

IBS coefficient

The IBS coefficients^{4,5} can be calculated:

$$IBS_{A,B} = \frac{1}{2} \begin{pmatrix} P(a1 \equiv b1) + P(a1 \equiv b2) \\ +P(a2 \equiv b1) + P(a2 \equiv b2) \end{pmatrix}$$
(1)

where $IBS_{A,B}$ =the IBS coefficient between A and B; a1, a2=a pair of chromosomes for A; b1, b2=a pair of chromosomes for B; $P(a1\equiv b1)$ =the probability that a1 and b1 are homozygous; $P(a1\equiv b2)$ =the probability that a1 and b2 are homozygous; $P(a2\equiv b1)$ =the probability that a2 and b1 are homozygous; and $P(a2\equiv b2)$ =the probability that a2 and b2 are homozygous.

The IBS coefficient for parents equals twice the homozygote coefficient (H) for their offspring. Thus, the H can be calculated:

$$H_{C} = \frac{1}{4} \begin{pmatrix} P(al \equiv b1) + P(al \equiv b2) \\ +P(a2 \equiv b1) + P(a2 \equiv b2) \end{pmatrix}$$
 (2)

where C=the offspring of A and B; H_C =the homozygote coefficient for C; a1, a2=a pair of chromosomes for A; b1, b2=a pair of chromosomes for B; $P(a1 \equiv b1)$ =the probability that a1 and b1 are homozygous; $P(a1 \equiv b2)$ =the probability that a1 and b2 are homozygous; $P(a2 \equiv b1)$ =the probability that a2 and b1 are homozygous; and $P(a2 \equiv b2)$ =the probability that a2 and b2 are homozygous.

As the cost for producing genotypic data is becoming less expensive, the dimensions of genotypic datasets are rapidly growing. The amount of computing workload can be represented:

$$w = n^2 m \tag{3}$$

where w= the amount of computational workload; n= the number of entities in a population; m= the number of markers.

According to equation 3, the growing dimension of genotypic dataset causes 2 computational challenges: (1) lengthy computational time and (2) low memory.

Functionality of Numericware i

Numericware i, written in C++, has a simple user interface. The software provides 2 special functionalities:

multithreading and forward chopping. The multithreading enables the computer to distribute the workload into multiple CPU threads. The forward chopping chops a dataset into multiple pieces that will not overextend memory capacity. Algorithm 1 shows the forward chopping algorithm.

Numericware i provides users with more conveniences:

- 1. Imputation not needed: The IBS computation is counting based. Numericware i skips counting missing genotypic data, assuming that the remaining genotypic data are of sufficiently large amount.
- 2. IBS computation for a haplotype: This allows computation of the IBS matrix for a partial genomic block.
- 3. Dataset integrity checking: This helps prevent a failure in the middle of analysis by checking the integrity of dataset at the beginning of work.
- 4. Dataset summary: This provides users with overview of genotypic data.
- 5. Supporting multiple types of datasets: This significantly reduces extra works for formatting the dataset. Numericware i accepts: alphanumeric, a pair of single-nucleotide polymorphisms (SNPs) and International Union of Pure and Applied Chemistry (IUPAC) formats.

Algorithm 1. Forward Chopping algorithm.

```
start_point = 0
2:
    for (j=1; j \leftarrow num\_pieces; j++){}
                                                                   // num_pieces = the total number of chopped pieces
     if (j <= width % num_pieces) {
3:
                                                                   // width = the total number of columns
4:
      chopped_width = ceil(width / num_pieces)
                                                                   // chopped_width = the width of a chopped piece
5:
6:
      chopped_width = floor(width / num_pieces)
7:
     }
8:
     start_point = start_point + 1
                                                                   // start_point = the first column coordinate of a chopped dataset
9:
     end_point = start_point + chopped_width - 1
                                                                   // end_point = the last column coordinate of a chopped dataset
10:
     for (string line; getline(data, line)) {
11:
       count = 1
12:
       while (getline(line, temp, ",")) {
13:
        if (count >= start_point) {
14:
           row.push_back(temp)
15:
        if (count == end_point) { break }
16:
17:
        count++
18:
19:
       table.push_back(row)
       row.clear()
20:
21:
      }
22:
    23:
      IBS matrix computation with 'table'
24:
    25:
      table.clear()
26:
      start_point = end_point
27:
```

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6. Transposing the dataset.

Regarding item 5, details about dataset formats are described in the user manual, and example datasets are included in the software package. Numericware i completes the IBS matrix by copying the upper diagonals to the lower diagonals based on its symmetric property to reduce workload.

Application of the IBS matrix

Homozygote coefficient index. A diagonal value for an entity A (IBS_{A,A}) in the IBS matrix implies the H_A as IBS_{A,A} = 1+ H_A , and IBS_{A,B} represents twice the H_C , in which C = the offspring of A and B. These principles can be useful in controlling homozygote level of progenies in a breeding program.

Best linear unbiased prediction. As a statistical model, the best linear unbiased prediction (BLUP)6 is widely used to estimate breeding values. The BLUP requires the genetic relationship matrix, for which Henderson⁶ suggested using the NRM. The IBS matrix is superior to the NRM in the following aspects. First, the IBS matrix fully has values greater than 0, whereas the NRM includes an identity matrix for a base population. The identity matrix results in underestimation of IBD coefficients within the NRM. Second, the IBS matrix provides an objective measure based on genotypic data whereas the NRM is based on statistical expectation. As the BLUP expands to genome-wide association study and genomic prediction, the IBS matrix can apply to these studies.7-11 The IBS matrix will be useful especially for plants since plant pedigrees are often unknown and imprecise.¹² Previous studies reported that the BLUP outperforms with genome-based genetic relationship matrices than the NRM.13-18 In this context, the IBS matrix will be useful in improving the BLUP accuracy.

Results and Discussion

Negative effect of marker screen to IBS matrix

Marker collections generally consist of markers screened based on allele frequency. Marker screening secures allele diversity but causes an ascertainment bias in calculating the IBS matrix because the removed markers must be informative in representing the identical genomic state between entities. Thus, it is recommended to use all markers in calculating the IBS matrix.

Similarity between IBD and IBS

The IBD and IBS coefficients range between 0 and 2 in common. If it is assured that any identical alleles at the same locus from different entities were generated not independently but inherently, the IBS and IBD coefficients should be equal.⁴ We hypothetically assume numerous unique mutations might inherently have flourished genetic diversity because the probability of the same mutations coincidentally occurring on the

same loci of multiple genomes could be extremely low. If this assumption is true, the IBS and IBD matrices can be equal.

Comparison of results from Numericware i, SPAGeDi, and TASSEL

The IBS matrix can be expanded by computing the NRM based on pedigrees of entities within the IBS matrix. The expanded IBS matrix will have overall increased elemental values than the NRM solely based on pedigrees. The expansion of IBS matrix can be calculated using Numericware N.19 Other popular software, SPAGeDi 20 and TASSEL,8 implement different algorithms for calculating the genetic relationship matrix, causing their results to have different characteristics, such as negative values (SPAGeDi and TASSEL) or mono-diagonal values (SPAGeDi with 0's). Thus, the resulting matrices from SPAGeDi and TASSEL cannot be expanded by the NRM algorithm. For comparison, we applied Numericware i, SPAGeDi, and TASSEL to the same dataset of 20 entities by 2000 SNPs (included in Supplementary file). The algorithms used by SPAGeDi and TASSEL are the ones by Loiselle et al²¹ and Yang et al²², respectively, and widely used for calculating the genetic relationship matrices. ^{7,23–26} Tables 1 to 3 are the resulting matrices. Pearson correlation coefficients among the 3 matrices (Table 4) indicate that the results from Numericware i and TASSEL are highly correlated at .9972, whereas the result from SPAGeDi shows low correlation coefficients with the results from Numericware i (0.0505) and TASSEL (0.0587). This illustrates that the results from Numericware i and TASSEL are substantially comparable, whereas SPAGeDi is not.

Performance

In our test, Numericware i took 382 minutes in computing an IBS matrix with a simulated dataset of 500 entities by 10 000 000 SNPs using 19 CPU threads (Intel Xeon processor E5-2600 v4) and 64 GB memory. For this test, the whole dataset was chopped into 3 pieces to circumvent the low memory, whereas SPAGeDi and TASSEL failed with the same dataset due to the low memory.

Conclusions

The IBS matrix can be useful as: (1) a foreseeing index about the homozygote coefficients for hybrid lines based on the IBS coefficient for parents being equal to twice the homozygote coefficient for an offspring, (2) an assessment of homozygote coefficient to an entity itself based on IBS $_{A,A}$ being equal to $1+H_A$, and (3) a component of the BLUP. Thus, Numericware i can be an essential tool for breeding. The multithreading and forward chopping reduce computing time and allow processing of extremely large amount of data. In contrast, other software are often limited by the physical memory size, and only a

Table 1. Identical by state matrix calculated using Numericware i.

ID20	0.49675	0.4795	0.499	0.48975	0.51675	0.4845	0.483	0.50625	0.49075	0.4765	0.5025	0.49325	0.484	0.4595	0.50525	0.5005	0.51	0.50175	0.48925	1.244
ID19	0.50775	0.49025	0.49575	0.511	0.49775	0.48775	0.496	0.485	0.4885	0.50125	0.49775	0.515	0.511	0.509	0.515	0.51225	0.4985	0.5055	1.251	0.48925
ID18	0.50625	0.48575	0.50625	0.5035	0.512	0.49575	0.49125	0.50425	0.48325	0.50375	0.51175	0.49875	0.5145	0.51	0.51275	0.5015	0.5155	1.2445	0.5055	0.50175
ID17	0.4865	0.5015	0.502	0.51275	0.506	0.499	0.4985	0.503	0.50525	0.49975	0.49525	0.4995	0.50125	0.48525	0.4945	0.48775	1.252	0.5155	0.4985	0.51
ID16	0.5145	0.497	0.50525	0.5035	0.5065	0.49575	0.50425	0.49125	0.49825	0.50725	0.5025	0.51475	0.50725	0.501	0.5135	1.2335	0.48775	0.5015	0.51225	0.5005
ID15	0.494	0.50925	0.49875	0.4855	0.5065	0.50975	0.526	0.5005	0.504	0.48725	0.50525	0.50475	0.50175	0.48775	1.2345	0.5135	0.4945	0.51275	0.515	0.50525
ID14	0.492	0.514	0.49775	0.515	0.491	0.509	0.48825	0.49925	0.51475	0.507	0.514	0.4875	0.5065	1.25	0.48775	0.501	0.48525	0.51	0.509	0.4595
ID13	0.50775	0.49375	0.4835	0.51225	0.51275	0.50275	0.4955	0.5015	0.5035	0.50625	0.5015	0.5005	1.2445	0.5065	0.50175	0.50725	0.50125	0.5145	0.511	0.484
ID12	0.47575	0.4935	0.50325	0.49375	0.507	0.5065	0.50675	0.50775	0.49925	0.50525	0.493	1.229	0.5005	0.4875	0.50475	0.51475	0.4995	0.49875	0.515	0.49325
ID11	0.49375	0.48225	0.505	0.50225	0.506	0.5	0.48425	0.507	0.501	0.49175	1.2485	0.493	0.5015	0.514	0.50525	0.5025	0.49525	0.51175	0.49775	0.5025
ID10	0.521	0.50525	0.50675	0.50475	0.505	0.5085	0.489	0.5075	0.50875	1.25	0.49175	0.50525	0.50625	0.507	0.48725	0.50725	0.49975	0.50375	0.50125	0.4765
ID9	0.50025	0.504	0.49475	0.51225	0.50325	0.49325	0.50975	0.503	1.2435	0.50875	0.501	0.49925	0.5035	0.51475	0.504	0.49825	0.50525	0.48325	0.4885	0.49075
ID8	0.4985	0.505	0.49925	0.48775	0.50975	0.49175	0.494	1.2665	0.503	0.5075	0.507	0.50775	0.5015	0.49925	0.5005	0.49125	0.503	0.50425	0.485	0.50625
ID7	0.4865	0.4905	0.49175	0.5025	0.49825	0.49725	1.244	0.494	0.50975	0.489	0.48425	0.50675	0.4955	0.48825	0.526	0.50425	0.4985	0.49125	0.496	0.483
1D6	0.4925	0.50625	0.49175	0.48425	0.48075	1.241	0.49725	0.49175	0.49325	0.5085	0.5	0.5065	0.50275	0.509	0.50975	0.49575	0.499	0.49575	0.48775	0.4845
ID5	0.493	0.497	0.50175	0.48075	1.2365	0.48075	0.49825	0.50975	0.50325	0.505	0.506	0.507	0.51275	0.491	0.5065	0.5065	0.506	0.512	0.49775	0.51675
ID4	0.5045	0.49275	0.51025	1.26	0.48075	0.48425	0.5025	0.48775	0.51225	0.50475	0.50225	0.49375	0.51225	0.515	0.4855	0.5035	0.51275	0.5035	0.511	0.48975
ID3	0.4935	0.50775	1.2365	0.51025	0.50175	0.49175	0.49175	0.49925	0.49475	0.50675	0.505	0.50325	0.4835	0.49775	0.49875	0.50525	0.502	0.50625	0.49575	0.499
ID2	0.48525	1.2555	0.50775	0.49275	0.497	0.50625	0.4905	0.505	0.504	0.50525	0.48225	0.4935	0.49375	0.514	0.50925	0.497	0.5015	0.48575	0.49025	0.4795
ID1	1.253	0.48525	0.4935	0.5045	0.493	0.4925	0.4865	0.4985	0.50025	0.521	0.49375	0.47575	0.50775	0.492	0.494	0.5145	0.4865	0.50625	0.50775	0.49675
	10	ID2	ID3	ID4	ID5	ID6	ID7	ID8	6QI	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	ID19	ID20

Table 2. Genetic relationship matrix calculated based on the method of Loiselle et al. (1995) using SPAGeDi.

וספטו	212	0.0039	-0.0077	0.0045	-0.0031	0.0153	-0.0036	-0.0046	0.0081	-0.0022	-0.013	0.0064	0.0004	-0.0079	-0.0228	0.0065	0.0032	0.0112	0.0037	-0.0034	0
ID19	2	0.0062	-0.0055	-0.0029	0.0062	-0.0029	-0.0066	-0.001	-0.0116	-0.009	-0.0013	-0.0021	0.0101	0.0054	0.0058	0.008	900.0	-0.0019	0.0011	0	-0.0034
ID 18	2	0.0037	-0.0101	0.0028	-0.0004	0.0054	-0.0026	-0.0057	0.0001	-0.014	-0.0011	900.0	-0.0025	0.0063	0.005	0.0049	-0.0028	0.0083	0	0.0011	0.0037
1017		-0.0079	0.0026	0.0017	0.0078	0.0032	0.0015	0.0011	0.0011	0.0029	-0.0019	-0.0034	-0.0001	-0.0009	-0.01	-0.0057	-0.0103	0	0.0083	-0.0019	0.0112
1016	2	0.0097	-0.002	0.0024	-0.0001	0.002	-0.0023	0.0036	-0.0084	-0.0034	0.0017	0	0.0088	0.0017	-0.0007	0.0058	0	-0.0103	-0.0028	900.0	0.0032
ID15	2	-0.0043	0.0064	-0.002	-0.0123	0.002	0.0074	0.0185	-0.0021	0.0006	-0.0119	0.002	0.002	-0.002	-0.0098	0	0.0058	-0.0057	0.0049	0.008	0.0065
ID14		-0.0037	0.0116	-0.0007	0.0098	-0.0066	0.0088	-0.0053	-0.0009	0.0099	0.0035	0.0099	-0.0078	0.0032	0	-0.0098	-0.0007	-0.01	0.005	0.0058	-0.0228
1013	2	0.0053	-0.0041	-0.0122	0.0061	0.0065	0.0027	-0.0022	-0.0012	0.0004	0.0012	-0.0004	-0.0008	0	0.0032	-0.002	0.0017	-0.0009	0.0063	0.0054	-0.0079
1019	j i	-0.0146	-0.0023	0.0032	-0.0046	0.0045	0.0072	0.0074	0.005	-0.0006	0.0025	-0.0043	0	-0.0008	-0.0078	0.002	0.0088	-0.0001	-0.0025	0.0101	0.0004
154	<u>.</u>	-0.0027	-0.0103	0.0041	0.0009	0.0035	0.0024	-0.0083	0.0041	0.0003	-0.0071	0	-0.0043	-0.0004	0.0099	0.002	0	-0.0034	900.0	-0.0021	0.0064
ID10		0.0143	0.0038	0.0036	0.001	0.0012	0.0066	-0.0067	0.0029	0.004	0	-0.0071	0.0025	0.0012	0.0035	-0.0119	0.0017	-0.0019	-0.0011	-0.0013	-0.013
POI		0.0012	0.004	-0.0035	0.0072	0.001	-0.0027	0.0086	0.0008	0	0.004	0.0003	-0.0006	0.0004	0.0099	0.0006	-0.0034	0.0029	-0.014	-0.009	-0.0022
aCI.	2	-0.0002	0.0044	-0.0007	-0.0098	0.0052	-0.004	-0.0024	0	0.0008	0.0029	0.0041	0.005	-0.0012	-0.0009	-0.0021	-0.0084	0.0011	0.0001	-0.0116	0.0081
107		-0.0053	-0.0023	-0.0027	0.0034	0.0005	0.0029	0	-0.0024	0.0086	-0.0067	-0.0083	0.0074	-0.0022	-0.0053	0.0185	0.0036	0.0011	-0.0057	-0.001	-0.0046
ID6		-0.0012	0.0084	-0.0027	-0.0091	-0.0115	0	0.0029	-0.004	-0.0027	0.0066	0.0024	0.0072	0.0027	0.0088	0.0074	-0.0023	0.0015	-0.0026	-0.0066	-0.0036
IDS		-0.004	-0.001	0.0011	-0.0146	0	-0.0115	0.0005	0.0052	0.001	0.0012	0.0035	0.0045	0.0065	-0.0066	0.002	0.002	0.0032	0.0054	-0.0029	0.0153
ID4	5	0.0039	-0.0039	0.0068	0	-0.0146	-0.0091	0.0034	-0.0098	0.0072	0.001	0.0009	-0.0046	0.0061	0.0098	-0.0123	-0.0001	0.0078	-0.0004	0.0062	-0.0031
EG	2	-0.0024	0.0076	0	0.0068	0.0011	-0.0027	-0.0027	-0.0007	-0.0035	0.0036	0.0041	0.0032	-0.0122	-0.0007	-0.002	0.0024	0.0017	0.0028	-0.0029	0.0045
	1	-0.0068	0	0.0076	-0.0039	-0.001	0.0084	-0.0023	0.0044	0.004	0.0038	-0.0103	-0.0023	-0.0041	0.0116	0.0064	-0.002	0.0026	-0.0101	-0.0055	-0.0077
Ξ	<u>.</u>	0	-0.0068	-0.0024	0.0039	-0.004	-0.0012	-0.0053	-0.0002	0.0012	0.0143	-0.0027	-0.0146	0.0053	-0.0037	-0.0043	0.0097	-0.0079	0.0037	0.0062	0.0039
		₽	ID2	ID3	ID4	ID5	ID6	ID7	ID8	601	ID10	1011	ID12	ID13	ID14	ID15	ID16	ID17	ID18	ID19	ID20

Table 3. Normalized identical by state matrix calculated based on the method of Yang et al. (2011) using TASSEL.

D20	-0.04571	-0.03686	-0.01861	-0.09108	-0.00182	-0.0489	-0.07538	-0.03179	-0.05892	-0.07347	-0.01673	-0.02779	-0.05494	-0.10051	-0.03	-0.07608	-0.02561	-0.04324	-0.06266	0.9201
Ö				·		·	·			·	·	·								
ID19	-0.04331	-0.07387	-0.03265	-0.03641	-0.06206	-0.07728	-0.07846	-0.06918	-0.05965	-0.03556	-0.07238	-0.01148	-0.02503	-0.06462	-0.0523	-0.03108	-0.06342	7 -0.02854	0.979937	-0.06266
ID18	-0.05719	-0.07973	-0.03638	-0.02074	-0.03478	-0.05117	-0.07736	-0.06389	-0.11517	-0.04125	-0.0468	-0.06049	-0.03562	-0.05541	-0.03786	-0.03571	-0.05425	0.975567	-0.02854	-0.04324
ID17	-0.0711	-0.04279	-0.04533	-0.01946	-0.04079	-0.06854	-0.05802	-0.04952	-0.03338	-0.04877	-0.05464	-0.04771	-0.04826	-0.07504	-0.05297	-0.0886	0.988198	-0.05425	-0.06342	-0.02561
ID16	-0.03706	-0.02896	-0.03182	-0.03923	-0.07029	-0.04114	-0.03824	-0.0677	-0.06662	-0.05284	-0.06394	-0.03686	-0.06508	-0.02666	-0.04718	0.945105	-0.0886	-0.03571	-0.03108	-0.07608
ID15	-0.07754	-0.04932	-0.05198	-0.07252	-0.03413	-0.02654	0.0015	-0.05593	-0.05587	-0.07237	-0.049	-0.03479	-0.05919	-0.09514	0.953138	-0.04718	-0.05297	-0.03786	-0.0523	-0.03
ID14	-0.01028	-0.0283	-0.04558	-0.0297	-0.06697	-0.00742	-0.04276	-0.03451	-0.06021	-0.02231	-0.0504	-0.0773	-0.03807	0.931201	-0.09514	-0.02666	-0.07504	-0.05541	-0.06462	-0.10051
ID13	-0.02087	-0.08701	-0.0907	-0.0491	-0.02515	-0.05783	-0.0444	-0.03663	-0.01943	-0.0829	-0.0497	-0.07892	0.968834	-0.03807	-0.05919	-0.06508	-0.04826	-0.03562	-0.02503	-0.05494
ID12	-0.09083	-0.04805	-0.05716	-0.05746	-0.053	-0.05604	-0.04842	-0.03071	-0.04378	-0.05985	-0.0346	0.955251	-0.07892	-0.0773	-0.03479	-0.03686	-0.04771	-0.06049	-0.01148	-0.02779
ID11	-0.03943	-0.0717	-0.02877	-0.06807	-0.03827	-0.03247	-0.06282	-0.03205	-0.07858	-0.05307	0.943432	-0.0346	-0.0497	-0.0504	-0.049	-0.06394	-0.05464	-0.0468	-0.07238	-0.01673
ID10	0.002185	-0.055	-0.04924	-0.04468	-0.06151	-0.05079	-0.07431	- 0.06069	-0.04427	0.980709	-0.05307	-0.05985	-0.0829	-0.02231	-0.07237	-0.05284	-0.04877	-0.04125	-0.03556	-0.07347
I 60I	-0.04992	-0.01471	- 0.05797	-0.00316	-0.03849	-0.05163	-0.0466	-0.05415	0.952509 -	-0.04427	-0.07858	-0.04378	-0.01943	-0.06021	-0.05587	-0.06662	-0.03338	-0.11517	-0.05965 -	-0.05892 -
ID8	-0.05198	-0.0388	-0.0629	- 0.09919	-0.05554	-0.06428 -	-0.03756 -	0.997001	-0.05415	- 69090.0-	-0.03205	-0.03071	-0.03663	-0.03451	-0.05593 -	- 0.0677	-0.04952	- 0.06389	-0.06918	-0.03179
ID7	-0.07975	-0.06972	-0.07476	-0.04032	-0.02142 -	-0.02279	0.9916	-0.03756	-0.0466	-0.07431	-0.06282	-0.04842	-0.0444	-0.04276	0.0015	-0.03824 -	-0.05802 -	-0.07736	-0.07846 -	-0.07538 -
ID6	-0.04866	-0.054	-0.0831	-0.0528	-0.06293	0.958312	-0.02279	-0.06428	-0.05163	-0.05079	-0.03247	-0.05604	-0.05783	-0.00742	-0.02654	-0.04114	-0.06854	-0.05117	-0.07728	-0.0489
ID5	-0.07634	-0.0615	-0.04241	-0.10577	0.953172	-0.06293	-0.02142	-0.05554	-0.03849	-0.06151	-0.03827	-0.053	-0.02515	-0.06697	-0.03413	-0.07029	-0.04079	-0.03478	-0.06206	-0.00182
ID4	-0.04347	-0.05987	-0.02535	0.958366	-0.10577	-0.0528	-0.04032	-0.09919	-0.00316	-0.04468	-0.06807	-0.05746	-0.0491	-0.0297	-0.07252	-0.03923	-0.01946	-0.02074	-0.03641	-0.09108
ID3	-0.07468	-0.02417	0.933578	-0.02535	-0.04241	-0.0831	-0.07476	-0.0629	-0.05797	-0.04924	-0.02877	-0.05716	-0.0907	-0.04558	-0.05198	-0.03182	-0.04533	-0.03638	-0.03265	-0.01861
ID2		0.999107	-0.02417	-0.05987	-0.0615	-0.054	-0.06972	-0.0388	-0.01471	-0.055	-0.0717	-0.04805	-0.08701	-0.0283	-0.04932	-0.02896	-0.04279	-0.07973	-0.07387	-0.03686
101	0.990677 -0.07475	-0.07475	-0.07468	-0.04347	-0.07634	-0.04866	-0.07975	-0.05198	-0.04992	0.002185	-0.03943	-0.09083	ID13 -0.02087	ID14 -0.01028	ID15 -0.07754	-0.03706	ID17 -0.0711	ID18 -0.05719	ID19 -0.04331	ID20 -0.04571
	10	ID2	ID3	Б	- 9OI	- 9QI	ID7 -	ID8	- 60I	ID10	1D11	ID12 -	ID13 .	ID14 .	ID15 .	- D16 -	ID17 .	ID18 .	ID19 .	ID20 .

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Table 4. Pearson correlation coefficients among results from Numericware i (Table 1), SPAGeDi (Table 2), and TASSEL (Table 3) for the same dataset.

	NUMERICWARE I	SPAGeDi	TASSEL
Numericware i	1	0.0505	0.9972
SPAGeDi	0.0505	1	0.0587
TASSEL	0.9972	0.0587	1

single CPU is supported. Numericware i is freely available for Windows and Linux under CC-BY 4.0 license and can be downloaded from https://figshare.com/s/f100f33a8857131eb2db.

Author Contributions

BK built software. BK and WDB analyzed, discussed, and wrote.

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