Use and limitations of various metrics to assess the quality of extreme sparse datasets in geotechnics

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January 5, 2023


FUTURISM
"Of course, there's no way to prove we're living in a simulation."
LK+LM

Source:[9]

Contents

Chapter 1

Data

1.1 Data preparation Classifiaction

The data for training the LM are chosen from the homepage of the "TC304 Engineering Practice of Risk Assessment & Management" of the International Society of Soil Mechanics and Geotechnical Engineering (ISSMGE). For classification 7 data sets are used. The data set C#1 [11] contains coarse grained soils, clays from Finnland, from 176 studies. The input and the classes for the LM are described in the Listing 1.1. All classes with less than 20 samples are removed from the data set. So 6 classes are given, as described below.

```
X = data[["Void ratio", "Water content (%)", "Unit weight (kN/m3)", "
    Effective in-situ stress (kPa)", "Pre-consolidation pressure (kPa)", "
    OCR", "Compression index", "Swelling index"]]
y = data['Soil typea'].values

Soil typea
Sa             241
liSa           158
laSa            63
Sa/Si           45
Sa/Lj           29
ljSa            21
```

Listing 1.1: Finish Clays; data set C#1

Data set C#2 [8] describes the compressive strength, tensile strength and friction properties for pyroclasts, andesits, basalts and dacite. Listing 1.2 shows the input data X and the classes y.

```
X = data[['porosity','UCS (MPa)', 'Youngs modulus (GPa)']]
y = data['rock_type_cat'].values
```

Listing 1.2: Volcanic Rocks; data set C#2

The C#3 data set [5] contains deformation modulus, elastic modulus, dynamic modulus, rock quality designation, rock mass rating, Q-system, geological strength index of a rock mass as well as intact-rock Young's modulus and intact-rock uniaxial compressive strength for 5876 rock mass cases. Listing 1.3 shows the input data X and the classes y. The classes are more or less balanced, beside the mudstone.

```
X = data[['Sigma ci (MPa) (intact rock)', 'RQD']]
y = data['Rock Type'].values

Rock Type
```

```
mudstone         104
gneiss            66
sandstone         62
andesite          35
basalt            31
siltstone         31
Serpentinite      30
limestone         29
Syenite           27
granite           27
```

Listing 1.3: Rock Masses of different kind of rocks; data set C#3

Data set C#4 [2] contains of 27.5% igneous rock, 59.4% sedimentary rocks and 13.1% metamorphic rock. Unit weight (kN/m^3), Dry unit weight (kN/m^3), water content (%), Porosity (%), Effective Porosity (%), Schmidt hammer hardness (RL), Shore scleroscope hardness(Sh), Is50 (MPa), P-wave velocity(km/s), σ_t Brazilian(MPa), UCS(MPa), Young's modulus E (GPa). Listing 1.5 shows the input data X and the classes y. The classes are more or less balanced, beside the limestone.

```
X = data[['Dry unit weight (kN/m^3)', 'P-wave velocity(km/s)', 'UCS(MPa)']]
y = data['Rock Type'].values

Rock Type
Limestone     75
Granite       55
Serpentine    52
Peridotite    35
```

Listing 1.4: Mixed Stone; data set C#4

[13] describes data set C#5 and contains shear wave velocity and the blow count (N) from the SPT. Listing 1.5 shows the input data X and the classes y. The classes are large enough so data imbalance is not so important, beside Silty soils.

```
X = data[["N", "Vs (m/s)"]]
y = data['Soil type'].values

Soiltype
Sandy soils              849
Clayey soils             441
Sandy silt/silty sand    260
Silty soils              229
Soft to stiff soil       180
Silty soils               35
```

Listing 1.5: N-Vs correlation; data set C#5

The data set C#6 is downloaded from the homepage of the TU Graz, (Source: [1]). It is a data set from the Geotechnik Premstaller GmbH from hundrets of cone penetration tests. Listing 1.6 shows the input data X and the classes y. The data are highly imbalanced.

```
X = data[['Depth (m)','qc (MPa)','fs (kPa)','Vs (m/s)']]
y = data["Oberhollenzer_classes"].values

Oberhollenzer_classes
7.0                      616
6.0                      476
1.0                      337
5.0                      304
```

```
0.0                          92
4.0                          54
2.0                          47
3.0                          24
```

Listing 1.6: CPT Getoechnik Premstaller; data set C#6

The data set C#7 [7] describe the properties of saturated hydraulic conductivity and Atterberg Classification for fine grained soils. Listing 1.7 shows the input data X and the classes y. The data set is highly imbalanced.

```
X = data[["void ratio", "k (m/s)", "wL", "wP", "IP", "Gs"]]
y = data['Atterberg classification'].values

Atterberg classification
CH                           366
CL                           230
MH                           184
ML                            59
```

Listing 1.7: Fine grained soils (clay); data set C#7

1.2 Data preparation Regression

Again all data for training the LM are chosen from the homepage of the "TC304 Engineering Practice of Risk Assessment & Management" of the International Society of Soil Mechanics and Geotechnical Engineering (ISSMGE). For regression 9 data sets are available. Scatter plots are used to check which input data X correlate with the output y. Figure 1.1 shows such a scatterplot. Here the correlation is shown between vertical preconsolidation pressure and undrained shear strength, from data set R#1 which is described later.

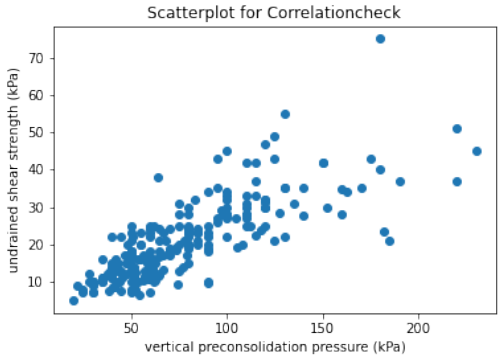

Figure 1.1: An example for checking if an input feature X shows correlation with predicted output y

Data set R#1 [6] describes the correlation of undrained finish clays. Field and laboratory measurements from 24 test sites are given. The input features X are effective vertical stress (s'v), vertical preconsolidation pressure (s'p), natural water content (w), liquid limit (LL), plastic limit (PL) and sensitivity (St=s_u/s_u^{re}). The predicted value is s_u from field vane test (s_u^{FV}). Listing 1.8 shows X and y.

```
X = data[["LL(%)", "PL(%)", "w(%)", "s'v (kPa)", "s'p (kPa)", "St"]]
y = data["su(test) (kPa)"]
```

Listing 1.8: Correlation for undrained finish clays; data set R#1

R#2 [1] is the same data set as C#6 are equal. The difference is that the shear wave velocity is now the value target instead of an input variable. Listing 1.9 shows the code.

```
X = data[['Depth (m)','qc (MPa)','fs (kPa)']]
y = data['Vs (m/s)']
```

Listing 1.9: CPT Getoechnik Premstaller; data set C#6

R#3 [2] is the same data set as C#4. Listing 1.10 shows the input feature X and the predicted output y for the given data set.

```
X = data[["Porosity (%)","Schmidt hammer hardness (RL)","Is50 (MPa)","P-
    wave velocity(km/s)"]]
y = data['UCS(MPa)']
```

Listing 1.10: Mixed Stone; data set R#3

R#4 [4] normalized undrained shear strength ($su/\sigma_v^{'}$, where $\sigma_v^{'}$ is the vertical effective stress), overconsolidation ratio ($OCR = \sigma_p^{'}/\sigma_v^{'}$, where $\sigma_p^{'}$ is the preconsolidation stress), normalized cone tip resistance $(q_t - \sigma_v)/\sigma_v$ (where σ_v is the vertical total stress), normalized effective cone tip resistance $(q_t - u_2)/\sigma_v^{'}$, normalized excess pore pressure $(u2 - u0)/\sigma_v^{'}$ (where u_0 is the static pore pressure), and pore pressure ratio $B_q = (u_2 - u_0)/(q_t - \sigma_v)$. Listing 1.11 shows the input feature X and the predicted output for the given data set.

```
X = data[["su/σ'v", "OCR", "(qt - σv)/σ'v", "(qt  -u2)/σ'v", "(u2 - u0)/σ'v
    ", "Bq"]]
y = data["σ'v(kPa)"]
```

Listing 1.11: Mixed Stone; data set R#4

R#5 [10] contains data from 124 test sites in the Jiangsu province. The data set is measured by piezocone testing devices and contains of resilient modulus (Mr) values at the in-situ stress condition, cone tip resistance (qc), sleeve frictional resistance (fs), moisture (w) and dry density (γd). Listing 1.12 shows the input feature X and the predicted output y for the given data set.

```
X = data[['qc (MPa)', 'fs (MPa)', 'w (%)', 'γd (kN/m\xa03)']]
y = data["Mr (MPa)"]
```

Listing 1.12: Jiangsu province piezocone testing indices; data set R#5

R#6 [14] is a combination for 11 clay parameters covering 50 sites in Shanghai with 4051 data points, covering an area of 145 km^2. Eleven parameters are given: LL(%), PI, LI, e, K0, $\sigma_v^{'}$ (kPa), Su(UCST) (kPa), St(UCST), Su(VST) (kPa), St(VST), ps (MPa), $\sigma_v^{'}$ (Pa), Su(UCST)/$\sigma_v^{'}$, Su(VST)/$\sigma_v^{'}$, ps/$\sigma_v^{'}$. Listing 1.13 shows the input feature X and the predicted output y for the given data set.

```
X = data[['PI',"ps/σ'v","e","ps\n(MPa)"]]
y = data['LL(%)']
```

Listing 1.13: Shangha clays; data set R#6

R#7 [8] is the same data set as C#2. Listing 1.13 shows the input feature X and the predicted output y for the given data set.

```
X = data[['porosity','Youngs modulus (GPa)']]
y = data['UCS (MPa)']
```

Listing 1.14: Volcanic rocks; data set R#7

R#8 [3] contains data of coarse grained soils from 176 studies. The data set provide the parameters Fines(%), D50(mm), Cu, Dr(%), OCR $\sigma_v^{'}$(kPa), (N1)60, qt1, $\phi_{cv}()$ and $\phi_p()$. Listing 1.15 shows the input feature X and the predicted output y for the given data set.

```
X = data[["σv'(kPa)", "(N1)60", "qt1", 'Dr(%)']]
y = data['φp(○)']
```

Listing 1.15: Data set of coarse-grained soils; data set R#8

Data set R#9 [12] describes the correlation of soft finish clays. The data are based on the oedometer test. The input features X are water content,fineness number, undrained shear strength, pre-consolidation pressure, OCR, compression index and the swelling index. The predictor output is the void ratio. Listing 1.16 shows X and y.

```
X = data[['Water content (%)','Fineness number','Undrained shear stregth (
    fall cone) (kPa)', 'Pre-consolidation pressure (kPa)', 'OCR', '
    Compression index', 'Swelling index']]
y = data['Void ratio']
```

Listing 1.16: Data set of soft finish clays; data set R#9

Chapter 2

Result of the Loop

2.1 KS p-value

The following tables show the results of the 300 time training and performance measuring loop. The red cells show p-values < 0.05. The histrograms of the p-value < 0.05 algorithm-metrics distributions are plotted in the appendex.

Table 2.1 shows the p-values and chosen distributions of data set C#1. The ABC algorithm includes 4 distributions which are not reaching the p-value > 0.05 criteria. The hamming-loss and the zero-one-loss show for multi class predictor the same value. The Figure A.1 shows, that the hamming-loss and the precision are not log-laplace probability distributed. The log-loss plot shows the form of the chosen probability distribution, so the reason for no p-value output is a problem of fitting the distribution by the fitter package.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	0.57997	0.708073	0.993205	0.521625	0.791577	0.485802	0.951955	0.864268	0.52163	6.418108	exponnorm
knn	0.206091	0.919687	0.825962	0.206091	0.875304	0.921724	0.95284	0.872892	0.206091	5.986682	beta
svm	0.197008	0.857426	0.441192	0.597949	0.790008	0.753941	0.224489	0.989998	0.597949	5.449961	loggamma
dtc	0.453821	0.964398	0.968934	0.432827	0.94412	0.432597	0.929211	0.975831	0.432827	6.534565	exponnorm
gnb	0.145032	0.981891	0.995995	0.241883	0.759843	0.992467	0.944814	0.903024	0.241883	6.206832	burr12
lda	0.126985	0.829815	0.859142	0.126995	0.644694	0.836764	0.575266	0.61704	0.126995	4.743695	skewnorm
abc	0.071947	0.350253	0.060927	0.01334	0.844859	NaN	0.000557	0.190476	0.01334	1.545699	loglaplace
qda	0.324811	0.954001	0.868535	0.300234	0.954092	0.542471	0.900821	0.981646	0.300234	6.126844	exponnorm
mlp	0.251229	0.989814	0.968402	0.251219	0.995221	0.944352	0.901505	0.999394	0.251219	6.552357	skewnorm
lrc	0.140093	0.851027	0.755936	0.140093	0.863189	0.927086	0.5666	0.532109	0.140093	4.916225	logistic

Table 2.1: The p-values and the chosen distribution of C#1. In red p-values < 0.05.

For binary classifier, accuracy, hamming-loss and zero-one-loss are equal. Table 2.2 shows the negative p-value criteria for data set C#2. The ABC-accuracy plot in Figure A.2 shows, that the metric distribution follows no probability distribution. Also the MLP-precision plot shows no normal probability distribution.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	*sum_rows*	*distribution*
rfc	0.236779	0.730176	0.729439	0.13814	0.698578	0.297998	0.845743	0.824085	0.13814	4.639078	weibull_max
knn	0.422616	0.951897	0.980593	0.422574	0.970246	0.690451	0.940962	0.982751	0.422574	6.784663	skewnorm
svm	0.435601	0.478548	0.882289	0.435603	0.601451	0.605145	0.441808	0.886166	0.435603	5.202213	t
dtc	0.492841	0.999108	0.850058	0.492833	0.982112	0.492833	0.977461	0.976476	0.492833	6.756556	beta
gnb	0.591067	0.612275	0.654787	0.557025	0.975491	0.920906	0.440689	0.982824	0.557039	6.292104	exponnorm
lda	0.458651	0.860686	0.393745	0.458651	0.728546	0.759467	0.154682	0.802207	0.458651	5.075287	norm
abc	3.09E-05	0.977633	0.924368	3.09E-05	0.691061	0.449267	0.917066	0.956739	3.09E-05	4.916227	logistic
qda	0.2583	0.953967	0.913645	0.2583	0.852891	0.350437	0.847234	0.715459	0.2583	5.408533	logistic
mlp	0.178113	0.975074	0.925489	0.178113	0.695265	0.832442	3.6E-08	0.674408	0.178113	4.637016	norm
lrc	0.291439	0.827785	0.541725	0.291439	0.880093	0.502971	0.39004	0.662296	0.291439	4.679228	logistic

Table 2.2: The p-values and the chosen distribution of C#2.

Table 2.3 shows the negative p-value criteria for data set C#3. The ABC-accuracy, ABC-hamming-loss, LDA-precision, LRC-fb-score and LRC-precision plot in Figure A.3 shows, that the algorithm-metric distributions follow no probability distribution. ABC-log-loss show similarities with the rayleigh probability distribution. It is possible that a misfit happened.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	0.194901	0.916991	0.988797	0.208516	0.916821	0.910623	0.45602	0.987497	0.208516	5.788683	burr12
knn	0.123633	0.993243	0.972432	0.113887	0.973963	0.830492	0.818732	0.970476	0.113887	5.910745	exponnorm
svm	0.125382	0.601701	0.920597	0.211812	0.763477	0.722158	0.792089	0.873719	0.211812	5.222746	f
dtc	0.363236	0.878977	0.966899	0.363397	0.535303	0.383744	0.969555	0.803685	0.363397	5.628191	gennorm
gnb	0.270851	0.998373	0.853447	0.299755	0.858112	0.062921	0.073033	0.97712	0.299755	4.693365	loggamma
lda	0.121954	0.992598	0.873546	0.075957	0.999672	0.957551	0.000622	0.886945	0.075957	4.984802	genlogistic
abc	0.02311	0.891657	0.981791	0.005064	0.667961	5.63E-05	0.978897	0.245007	0.005064	3.798608	rayleigh
qda	0.304305	0.743175	0.986806	0.304305	0.934414	0.224697	0.695563	0.750941	0.304305	5.24851	norm
mlp	0.256924	0.699799	0.997811	0.256924	0.920281	0.141807	0.534722	0.472073	0.256924	4.537263	logistic
lrc	0.369639	0.088822	0.026905	0.369639	0.192909	0.49018	0.000993	0.461636	0.369639	2.370361	logistic

Table 2.3: The p-values and the chosen distribution of C#3.

Table 2.4 shows the negative p-value criteria for data set C#4. Figure A.4 shows, that the ABC algorithm have all a logistic probability distribution but at the values higher 0.7 the distribution shows an additional peak. The DTC algorithm show also loggamma probability distribution, but the sparse data density make it hard to fit the distribution in a correct way. MLP algorithm have at all no common probability distribution. The results are random. QDA and RFC algorithm are similar to the DTC algorithm, where the data are to sparse for good fitting. The SVM-precision has no common probability distribution.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	0.002529	0.648177	0.771426	0.001781	0.891558	0.962075	0.808853	0.991506	0.001781	5.079684	burr12
knn	0.142586	0.931733	0.977299	0.142585	0.936192	0.355545	0.855755	0.723203	0.142588	5.207486	beta
svm	0.135645	0.849677	0.680114	0.135649	0.974484	0.89688	0.031729	0.622203	0.135649	4.462029	beta
dtc	0.004504	0.993715	0.997599	6.62E-06	0.981581	6.62E-06	0.996613	0.958749	6.62E-06	4.932782	loggamma
gnb	0.036248	0.947712	0.945477	0.036247	0.913763	0.589508	0.8839	0.996421	0.036248	5.385524	beta
lda	0.001222	0.762966	0.890237	0.001222	0.825786	0.051845	0.576448	0.474589	0.001222	3.585536	logistic
abc	0.417552	0.000223	0.000269	0.417552	0.01232	0.222116	8.53E-08	0.009035	0.417552	1.496618	logistic
qda	0.000492	0.226978	0.749703	0.000492	0.366216	0.031947	0.808079	0.4829	0.000492	2.667299	logistic
mlp	5.64E-33	NaN	7.66E-30	NaN	3.45E-34	2.98E-06	2.65E-27	1.78E-34	1.12E-07	3.09E-06	wald
lrc	0.052169	0.531656	0.21872	0.052169	0.28168	0.560395	0.156404	0.389363	0.052169	2.294725	logistic

Table 2.4: The p-values and the chosen distribution of C#4.

Table 2.5 shows the negative p-value criteria for data set C#5. The SVM algorithm with negative p-value criteria are not beta distributed. In Figure A.5 one can see that the results of the loop show a probability distribution like beta. Only SVM-recall shows no common distribution. The MLP-algorithm histograms could be described by a logistic probability distribution, so the fitted p-value is real.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	0.377532	0.954199	0.999984	0.377515	0.965694	0.611735	0.995235	0.853191	0.377515	6.512601	johnsonsb
knn	0.447143	0.997558	0.963923	0.62921	0.98849	0.802221	0.670148	0.981237	0.62921	7.109142	norminvgauss
svm	0.916918	1.42E-10	1.29E-13	0.916916	3.11E-05	0.996092	2.01E-19	1.06E-85	0.916917	3.746874	beta
dtc	0.701162	0.680735	0.89384	0.701162	0.738372	0.701162	0.830248	0.88899	0.701162	6.836835	logistic
gnb	0.831493	0.691683	0.828167	0.831493	0.493957	0.784019	0.730611	0.336022	0.831493	6.358938	logistic
lda	0.662172	0.534186	0.896952	0.814236	0.65121	0.848153	0.099532	0.954187	0.814236	6.274865	exponnorm
abc	0.903965	0.86067	0.83413	0.903965	0.997664	0.950161	0.226359	0.864446	0.903965	7.445325	norm
qda	0.523842	0.970911	0.864815	0.523842	0.950088	0.361544	0.23151	0.620977	0.523842	5.57137	logistic
mlp	0.040994	8.49E-05	0.004062	0.040994	0.000206	0.761444	0.025492	8.51E-12	0.040994	0.914272	logistic
lrc	0.377226	0.605029	0.365018	0.377226	0.932405	0.961125	0.56947	0.419191	0.377226	4.983918	logistic

Table 2.5: The p-values and the chosen distribution of C#5.

Table 2.6 shows the negative p-value criteria for data set C#6. In Figure A.6, the ABC-log-loss shows a logistic probability distribution, but with a low standard deviation. The low p-value equates the real distribution. The KNN-precision is an example why the other precision distributions do not reaching the criteria. The histograms shows no common probability distribution.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	0.932356	0.965836	0.649814	0.932247	0.945016	0.99689	0.691279	0.851339	0.932247	7.897024	skewnorm
knn	0.669011	0.9133	0.824995	0.66901	0.929595	0.987217	0.002719	0.929639	0.66901	6.594497	gennorm
svm	0.562352	0.732459	0.815636	0.6509	0.855912	0.958847	0.001618	0.604047	0.6509	5.832671	gamma
dtc	0.639982	0.799687	0.983697	0.643317	0.915409	0.626159	0.905314	0.7604	0.64514	6.919105	skewnorm
gnb	0.916433	0.799318	0.980996	0.916432	0.723432	0.811044	0.871193	0.600609	0.916432	7.53589	beta
lda	0.887719	0.912305	0.930502	0.887719	0.981743	0.331163	0.99663	0.903868	0.887719	7.719366	norm
abc	0.911338	0.677632	0.965003	0.911338	0.977608	0.005919	0.796877	0.407187	0.911338	6.564241	logistic
qda	0.349784	0.963602	0.818277	0.349784	0.796336	0.688117	0.048	0.195086	0.349784	4.55877	logistic
mlp	0.570319	0.347745	0.170447	0.570319	0.285596	0.689153	0.615077	0.335033	0.570319	4.154009	logistic
lrc	0.616561	0.48336	0.826029	0.616561	0.55116	0.373035	0.909656	0.672655	0.616561	5.665578	norm

Table 2.6: The p-values and the chosen distribution of C#6.

Table 2.7 shows the negative p-value criteria for data set C#7. In Figure A.7 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution.

KS p-value	*acc*	*f1*	*fb*	*hamming*	*jaccard*	*log*	*prec*	*rec*	*zero*	**sum_rows**	**distribution**
rfc	1.17E-83	3.07E-86	1.17E-89	9.7E-107	1.15E-78	0.90029	1.43E-86	1.47E-80	1.3E-117	0.90029	invgamma
knn	6.89E-38	1.18E-42	7.05E-63	1.5E-101	NaN	0.994528	5.3E-43	NaN	NaN	0.994528	johnsonsb
svm	0.60386	0.615581	0.357817	0.603821	0.564494	0.537646	0.396105	0.973999	0.603821	5.257144	skewnorm
dtc	1.76E-53	3.25E-89	2.66E-52	NaN	5.98E-82	6.75E-07	4.9E-49	3.28E-49	3.71E-86	6.75E-07	t
gnb	0.250965	0.64485	0.805845	0.201457	0.852404	0.927562	0.981968	0.627977	0.201457	5.494484	gamma
lda	0.330626	0.751709	0.597549	0.330623	0.921534	0.975595	0.724707	0.867683	0.330623	5.830647	beta
abc	0.315205	0.968927	0.951374	0.298521	0.926438	0.675836	0.926438	NaN	0.298521	5.361261	genlogistic
qda	0.172221	0.830813	0.714404	0.172221	0.41384	0.960201	0.421158	0.3019	0.172221	4.158979	logistic
mlp	0.152663	0.183429	0.089014	0.152663	0.527191	0.501892	0.007632	0.019754	0.152663	1.786902	logistic
lrc	0.18407	0.689785	0.703798	0.18407	0.795343	0.03502	0.706292	0.575526	0.18407	4.057974	logistic

Table 2.7: The p-values and the chosen distribution of C#7.

Table 2.8 shows the negative p-value criteria for data set R#1. In Figure A.8 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. Only the MLP-r2 and the DTR-r2 could be described by inverse gamma and skewnorm probability distribution. So the low p-value fitted by the package is trust-able.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	4.76E-05	0.971675	0.880751	0.98036	0.968456	0.925566	4.726856	genlogistic
las	0.000143	0.858197	0.919099	0.918009	0.988635	0.761496	4.445578	burr12
svr	2.65E-11	0.996677	0.537335	0.870867	0.915548	0.791199	4.111627	skewnorm
rid	5E-05	0.971295	0.880437	0.980057	0.967278	0.925277	4.724394	genlogistic
enc	9.56E-05	0.763221	0.753573	0.966068	0.8915	0.962133	4.33659	genlogistic
mlp	0.553692	0.670775	0.533055	0.994147	0.605352	NaN	3.357021	invgamma
dtr	0.000256	0.727302	0.938244	0.947733	5.64E-15	3.65E-05	2.61357	skewnorm
rfr	6.25E-06	0.838852	NaN	0.845236	0.998861	0.376532	3.059487	skewnorm
knn	NaN	0.935514	0.290581	0.636907	0.128683	0.970824	2.96251	genlogistic

Table 2.8: The p-values and the chosen distribution of R#1.

Table 2.9 shows the negative p-value criteria for data set R#2. In Figure A.9 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. Only KNN-mer shows approximating a generalized normal distribution. The p-value is trust-able. DTR-mee is not fit-able because of sparse data set.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	9.76E-08	0.984139	0.939401	0.7998	0.325616	0.987885	4.036841	beta
las	8.92E-08	0.985705	0.94566	0.801113	0.314321	0.988358	4.035157	beta
svr	0	0.822944	0.826051	0.591481	0.771788	0.846788	3.859051	genlogistic
rid	9.76E-08	0.984249	0.939413	0.7998	0.322955	0.987884	4.034301	beta
enc	7.5E-06	0.963628	0.825676	0.713737	0.820744	0.843571	4.167364	burr12
mlp	0.001769	0.887085	0.995981	0.873132	0.947631	0.694528	4.400127	beta
dtr	0.086733	0.602758	0.46451	0.610289	0.002474	0.407751	2.174514	genlogistic
rfr	0.071777	0.993488	0.969736	0.92921	0.91717	0.860164	4.741546	johnsonsb
knn	0.001286	0.918747	0.883666	0.408028	0.302974	0.965482	3.480183	gennorm

Table 2.9: The p-values and the chosen distribution of R#2.

Table 2.10 shows the negative p-value criteria for data set R#3. In Figure A.10 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. Only the R2 algorithm metrics could be described by right- and left-aligned probability distributions. The p-values for the negative p-value criteria histograms of R2 are trust-able.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	0.394158	0.956029	0.821213	0.993026	0.726032	7.11E-07	3.890457	burr12
las	0.057147	0.983387	0.853169	0.97837	0.947818	0.033166	3.853057	johnsonsu
svr	4.83E-18	0.753468	0.034745	0.83861	0.656818	0.496831	2.780472	nakagami
rid	0.279148	0.925846	0.775652	0.975561	0.830065	4.37E-09	3.786273	burr12
enc	0.003101	0.690724	0.859179	0.83876	0.984263	9.73E-06	3.376036	mielke
mlp	0.059275	0.577093	0.399032	0.927236	0.345946	0.085416	2.393998	mielke
dtr	0.000155	0.957742	0.730232	0.440507	0.337108	NaN	2.465744	mielke
rfr	3.55E-05	0.653488	0.024797	0.276842	0.907684	0.006935	1.869782	burr
knn	NaN	0.871713	0.429561	0.993647	0.536536	0.727869	3.559326	mielke

Table 2.10: The p-values and the chosen distribution of R#3.

Table 2.11 shows the negative p-value criteria for data set R#4. In Figure A.11 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. All histograms show random distributed values with no probability.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	1.11E-07	0.826488	0.806131	0.986137	0.958952	0.970107	4.547815	skewnorm
las	3.74E-07	0.813352	0.832004	0.8829	0.718076	0.971776	4.218109	genlogistic
svr	2.06E-18	0.899939	0.906075	0.896499	0.945556	0.740812	4.388881	beta
rid	7.63E-08	0.926105	0.797583	0.851331	0.914994	0.980306	4.470319	skewnorm
enc	5.6E-08	0.754745	0.818384	0.968244	0.832933	0.781403	4.15571	genlogistic
mlp	4.45E-07	0.932181	0.917257	0.909	0.868165	0.787663	4.414267	skewnorm
dtr	5.41E-09	0.947645	0.997151	0.86262	0.263178	0.965576	4.036169	genlogistic
rfr	3.67E-06	0.918334	0.662312	0.834865	0.864208	0.98788	4.267602	skewnorm
knn	7.41E-06	0.487407	0.537748	0.715585	0.850577	0.781657	3.372981	exponnorm

Table 2.11: The p-values and the chosen distribution of R#4.

Table 2.12 shows the negative p-value criteria for data set R#5. In Figure A.12 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. The LIR-msle, RID-msle and ENC-msle histograms show left-aligned distributions, so the p-value is trust-able.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	3.54E-08	0.965254	0.933981	2.74E-10	0.889558	0.900499	3.689292	johnsonsu
las	0.007924	0.924878	0.856319	0.406695	0.300095	0.992931	3.488842	johnsonsu
svr	0.003516	0.731014	0.864272	0.91282	0.476257	0.977307	3.965186	genlogistic
rid	0.000132	0.784526	0.445139	0.000113	0.990646	0.899074	3.11963	weibull_min
enc	0.78853	0.481528	0.870103	0.00512	0.427768	0.972062	3.545111	genlogistic
mlp	0.012646	0.834455	0.823287	0.997767	0.958667	0.897669	4.52449	burr12
dtr	0.386687	0.585021	0.853321	0.950138	0.360246	0.998126	4.133539	genlogistic
rfr	0.943795	0.795287	0.240578	NaN	0.934502	0.949572	3.863733	genlogistic
knn	0.021385	0.821087	0.942787	0.971591	0.663269	0.900084	4.320203	genlogistic

Table 2.12: The p-values and the chosen distribution of R#5.

Table 2.13 shows the negative p-value criteria for data set R#6. In Figure A.13 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution. The KNN-mee histogram shows a skewnorm distribution, but the data are too sparse.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	4.36E-09	0.876945	0.759472	0.725052	0.985555	0.913907	4.260931	burr12
las	0	0.817949	0.960104	0.705183	0.827122	0.88952	4.199878	powernorm
svr	1.09E-30	0.91857	0.663466	0.945965	0.763329	0.714485	4.005815	beta
rid	6.78E-77	0.808636	0.597068	0.965368	0.832605	0.94769	4.151366	beta
enc	4.51E-89	0.781198	0.697022	0.963537	0.999979	0.989779	4.431515	beta
mlp	NaN	0.997201	0.995103	0.987218	0.834535	0.845176	4.659233	beta
dtr	NaN	0.993853	0.610842	0.854023	1.49E-12	0.790652	3.249371	beta
rfr	0.00017	0.624637	0.66436	0.976823	0.561325	0.932531	3.759846	skewnorm
knn	0.000314	0.894577	0.846353	0.973941	0.004579	0.99998	3.719744	skewnorm

Table 2.13: The p-values and the chosen distribution of R#6.

Table 2.14 shows the negative p-value criteria for data set R#7. In Figure A.14 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	0.036072	0.876563	0.512755	0.815288	0.957729	0.935203	4.133611	loggamma
las	0.001124	0.944134	0.771946	0.818814	0.999654	0.967558	4.50323	beta
svr	5.98E-05	0.963966	0.882417	0.990818	0.848692	0.989293	4.675245	beta
rid	0.001107	0.849709	0.638703	0.997704	0.591852	0.96357	4.042645	burr12
enc	0.000955	0.897137	0.752135	0.917028	0.9898	0.867698	4.424753	beta
mlp	0.000116	0.934655	0.561697	0.592995	0.856243	0.957965	3.903671	burr12
dtr	1.41E-07	0.94517	0.928546	0.971239	0.723243	0.997192	4.565391	burr12
rfr	0.49824	0.959156	0.9473	0.901441	0.805303	0.556728	4.668168	burr12
knn	0.032457	0.558924	0.586566	0.726943	0.803951	0.461127	3.169968	skewnorm

Table 2.14: The p-values and the chosen distribution of R#7.

Table 2.15 shows the negative p-value criteria for data set R#8. The histograms are not plotted in the annex, they are stored on the Github server stated before. All algorithm-metric results with a negative p-value criteria show no common probability distribution.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	0.000129	6.11E-06	0.004506	0.002667	6.11E-06	1.99E-63	0.007314	invweibull
las	2.13E-29	1.94E-05	6.77E-28	5.08E-23	1.94E-05	3.06E-23	3.89E-05	beta
svr	2.05E-07	7.26E-10	1.32E-38	1.11E-06	7.26E-10	1.47E-43	1.32E-06	skewcauchy
rid	3.91E-06	NaN	0.000346	0.000773	NaN	NaN	0.001123	geninvgauss
enc	8.3E-11	1.94E-06	2.02E-15	3.52E-13	1.94E-06	3.59E-43	3.88E-06	levy
mlp	1.41E-06	0.026076	0.022742	9.17E-05	0.026076	9.96E-10	0.074986	skewcauchy
dtr	9.71E-24	2.16E-26	5.84E-27	1.31E-29	2.16E-26	NaN	9.76E-24	genlogistic
rfr	NaN	NaN	NaN	NaN	NaN	NaN	0	johnsonsb
knn	8.76E-06	5.89E-07	1.9E-08	1.02E-07	NaN	7.74E-08	9.55E-06	skewcauchy

Table 2.15: The p-values and the chosen distribution of R#8.

Table 2.16 shows the negative p-value criteria for data set R#9. In Figure A.15 one can see, that all algorithm-metric results with a negative p-value criteria show no common probability distribution.

KS p-value	mer	mae	mse	msle	mee	r2	sum_rows	distribution
lir	4.66E-08	0.780292	0.324148	0.018329	0.736459	0.004303	1.863531	skewnorm
las	2.64E-33	0.771123	7.18E-05	0.003994	0.876193	1.61E-05	1.651398	beta
svr	0.008118	0.898792	0.296604	0.94329	0.959033	0.163533	3.26937	beta
rid	2.07E-08	0.872863	0.160968	0.00315	0.987992	3E-08	2.024974	nakagami
enc	4.72E-14	0.860915	0.002059	3.58E-07	0.873281	9.45E-14	1.736256	beta
mlp	0.003985	0.982034	0.946104	0.976065	0.83765	0.792432	4.538269	skewnorm
dtr	7.72E-12	0.997244	0.241646	0.467813	0.155191	2.41E-06	1.861896	exponnorm
rfr	2.93E-07	0.878832	0.014669	6.71E-05	0.916533	6.21E-05	1.810163	exponnorm
knn	1.1E-05	0.845874	0.320779	0.832242	0.633973	0.694695	3.327572	gamma

Table 2.16: The p-values and the chosen distribution of R#9.

2.2 Normalized standard deviation

With the output parameters of the fitted distributions in the section before, the normalized standard deviation is calculated. The negative criteria for the normalized standard deviation $s_n > 0.5$ enable only a small spreading of the distributions. The cells in red show the negative criteria of the data set. The green cell border implements the algorithm-metric s_n with a negative p-value criteria.

Table 2.17 is the normalized standard deviation of the data C#1. The ABC-log, with a NaN p-value, has also no standard deviation. The p-value = 0.000557 of the ABC-prec and the p-value = 0.01334 of the ABC-hamming/ABC-zero implies that s_n is not trust-able for the interpretation.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	0.055976	0.10953	0.116305	0.072016	0.123426	0.204599	0.140837	0.105894	0.072016
knn	0.064754	0.104066	0.112711	0.072042	0.118419	0.162536	0.141139	0.099908	0.072042
svm	0.074246	0.124953	0.13978	0.075	0.133199	0.042221	0.16414	0.108536	0.075
dtc	0.080118	0.12204	0.127007	0.074588	0.140176	0.074588	0.138894	0.126498	0.074588
gnb	0.074783	0.109771	0.123191	0.057493	0.13266	0.150845	0.134011	0.090124	0.057493
lda	0.06228	0.103226	0.109536	0.074889	0.11643	0.091086	0.130282	0.100176	0.074889
abc	0.117822	0.179298	0.287938	*0.314322*	0.164237	*NaN*	*0.735793*	0.124503	*0.314322*
qda	0.065	0.09691	0.100295	0.06837	0.110653	0.195408	0.107321	0.105011	0.06837
mlp	0.06247	0.123747	0.133552	0.070008	0.132448	0.078835	0.162274	0.115811	0.070008
lrc	0.069131	0.121666	0.130496	0.077272	0.133416	0.051804	0.158396	0.109219	0.077272

Table 2.17: The normalized standard deviation of C#1.

Table 2.18 is the normalized standard deviation of the data C#2. The s_n is for all algorithm-metric distribution < 0.5 and only four of them are not reaching the p-value criteria. The s_n for hamming and zero are for multi class predictor equal. The results are highly use-able for the interpretation of the stability of the metrics, because most of the p-values are > 0.05.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	0.037372	0.061087	0.061865	0.101192	0.077494	0.220847	0.067984	0.064237	0.101192
knn	0.05208	0.08086	0.084388	0.069246	0.093537	0.16917	0.09519	0.07977	0.069246
svm	0.056945	0.096607	0.11343	0.079815	0.110239	0.040385	0.161883	0.078224	0.079815
dtc	0.047081	0.063417	0.063693	0.094231	0.082644	0.094231	0.065117	0.06753	0.094231
gnb	0.05533	0.066101	0.073665	0.070761	0.081158	0.094991	0.103471	0.061735	0.070761
lda	0.045803	0.068315	0.081285	0.089981	0.08331	0.072523	0.065786	0.049152	0.089981
abc	*0.188307*	0.12342	0.125284	*0.210155*	0.1569	0.035576	0.134485	0.111331	*0.210155*
qda	0.051578	0.066948	0.067065	0.077089	0.082949	0.1176	0.068063	0.064318	0.077089
mlp	0.088235	0.109948	0.152169	0.118051	0.126348	0.063452	*0.349067*	0.082804	0.118051
lrc	0.056276	0.064876	0.080905	0.074829	0.086602	0.039288	0.112713	0.055016	0.074829

Table 2.18: The normalized standard deviation of C#2.

Table 2.19 is the normalized standard deviation of the data C#3. Like for data set C#2, also these results are highly use-able for the selection of the stability of the metrics. Here the criteria of the p-value will be the basic for the recommendation of the reliability of the data.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	0.080839	0.100849	0.10362	0.065771	0.111902	0.178516	0.113225	0.099041	0.065771
knn	0.087272	0.109503	0.118345	0.073107	0.127539	0.117241	0.138577	0.103337	0.073107
svm	0.085332	0.107167	0.134436	0.060934	0.123381	0.036048	0.19736	0.083679	0.060934
dtc	0.090684	0.109857	0.112777	0.063002	0.123935	0.062954	0.118657	0.110038	0.063002
gnb	0.093449	0.130789	0.154639	0.064259	0.158246	0.091249	0.203245	0.100326	0.064259
lda	0.103159	0.178051	0.240048	0.06063	0.197042	0.048342	*0.333728*	0.109462	0.06063
abc	*0.363928*	0.333977	0.350282	*0.09202*	0.36453	*0.08663*	0.377786	0.329436	*0.09202*
qda	0.089825	0.122286	0.148601	0.062156	0.141869	0.096097	0.206538	0.09404	0.062156
mlp	0.096237	0.115598	0.144683	0.06203	0.127894	0.089875	0.213207	0.095207	0.06203
lrc	0.135557	0.328622	*0.383782*	0.066846	0.369399	0.039886	*0.429883*	0.190425	0.066846

Table 2.19: The normalized standard deviation of C#3.

Table 2.20 is the normalized standard deviation of the data C#4. The s_n over-all MLP-metrics and the QDA-log reach the negative criteria. For the MLP the negative p-value criteria describes

the s_n value. The QDA-log distribution is strongly scattered. 1/3 of the p-values do not reach the >0.05 criteria, so the data set is less valuable for the recommendation of metric stability.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	*0.036651*	0.032115	0.032209	*0.417349*	0.054205	0.229512	0.031785	0.030369	*0.417349*
knn	0.096997	0.102952	0.088314	0.138879	0.14823	0.414182	0.071958	0.106092	0.138879
svm	0.15317	0.227565	0.223949	0.117307	0.256029	0.050777	*0.19998*	0.149981	0.117307
dtc	*0.041884*	0.036811	0.035813	*0.381243*	0.060272	*0.381243*	0.035009	0.037388	*0.381243*
gnb	*0.042364*	0.037761	0.03793	*0.256433*	0.060245	0.282413	0.037583	0.036091	*0.256433*
lda	*0.051842*	0.042922	0.042385	*0.209865*	0.059589	0.273401	0.043013	0.044988	*0.209865*
abc	0.106415	*0.111152*	*0.134729*	0.21467	*0.117123*	0.175279	*0.183421*	*0.091928*	0.21467
qda	*0.03726*	0.03237	0.032745	0.38121	0.054808	0.514061	0.032016	0.029008	*0.38121*
mlp	*0.806459*	*0.901193*	*0.930722*	*0.965673*	*0.991827*	*0.857828*	*0.951307*	*0.762152*	*0.965673*
lrc	0.11267	0.129708	0.13157	0.17369	0.146542	0.077147	0.12596	0.109143	0.17369

Table 2.20: The normalized standard deviation of C#4.

Table 2.21 is the normalized standard deviation of the data C#5. The s_n ABC metrics tend to higher values. 13 out of 90 p-values reach the negative criteria. So the data set is good for the recommendation of the algorithm-metric context based on the normalized standard deviation.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	0.039155	0.069289	0.074956	0.032515	0.073722	0.110448	0.087536	0.066629	0.032515
knn	0.040432	0.071447	0.096113	0.027398	0.072097	0.066442	0.154163	0.055547	0.027398
svm	0.037385	*0.054081*	*0.080356*	0.027761	*0.059807*	0.019613	*0.10554*	*0.010806*	0.027761
dtc	0.04816	0.076575	0.078858	0.032111	0.083383	0.032111	0.083213	0.080644	0.032111
gnb	0.042479	0.102002	0.10559	0.033341	0.106115	0.02341	0.128028	0.064956	0.033341
lda	0.039644	0.057403	0.07254	0.030289	0.065161	0.019049	0.145449	0.042601	0.030289
abc	0.149714	0.112499	0.11931	0.072981	0.117764	0.006801	0.159092	0.106583	0.072981
qda	0.039119	0.065274	0.086779	0.032643	0.067825	0.027893	0.129705	0.048384	0.032643
mlp	*0.072721*	*0.263725*	*0.333267*	*0.051931*	*0.223118*	0.027682	*0.435756*	*0.13146*	*0.051931*
lrc	0.040005	0.087923	0.147124	0.028926	0.076862	0.017	0.229965	0.025449	0.028926

Table 2.21: The normalized standard deviation of C#5.

Table 2.22 is the normalized standard deviation of the data C#6. ABC-log, RFC-, KNN- and QDA-prec are based on the negative p-value criteria. At all the data set is highly use-able for the recommendation of the algorithm-metric relation.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	0.021165	0.057287	0.065791	0.032797	0.058493	0.083851	*0.095477*	0.052003	0.032797
knn	0.024718	0.058527	0.078721	0.022746	0.056611	0.051349	*0.147339*	0.048991	0.022746
svm	0.023702	0.076988	0.108432	0.023664	0.070955	0.018763	0.31113	0.041884	0.023664
dtc	0.028666	0.069416	0.069631	0.029806	0.07008	0.029818	0.073675	0.077511	0.029797
gnb	0.057941	0.083102	0.100038	0.031419	0.084085	0.044569	0.160604	0.094522	0.031419
lda	0.023582	0.048631	0.052623	0.024271	0.055089	0.031046	0.060183	0.046806	0.024271
abc	0.252613	0.243364	0.22885	0.086344	0.255923	*0.034944*	0.202352	0.207907	0.086344
qda	0.045088	0.08158	0.090782	0.026257	0.083374	0.049428	*0.149743*	0.080341	0.026257
mlp	0.029832	0.217903	0.178538	0.030906	0.220549	0.040102	0.174125	0.213969	0.030906
lrc	0.023166	0.053614	0.06028	0.024705	0.054531	0.017292	0.080019	0.046307	0.033255

Table 2.22: The normalized standard deviation of C#6.

Table 2.23 is the normalized standard deviation of the data C#7. Around 1/3 of the p-values reach negative criteria. All negative s_n criteria are based on negative p-value criteria.The results show that the recommendation based on this data set is driven by p-value and s_n.

standard deviation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	*0.00233*	*0.001959*	*0.001601*	*-inf*	*0.00408*	-0.37274	*0.001415*	*0.002488*	*-inf*
knn	*0.037847*	*0.05977*	*0.025488*	*1.406257*	*0.064553*	0.525843	*0.04242*	*0.055448*	*1.406253*
svm	0.033379	0.033038	0.035133	0.233927	0.058878	0.140794	0.035754	0.026769	0.233927
dtc	*3.13E-06*	*NaN*	*0.005866*	*6.548546*	*0.007184*	*0.004462*	*NaN*	*NaN*	*6.548546*
gnb	0.053121	0.051256	0.05248	0.174142	0.078663	0.250068	0.049966	0.039539	0.174142
lda	0.03968	0.038069	0.037086	0.115281	0.061026	0.064251	0.037447	0.041968	0.115281
abc	0.034751	0.018582	0.02704	0.086288	0.031973	0.00037	0.031973	*3.34E-22*	0.086288
qda	0.049047	0.061311	0.069611	0.137523	0.08666	0.122038	0.044091	0.045492	0.137523
mlp	0.027605	0.054845	0.047704	0.438445	0.088872	0.233852	*0.042826*	*0.062314*	0.438445
lrc	0.023828	0.034635	0.033786	0.20788	0.053621	*0.093584*	0.034294	0.037548	0.20788

Table 2.23: The normalized standard deviation of C#7.

Table 2.24 is the normalized standard deviation of the data R#1. Beside the mer, the results are based on positive p-value criteria. The only negative s_n criteria is not trust-able because of negative p-value criteria. The data set is dominated by the s_n and so the recommendation is mainly influeced by this value.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.29052*	0.101738	0.278022	0.190694	0.147567	0.153469
las	*0.273824*	0.10394	0.28964	0.185631	0.141102	0.152112
svr	*0.343976*	0.123824	0.361241	0.183287	0.138341	0.135582
rid	*0.290826*	0.101739	0.27803	0.190691	0.147563	0.153468
enc	*0.268392*	0.103862	0.269121	0.187971	0.158204	0.144488
mlp	0.407687	0.124194	0.380329	0.368882	0.145088	*0.275252*
dtr	*0.394177*	0.125707	0.370739	0.189699	*0.15982*	*0.866403*
rfr	*0.387491*	0.114617	*0.345816*	0.205218	0.128553	0.161104
knn	*0.36286*	0.106496	0.335057	0.192267	0.136249	0.111909

Table 2.24: The normalized standard deviation of R#1.

Table 2.25 is the normalized standard deviation of the data R#2. Beside the mer, the results are based on positive p-value criteria. The negative s_n of DTR-r2 is based on a negative mean of the r2 metric. The data set is highly use-able for recommendation based on the s_n

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.06681*	0.031379	0.105046	0.15281	0.039834	0.135019
las	*0.066707*	0.031372	0.105013	0.152802	0.03968	0.134705
svr	*0.039065*	0.033757	0.098095	0.149579	0.031857	0.114041
rid	*0.06681*	0.031381	0.105046	0.15281	0.039832	0.135018
enc	*0.056775*	0.032004	0.107294	0.152215	0.040809	0.127766
mlp	*0.043565*	0.032737	0.11122	0.161076	0.040789	0.096724
dtr	0.054812	0.039497	0.101692	0.145068	*0.047179*	-1.10726
rfr	0.068765	0.025467	0.106708	0.167146	0.037726	0.10432
knn	*0.077931*	0.027089	0.093472	0.155913	0.034369	0.128748

Table 2.25: The normalized standard deviation of R#2.

Table 2.26 is the normalized standard deviation of the data R#3. Only a few p-value reach the negative criteria. MSE shows over-all $s_n > 0.5$. Most of the negative s_n criteria are based on

positive p-value criteria. So the data set is use-able for the recommendation based on the s_n.

standard deviation	mer	mae	mse	msle	mee	r2
lir	0.379323	0.193289	0.503186	0.468667	0.264604	*0.303063*
las	0.489541	0.189946	0.585456	0.453853	0.211148	*0.601712*
svr	*0.439699*	0.279329	*0.662278*	0.320819	NaN	NaN
rid	0.486793	0.192416	0.56822	0.495794	0.248886	*0.288088*
enc	*0.913264*	0.209755	0.900346	0.566349	0.200841	*NaN*
mlp	0.364799	0.244276	0.547318	0.49509	0.504332	NaN
dtr	*0.409411*	0.313967	0.543758	0.411549	0.437757	*-6.5E-06*
rfr	*0.509899*	0.39456	*2.255789*	0.430837	0.458518	*0.186703*
knn	*NaN*	0.407128	inf	0.471667	0.367832	NaN

Table 2.26: The normalized standard deviation of R#3.

Table 2.27 is the normalized standard deviation of the data R#4. The three negative s_n criteria are based on positive p-value criteria. The data set is highly use-able for the recommendation based on the s_n criteria.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.284155*	0.051738	0.158375	0.116341	0.067704	0.504653
las	*0.308531*	0.052658	0.158441	0.114607	0.069782	0.381729
svr	*0.233201*	0.068421	0.175989	0.088732	0.056944	4.949006
rid	*0.283405*	0.051688	0.157803	0.113012	0.068566	0.489343
enc	*0.297339*	0.052196	0.157796	0.112242	0.06554	0.342169
mlp	*0.342421*	0.055582	0.187452	0.116372	0.075386	0.272173
dtr	*0.204458*	0.094672	0.205237	0.143752	0.137693	-2.21527
rfr	*0.363943*	0.069231	0.233348	0.113409	0.090208	0.231218
knn	*0.301405*	0.065437	0.217859	0.104638	0.098044	0.27225

Table 2.27: The normalized standard deviation of R#4.

Table 2.28 is the normalized standard deviation of the data R#5. Two out of three negative s_n of the msle are related to the negative p-value criteria. Again the data set has a high quality for recommendation based on the s_n.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.299759*	0.115752	0.265862	*6.657807*	0.182362	0.022769
las	*0.134913*	0.108226	0.201083	0.56616	0.177986	0.030131
svr	*0.189635*	0.116513	0.235764	0.234297	0.133522	0.248865
rid	*0.188035*	0.104398	0.197419	*0.604153*	0.166201	0.033696
enc	0.122522	0.109793	0.204411	*0.391854*	0.163686	0.035568
mlp	*0.200685*	0.117814	0.230451	0.404617	0.168879	0.024971
dtr	0.212072	0.154151	0.297668	0.314812	0.213266	0.105603
rfr	0.195863	0.155856	0.321283	0.372076	0.196292	0.033489
knn	*0.181704*	0.116404	0.21911	0.260575	0.170074	0.176561

Table 2.28: The normalized standard deviation of R#5.

Table 2.29 is the normalized standard deviation of the data R#6. The data set shows similar results to the R#5 with similar quality for the recommendation. The two negative s_n criteria are based on a negative p-value criteria.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.243829*	0.039106	0.078317	0.099524	0.059475	0.009361
las	*NaN*	0.040968	0.078839	0.105813	0.067847	0.009602
svr	*0.507276*	0.050212	0.157697	0.148317	0.069007	0.014013
rid	*0.345519*	0.039034	0.076918	0.097805	0.059698	0.00916
enc	*0.328004*	0.038635	0.075043	0.095186	0.064133	0.009284
mlp	*0.25797*	0.040748	0.081946	0.096825	0.059505	0.010251
dtr	*0.317557*	0.051994	0.106357	0.106254	*0.088166*	0.017821
rfr	*0.3177*	0.048663	0.119607	0.110355	0.073971	0.009589
knn	*0.317719*	0.051276	0.125743	0.13146	*0.075795*	0.012203

Table 2.29: The normalized standard deviation of R#6.

Table 2.30 is the normalized standard deviation of the data R#7. The data set has no negative s_n criteria and only the mer metric shows negative p-value criteria.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.127923*	0.071409	0.167865	0.145593	0.067032	0.05841
las	*0.126978*	0.075076	0.163111	0.213576	0.101042	0.064513
svr	*0.195733*	0.089718	0.24207	0.12051	0.065761	0.12374
rid	*0.109444*	0.073754	0.169767	0.146172	0.068878	0.059543
enc	*0.123906*	0.075094	0.163163	0.215719	0.102915	0.065574
mlp	*0.116186*	0.076593	0.165684	0.278061	0.124747	0.061869
dtr	*0.172367*	0.095917	0.218865	0.187778	0.142596	0.145278
rfr	0.196712	0.088452	0.209498	0.169524	0.110678	0.070551
knn	*0.185083*	0.077459	0.172351	0.150669	0.105946	0.091748

Table 2.30: The normalized standard deviation of R#7.

Table 2.31 is the normalized standard deviation of the data R. All p-values and most of the s_n values show negative criteria. For this reason the data set will not be used for the recommendation of the algorithm-metrics relation.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.213799*	*0.240207*	*0.119523*	*0.032134*	*0.240207*	*NaN*
las	*0.562711*	*0.775496*	*0.966436*	*1.227257*	*0.775496*	*-2.42839*
svr	*45.40154*	*0.575481*	*4.871285*	*2.118756*	*0.575481*	*NaN*
rid	*NaN*	*1.84E-12*	*NaN*	*NaN*	*1.84E-12*	*-1.4E-13*
enc	*-0.63922*	*NaN*	*NaN*	*-4.02772*	*NaN*	*NaN*
mlp	*NaN*	*NaN*	*8.19E-05*	*0.33252*	*NaN*	*NaN*
dtr	*0.671902*	*0.691067*	*0.766903*	*0.828223*	*0.691067*	*-1.1698*
rfr	*0.646356*	*0.628681*	*0.982015*	*1.033859*	*0.628681*	*-6.8982*
knn	*3.55E+90*	*295.9816*	*330.5595*	*1081.443*	*295.9816*	*NaN*

Table 2.31: The normalized standard deviation of R#8.

Table 2.32 is the normalized standard deviation of the data R. Around 40% of the results reach negative p-value criteria. All mer are negative. Half of the negative s_n criteria are based on negative p-values. So the data set has limited useability for recommendation.

standard deviation	mer	mae	mse	msle	mee	r2
lir	*0.470544*	0.157709	0.541559	*0.442717*	0.175139	*0.012582*
las	*0.713861*	0.175848	*0.525232*	*0.394249*	0.176843	*0.012666*
svr	*0.464136*	0.213729	0.654192	0.453029	0.176498	0.028767
rid	*0.46918*	0.154781	0.542401	*0.439443*	0.166927	*NaN*
enc	*0.62822*	0.172495	*0.553256*	*0.471707*	0.162386	*0.0149*
mlp	*0.29196*	0.179433	0.415003	0.15156	0.190417	-0.35
dtr	*0.366827*	0.205429	0.618641	0.408734	0.171335	*0.039553*
rfr	*0.497487*	0.192672	*0.767002*	*0.588627*	0.177871	*0.021984*
knn	*0.336442*	0.138613	0.380925	0.267929	0.191598	0.02702

Table 2.32: The normalized standard deviation of R#9.

Chapter 3

Interpretation and Recommendation

The results discussed in chapter 2 are the basics for the recommendation, which algorithm-metric relation is useful in geotechnic. First an over-all recommendation is given, where the sum of all negative p-value criteria and negative s_n criteria gives the hint for the decision. In a second step every type of data set is discussed separately.

Table 3.1 is the recommendation for regessors. The criteria for green (+; use-able for all data sets), orange ($\sim$; depends on data set), red (- not use-able for all data sets) is based on the p-value and s_n. For regression, results of nine data sets are available. First the negative p-value criteria is summed up. The negative s_n criteria counts double if it is not based on a negative p-value criteria, else it will not be summed into the recommendation. The sum is refered to the number of data sets. Equation 3.1 shows the summation criteria for the regressor. If the value reaches >30% the over-all recommendation is $\sim$. For values > 50% it is $-$.

$$Regressor_{crit} = \frac{\sum pvalue_{neg} + 2 * s_n(pvalue_{pos})}{n_{datasets}} * 100 \tag{3.1}$$

The results show for mer a negative over-all recommendation. This is based on the negative p-value criteria, for mer between 7-9 times of the cycle. mse is mostly acceptable, but for LIR, RID and DTR not use-able. Here the 1-2 negative s_n criteria have an impact. The same is for r2, but here the p-value has more impact. MEE and mae are over-all metrics use-able. The SVR-mee and MLP-mee shows a $\sim$ criteria because of one time negative p-value and s_n criteria. LIR-msle and RID-msle is based on three p-value criteria, LAS-msle one s_n and two p-value, ENC-msle one s_n and three p-value criteria.

recommendation	mer	mae	mse	msle	mee	r2
lir	-	+	-	~	+	-
las	-	+	~	~	+	~
svr	-	+	~	+	~	-
rid	-	+	-	~	+	~
enc	-	+	~	-	+	~
mlp	-	+	~	+	~	~
dtr	-	+	-	+	+	-
rfr	-	+	~	+	+	~
knn	-	+	~	+	+	~

Table 3.1: Recommendation for the relationship algorithm-metric of the regressor. + (use-able for all data sets), ∼ (depends on data set), - (not use-able for all data sets).

Table 3.2 is the recommendation for the classification task. Here the results of seven data sets are summed up. The same criteria for +, ∼ and − are given. The Equation 3.1 is also the summation criteria for the classification. Only six out of ninety algorithm-metric relations are not rated with +. ABC-hamming, -log, and -zero, SVM-prec and MLP-rec are all based on three negative p-value criteria. MLP-prec is grouped by four negative p-value criteria.

recommendation	acc	f1	fb	hamming	jaccard	log	prec	rec	zero
rfc	+	+	+	+	+	+	+	+	+
knn	+	+	+	+	+	+	+	+	+
svm	+	+	+	+	+	+	~	+	+
dtc	+	+	+	+	+	+	+	+	+
gnb	+	+	+	+	+	+	+	+	+
lda	+	+	+	+	+	+	+	+	+
abc	+	+	+	~	+	~	+	+	~
qda	+	+	+	+	+	+	+	+	+
mlp	+	+	+	+	+	+	-	~	+
lrc	+	+	+	+	+	+	+	+	+

Table 3.2: Recommendation for the relation algorithm-metric of the classifier. + (use-able for all data sets), ∼ (depends on data set), - (not use-able for all data sets).

Data set C#1, **coarse grained soils**, trained as multi-class predictor shows for most of the algorithm-metrics good p-values and normalized standard deviation. The input features, different geological and geotechnical parameters, let the predictor perform well. Here all metrics can be recommended. The ABC algorithm shows for four metrics weak performance.

Data set C#2, **volcanic rocks**, with three geotechnical input parameters, show also good p-values and normalized standard deviation. Although fewer input parameters than in C#1, the per-

formance is good. Also here the ABC-algorithm has no good performance for three metrics.

Data set C#3, **different rock types**, shows as C#2 with three geotechnical input parameters a stable data set. Beside the ABC-, also LRC-algorithm show for some metrics poorer performance. For the rest, all metrics perform well and are recommendable.

Data set C#4, **metamrophic and igneauos rocks**, with three geophysical-geotechnical inputs, a weaker performance for the rock type classification. For most algorithms, acc is not recommendable. Same for hamming and zero. MLP is for metrics not recommendable. Also ABC shows weak performance for most metrics. In general, all KNN-metrics and LRC-metrics can be recommended. Also the f1-metric, fb-metric, jaccard-metric and rec-metric are highly recommendable for this kind of data set.

Data set C#5, **different soils**, with two blow count inputs, a very good performance for most of the algorithm. MLP shows over-all metrics, beside log, a weak performance and is not recommendable. Also SVM is for most of the metrics not recommendable.

Data set C#6, **different soils**, with the input of the SPT parameters, shows high performance over most of the metrics. Only prec is moderate recommendable. The rest of the metrics perform well.

Data set C#7, **fine grained soils**, with six geotechnical inputs and the Atterberg classification as classifier output, shows for RFC, KNN and DTC for all metrics no recommendation. For the MLP, prec and rec is not useful. The rest of the algorithm-metric relation is highly recommendable.

Data set R#1, **undrained finish clays**, with six geotechnical inputs and the undrained shear strength as output of the regressor. The mer metric is, beside MLP-mer, not at all recommendable based on the p-value. DTR-mee and -r2, RFR-mse and MLP-r2 are also based on the negative p-value criteria. All other algorithm-metrics are recommendable.

Data set R#2, **different soils**, is the same data set as C#6. Here the regressor predicts the shear wave velocity by the SPT parameters. All of the mer, beside the DTR RFR, and the DTR-mee do not reach the p-value criteria. The DTR-r2 does not reach the s_n value. All other algorithm-metric relations are recommendable.

Data set R#3, **mixed stone**, is the same as the data set C#4. Geotechnical and geophysical input parameters are the basics for the prediction of the UCS. All mse show negative s_n criteria, SVR and RFR based on negative p-value criteria. Also all r2 metrics are based on negative p-value criteria or show no calculated values. The mer metric is for SVR, ENC, DTR, RFR and KNN not recommendable. The ENC-msle and MLP-mee show also negative s_n criteria, SVR-mee show no results. All other algorithm-metrics are recommendable.

Data set R#4, **mixed stone**, with input parameters of different geotechnical parameters, the predictor calculates the vertical strain. Here all mer show negeative p-value criteria and LIR-r2, SVR-r2 and DTR-r2 are negative by s_n criteria. So the data set has a high quality for recommendation.

Data set R#5, **different soil**, with input parameters of the piezocene testing indices, the predictor calculates the resilient modulus, which describes the elasticity modulus for quick/short applied loads. Beside ENC, DTR and RFR, all mer are negative p-values. Also LIR-, RID- and ENC-msle are based on negative p-value. The LAS-msle shows negative s_n criteria. All other algorithm-metrics are recommendable.

Data set R#6, **clays**, with four geotechnical input parameters and the liquid limit as the predictor output. Again mer shows for all algorithms negative p-value. The DTR-mer and KNN-mer are also with negative p-value.

Data set R#7, **volcanic rocks**, with two geotechnical input parameters and the UCS as the predictor output. Here only the mer algorithms, beside the RFR, show negative p-values.

Data set R#8, **coarse grained soils**, with four input parameters of the SPT test and the porosity

for the predictor output. Here all algorithm-metrics show negative p-values, so the data set is not use-able.

Data set R#9, **soft finish clays**, with seven input parameters of the oedometer test and the void ratio as the predictor output. Here mer shows negative p-value criteria. The msle and r2 of LIR, LAS, RID, ENC and RFR have negative p-value. Also the LAS-, ENC-, RFR-mse and DTR-r2 show the same behaviour. The LIR, SVR, RID and DTR-mse have negative s_n criteria. These algorithm-metrics are not recommendable at all. The mar and mee metrics are for this data set over-all algorithms recommendable.

Chapter 4

Conclusion

In summary most of the algorithm-metric relations are recommendable. For different data sets, this recommendation varies strongly. Repeated training and testing of the algorithms with a finite number of data sets gives a first idea, how future recommendations of the algorithm-metric recommendation can look like. In the sklearn package, a lot of other metrics and algorithm are available. Here more investigation must be done. Also with more different data sets, one can give a better and more detailed recommendation. The question is, if the scientific community is interested in such recommendations. Most supervisors use standard metrics and algorithm. If there is a need, the first step should be to check, which algorithm-metrics are mostly used by the geotechnical/geological community. One problem is, that in this field the ML is a young science and not widely known or applied. So investigation for recommendation of algorithm-metric relations will grow step by step with the growing knowledge and application of this scientific domain. Another future investigation could be the impact of the size of the data sets, especially for classification. Imbalanced classes can be a problem for training the algorithm and so the recommendation of the algorithm-metric could be not precise enough. In the end, all statements in chapter 3 are recommendations with a subjective influence, although trying to minimize these impacts. So by furthermore investigation, it could be that there will be never a clear decision criteria for choosing the right algorithm-metric pair for ones special data set case.

Chapter 5

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Appendix A

Appendix

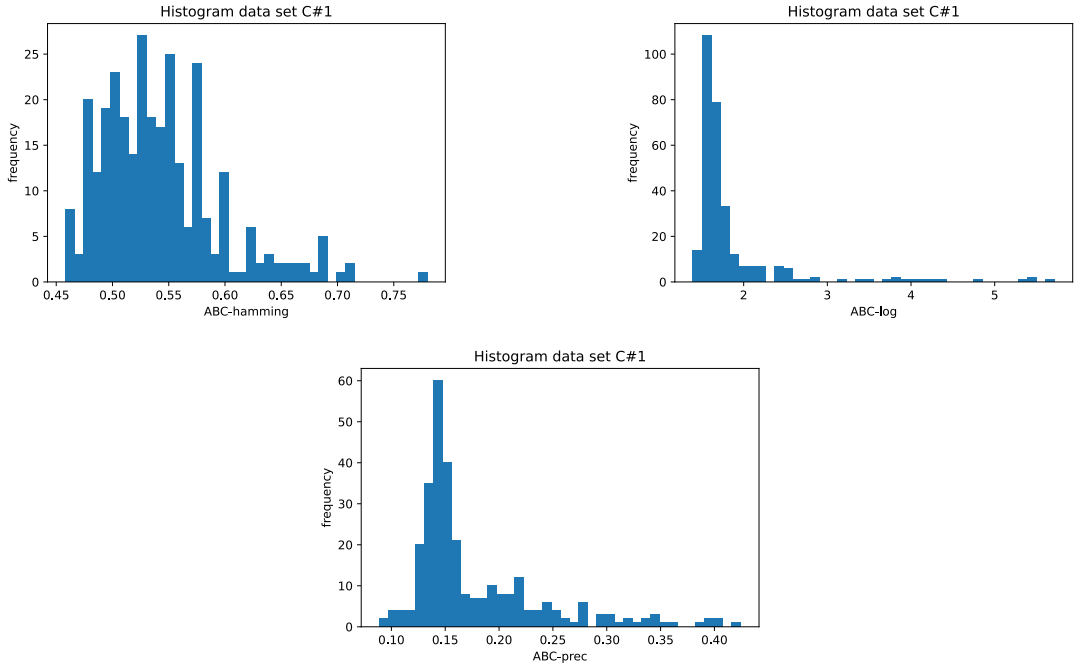


Figure A.1: Left top: Histogram of the ABC-hamming-loss; Right top: Histogram of the ABC-log-loss; Middle bottom: Histogram of the ABC-precision; related to Table 2.1 and data set C#1.

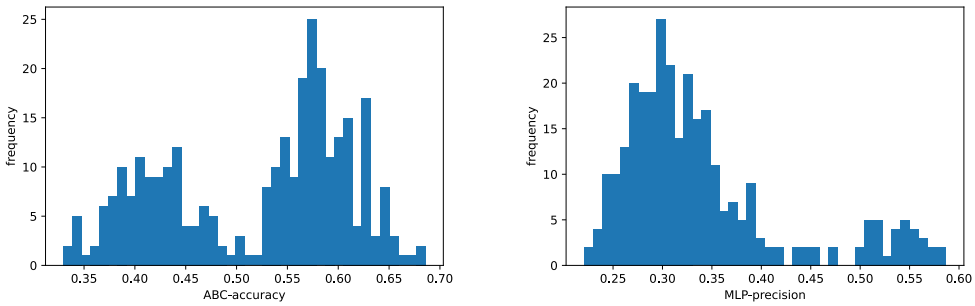


Figure A.2: Left: Histogram of the ABC-accuracy; Right: Histogram of the MLP-precision; related to Table 2.2 and data set C#2.

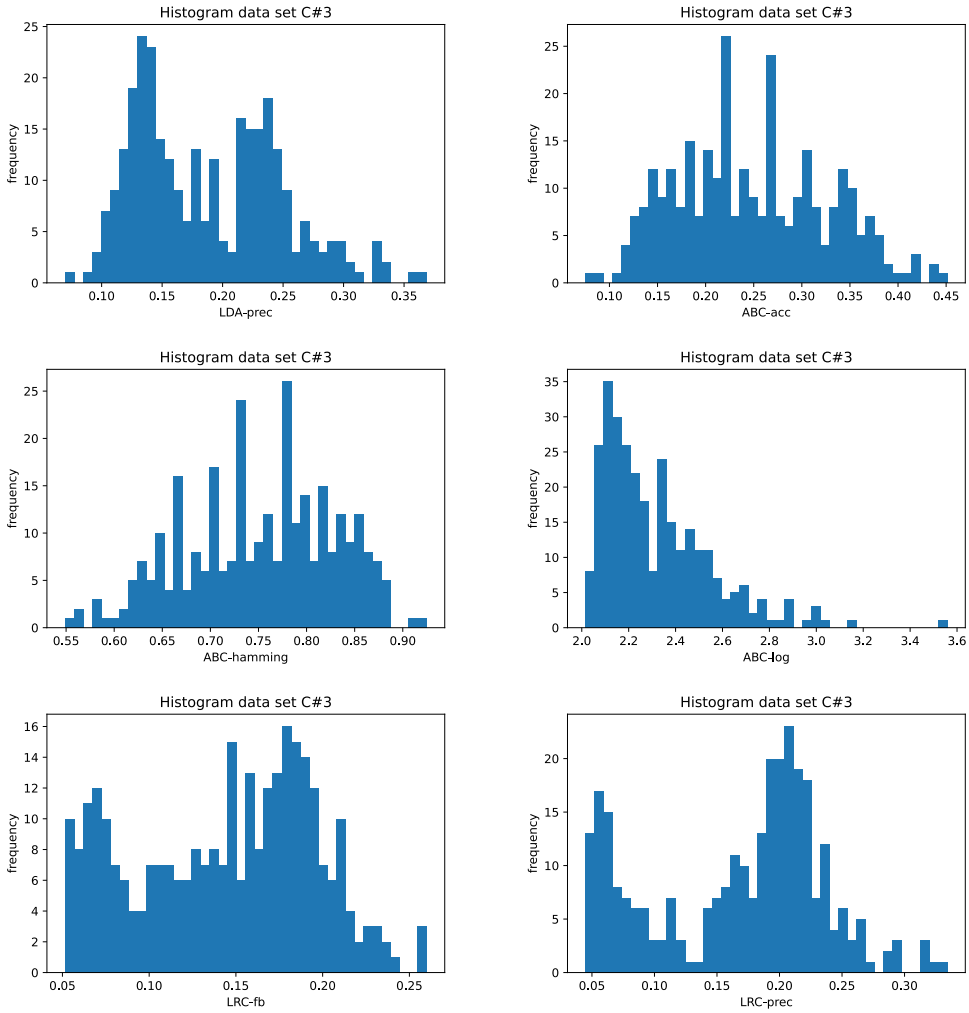
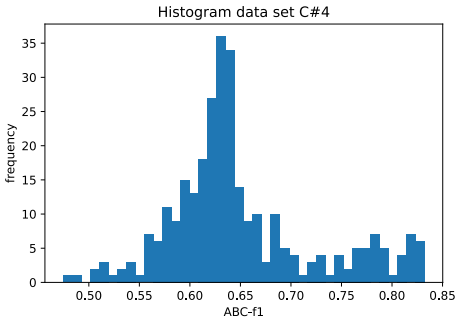


Figure A.3: Left top: Histogram of the LDA-precision; Right top: Histogram of the ABC-accuracy; Left middle: Histogram of the ABC-hamming-loss; Right middle: Histogram of the ABC-log-loss; Left bottom: Histogram of the LRC-fb-score; Right bottom: Histogram of the LRC-precision; related to Table 2.3 and data set C#3.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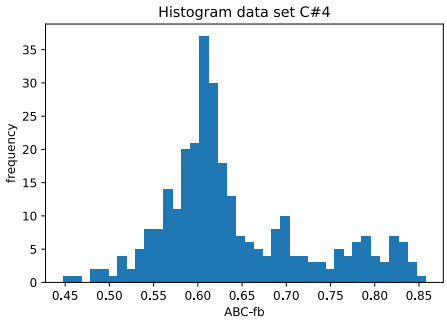
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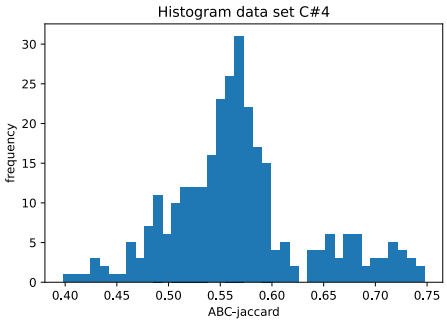
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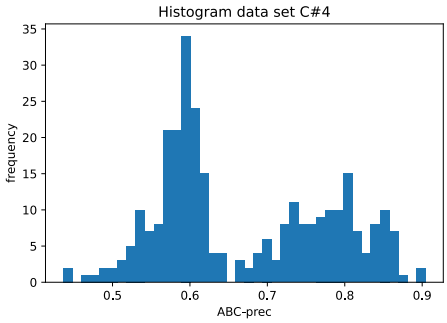
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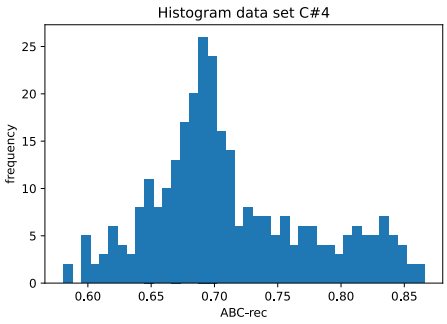
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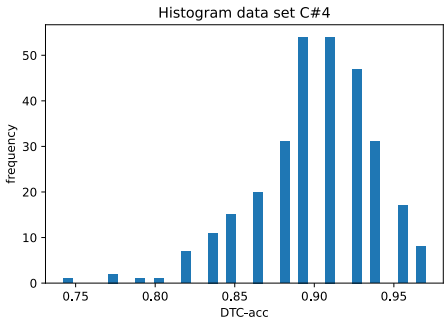
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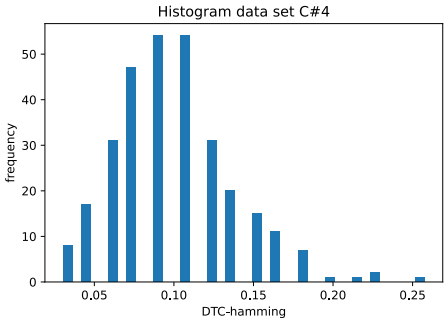
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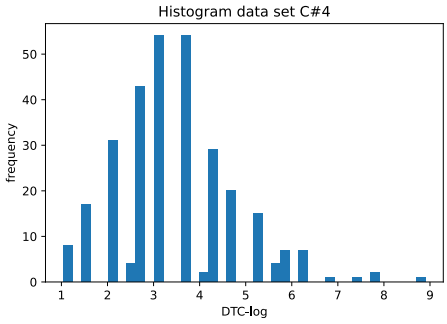
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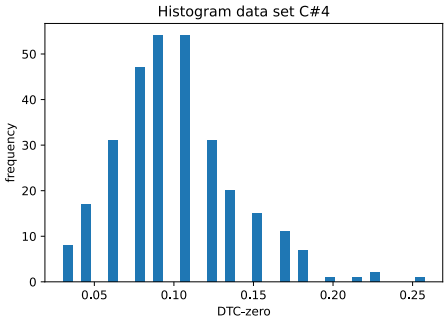
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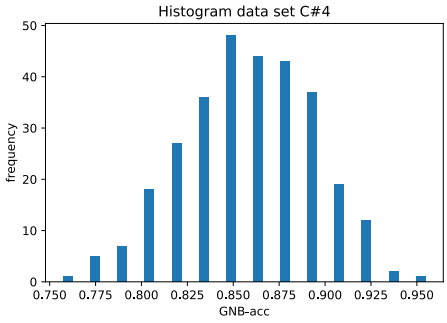
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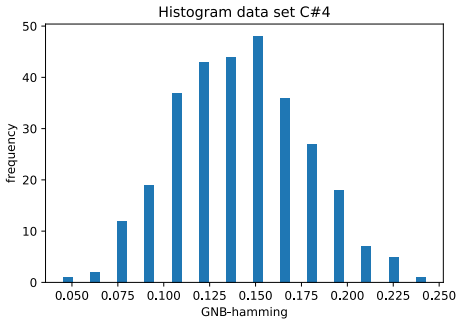
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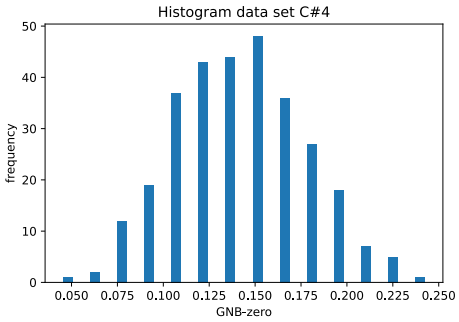
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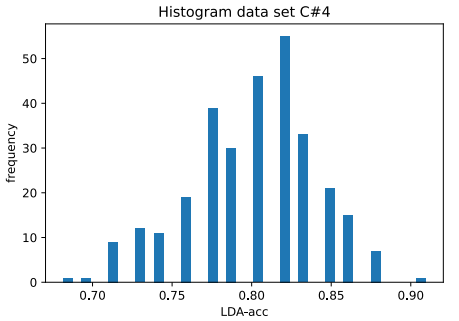
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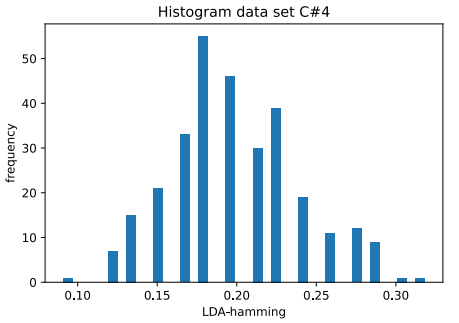
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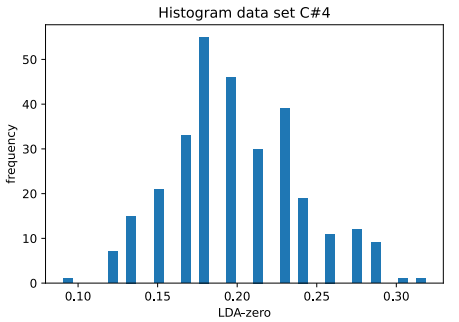
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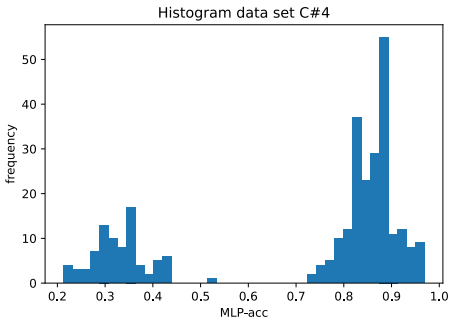
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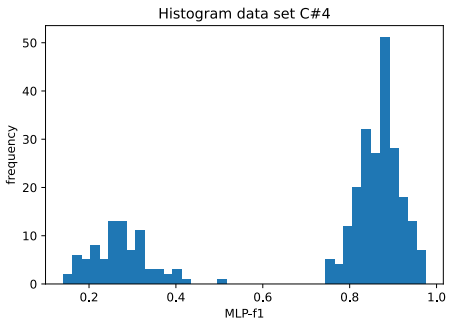
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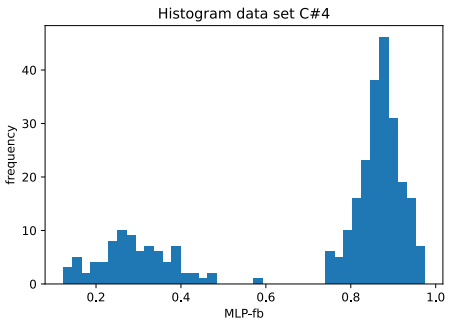
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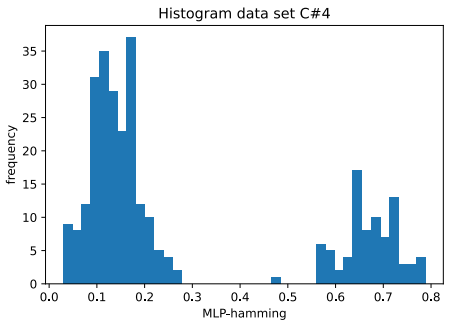
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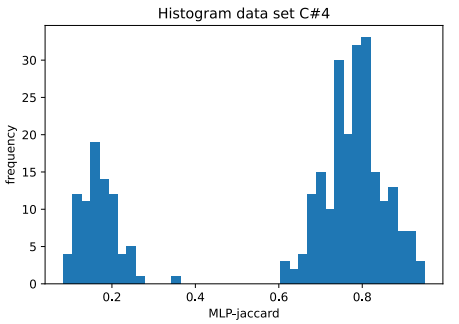
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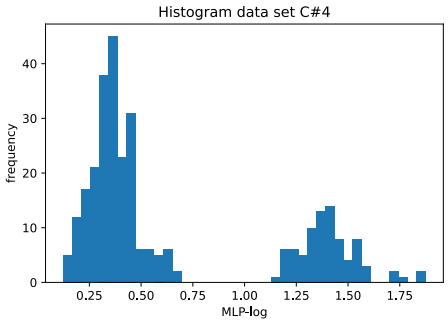
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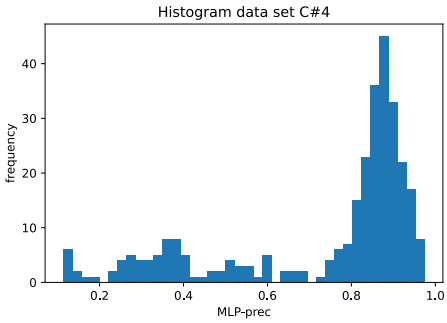
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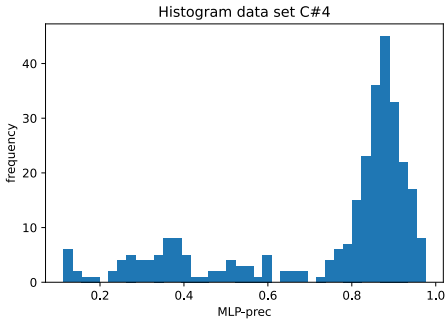
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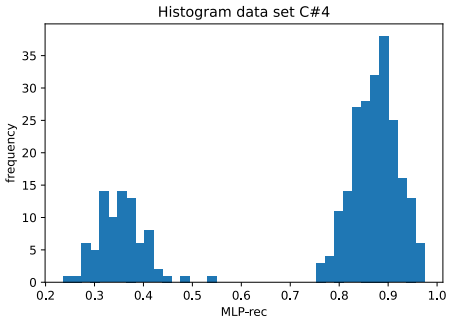
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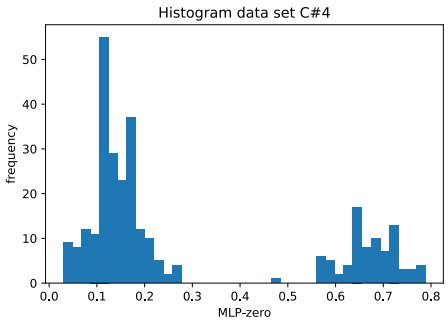
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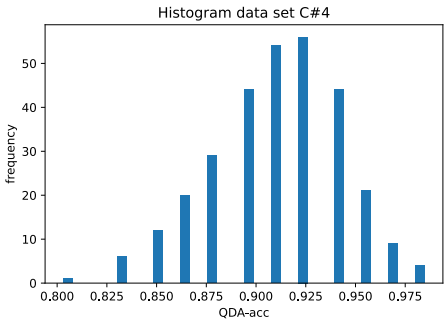
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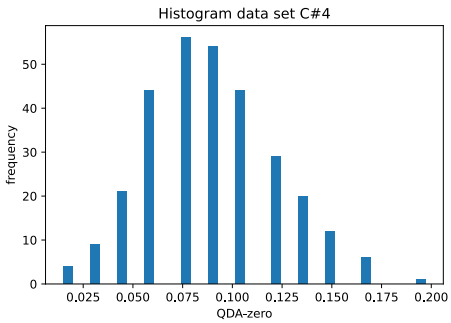
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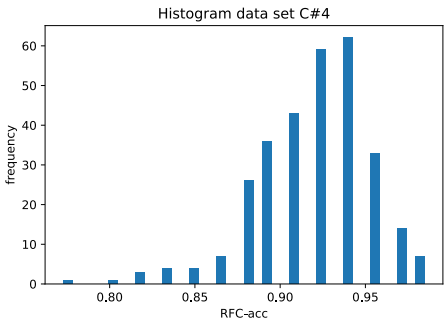
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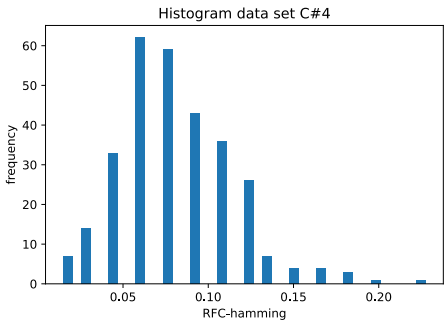
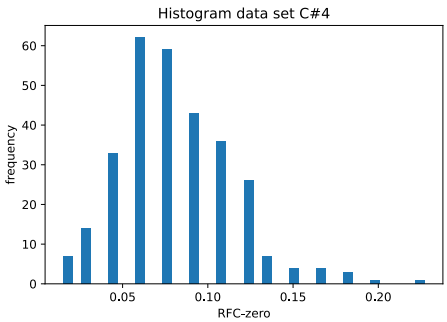

Histogram data set C#4
frequency
RFC-hamming


Histogram data set C#4
frequency
RFC-zero

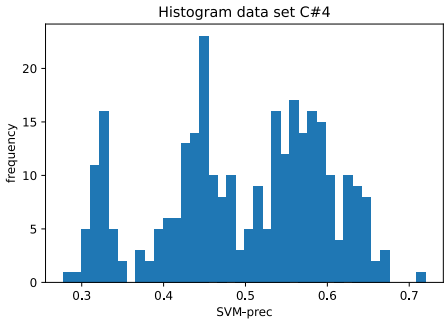
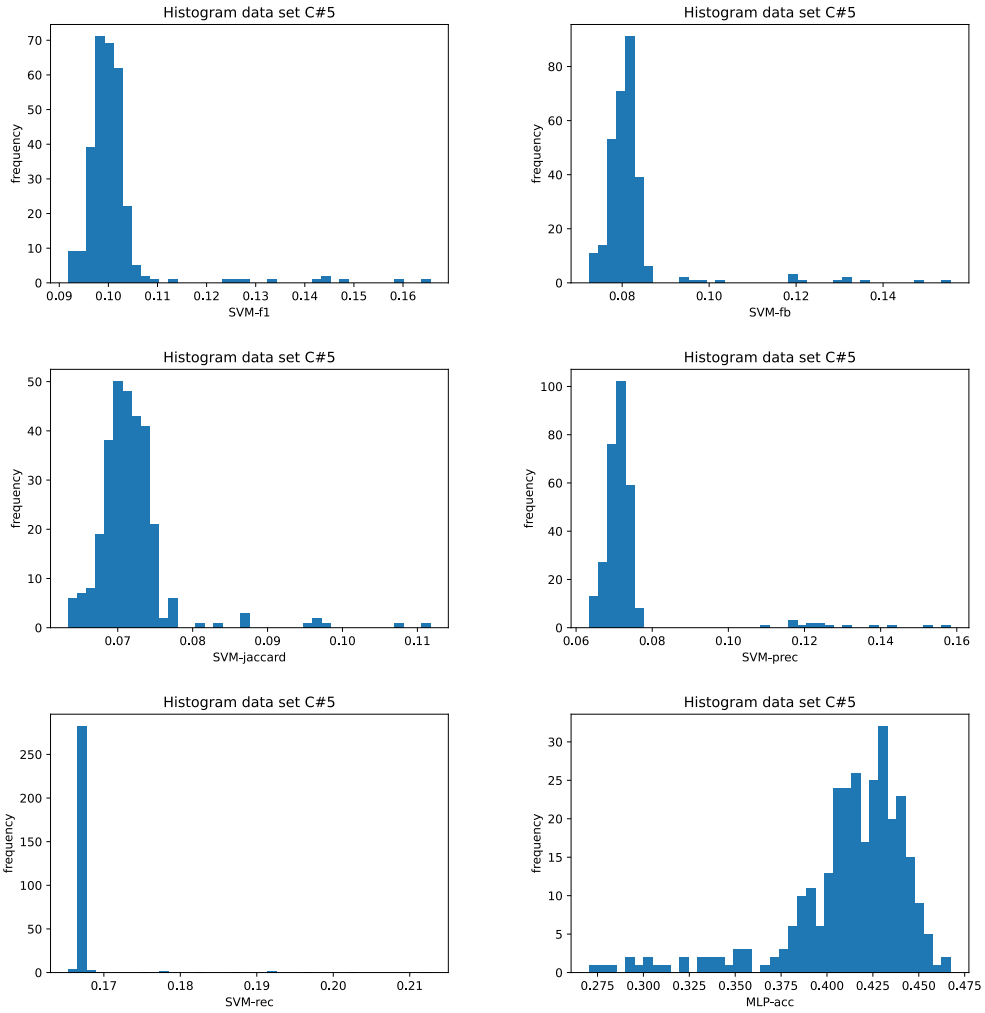


Figure A.4: Histograms of the algorithm-metrics distribution, which don not reach the p-value criteria; related to Table 2.4 and data set C#4.



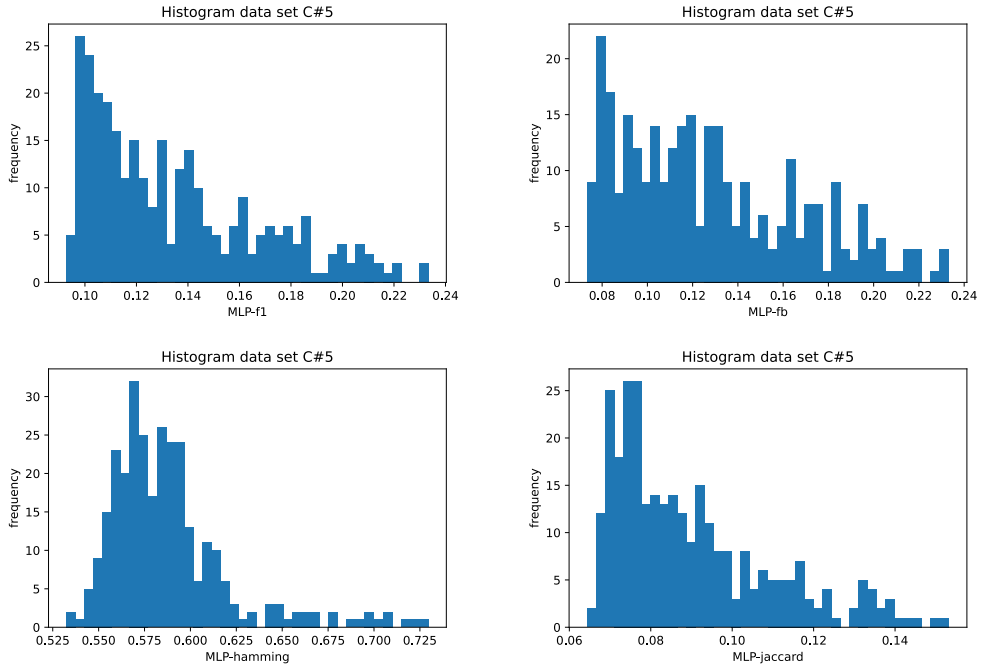


Figure A.5: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.5 and data set C#5.

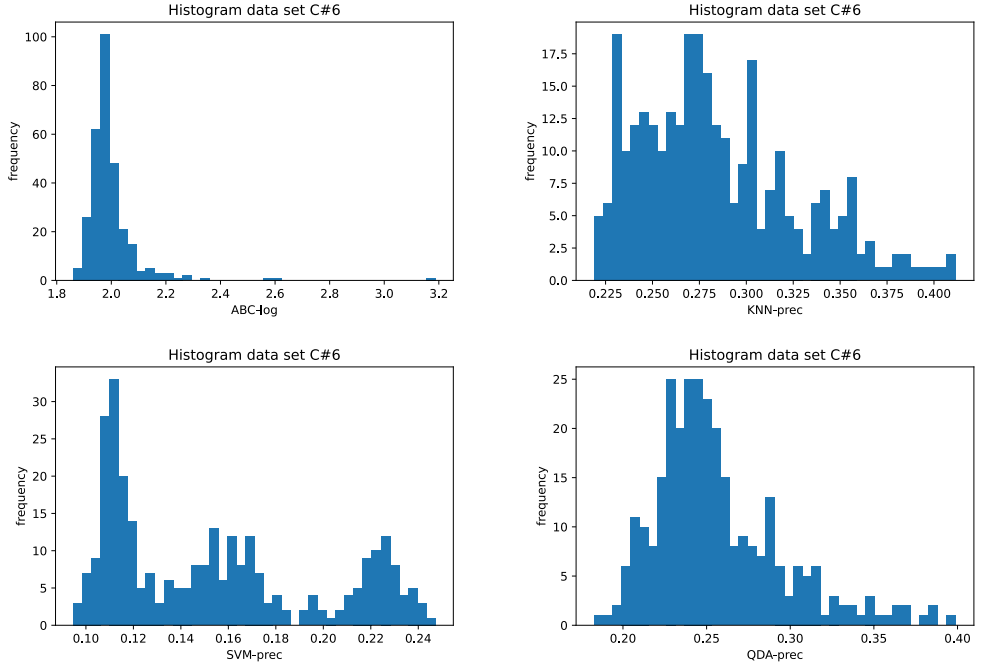
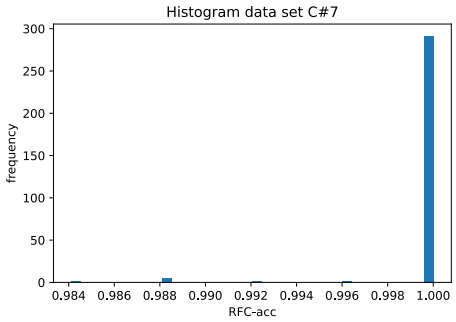
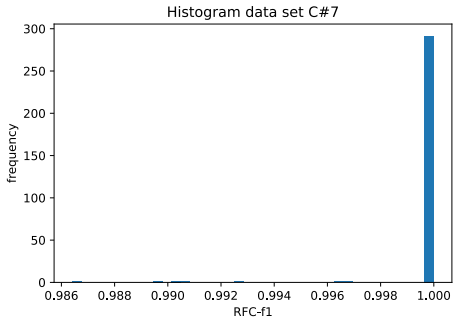
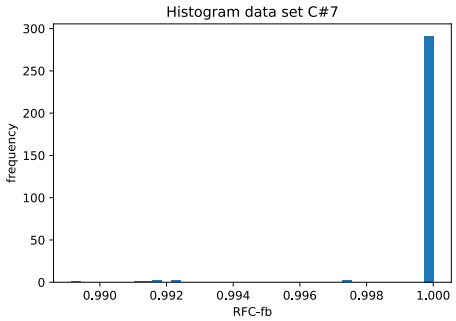
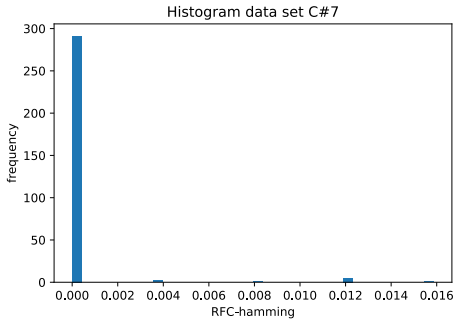


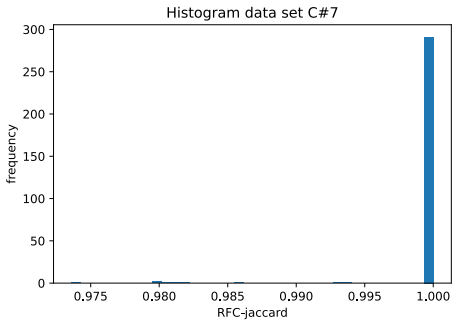
Figure A.6: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.6 and data set C#6.

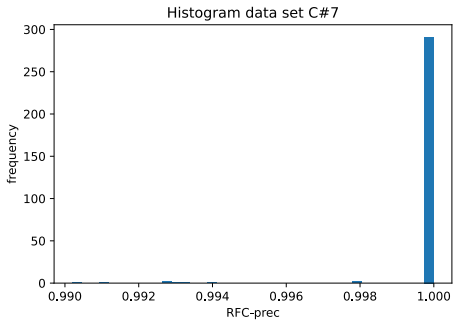

Histogram data set C#7
frequency
RFC-acc

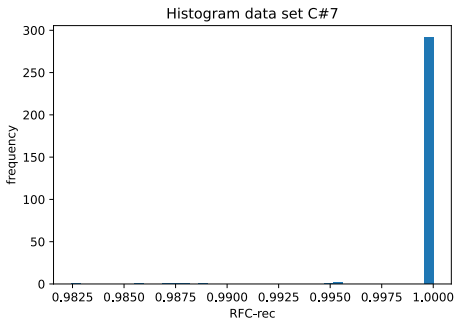

Histogram data set C#7
frequency
RFC-f1

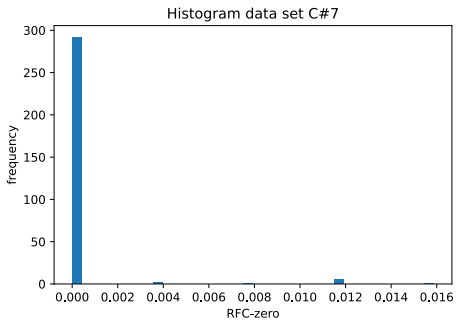

Histogram data set C#7
frequency
RFC-fb

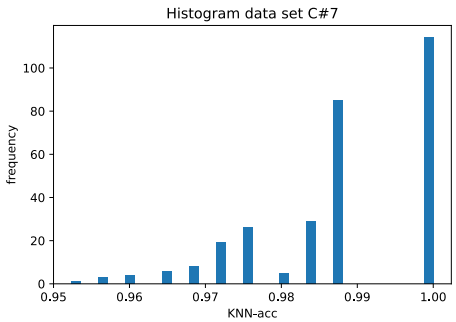

Histogram data set C#7
frequency
RFC-hamming

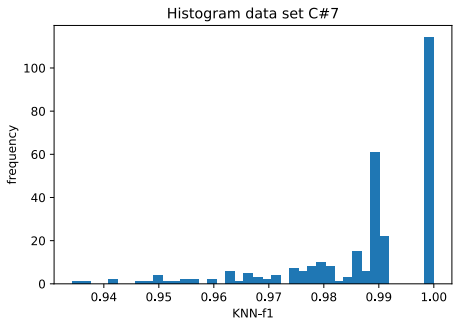

Histogram data set C#7
frequency
RFC-jaccard

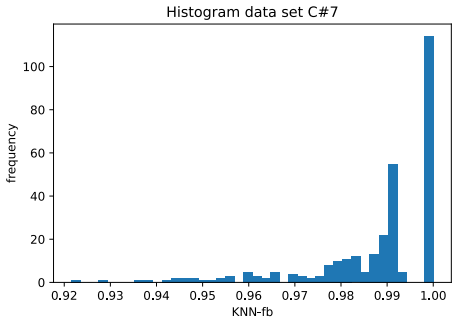

Histogram data set C#7
frequency
RFC-prec

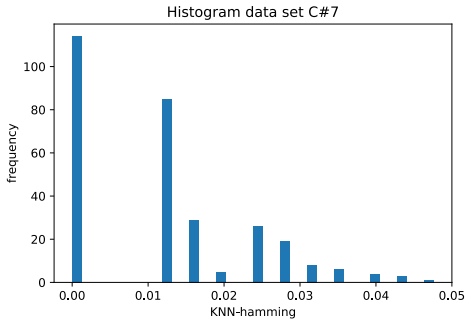

Histogram data set C#7
frequency
RFC-rec

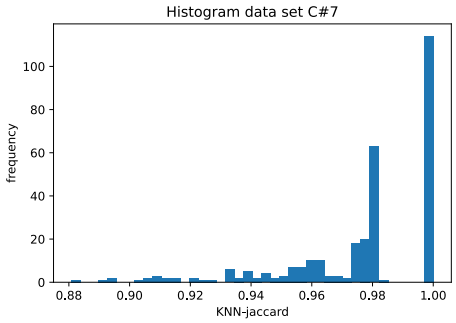

Histogram data set C#7
frequency
RFC-zero

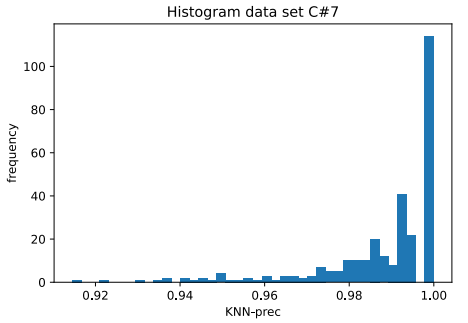

Histogram data set C#7
frequency
KNN-acc

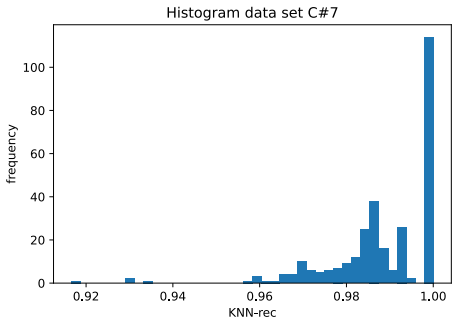

Histogram data set C#7
frequency
KNN-f1

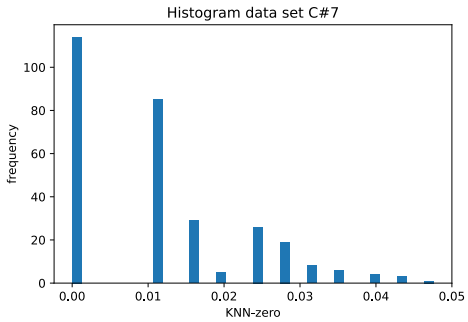

Histogram data set C#7
frequency
KNN-fb

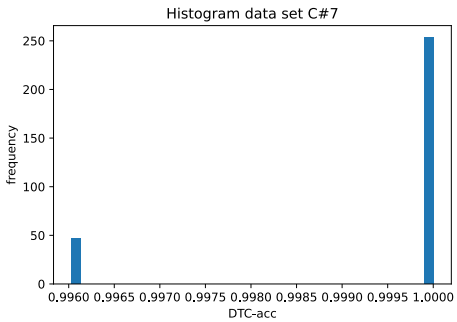

Histogram data set C#7
frequency
KNN-hamming

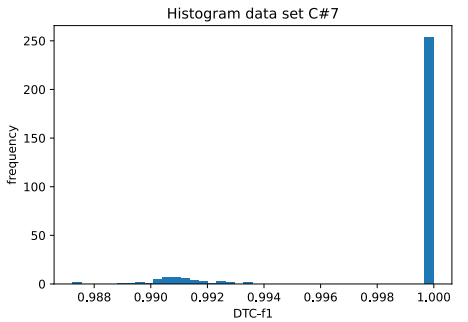

Histogram data set C#7
frequency
KNN-jaccard

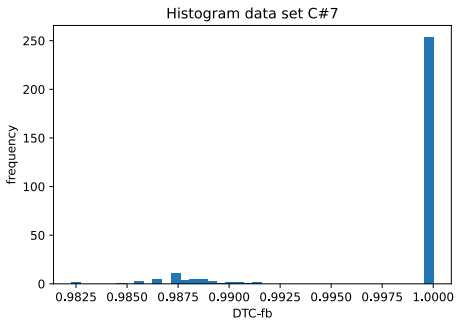

Histogram data set C#7
frequency
KNN-prec

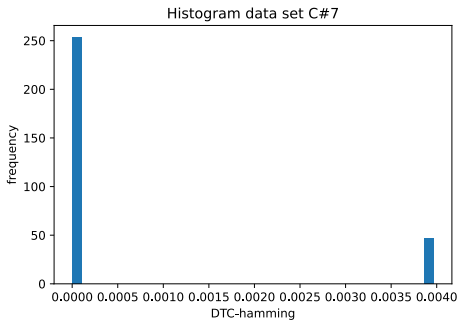

Histogram data set C#7
frequency
KNN-rec


Histogram data set C#7
frequency
KNN-zero


Histogram data set C#7
frequency
DTC-acc


Histogram data set C#7
frequency
DTC-f1


Histogram data set C#7
frequency
DTC-fb


Histogram data set C#7
frequency
DTC-hamming

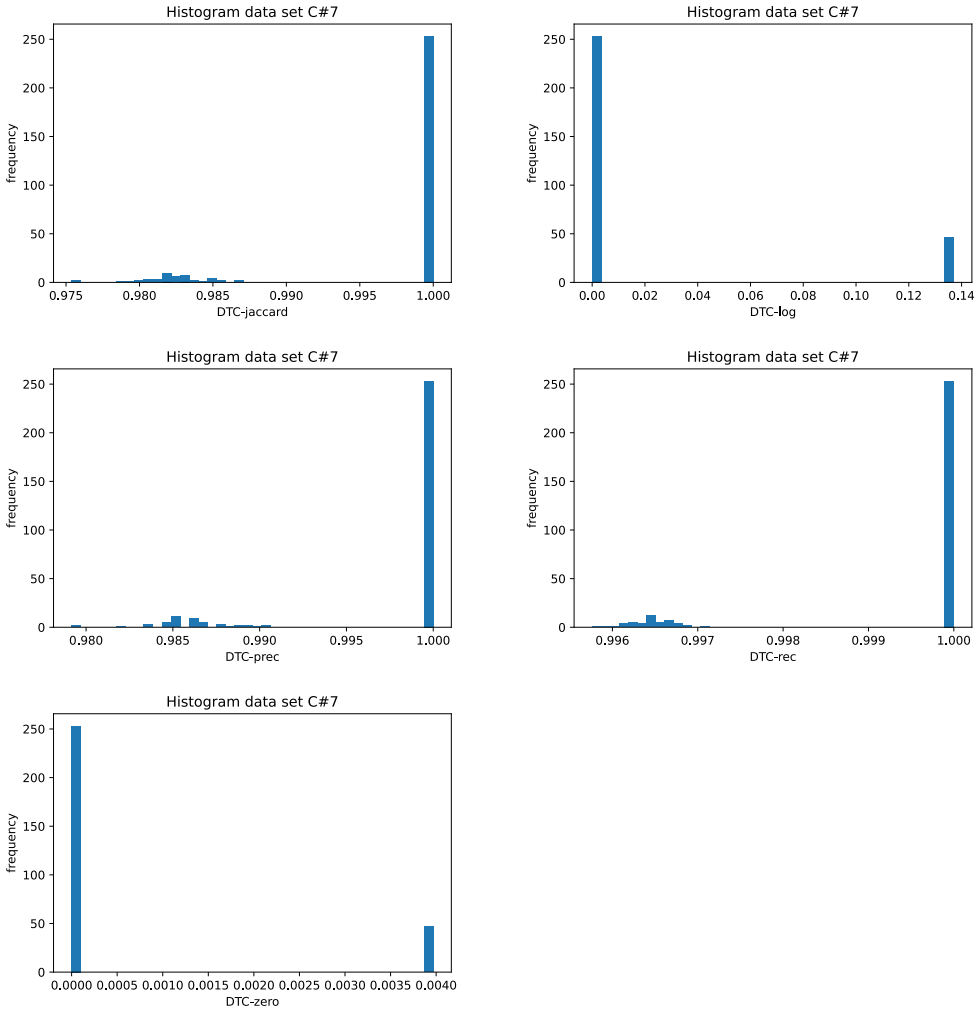
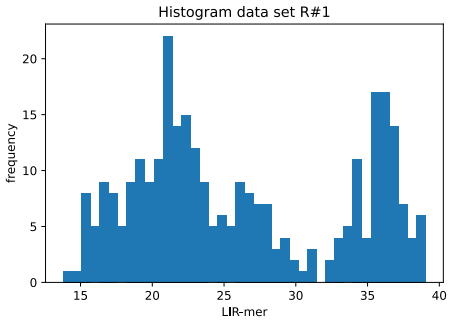
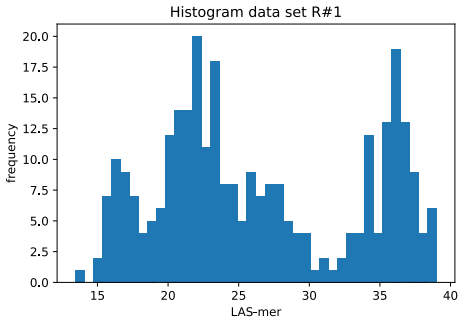
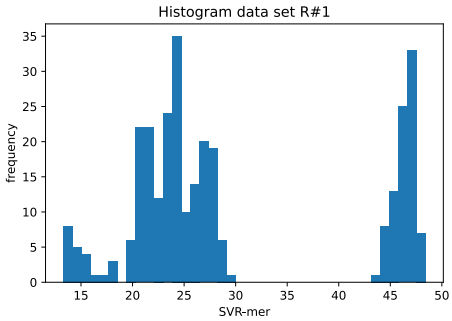
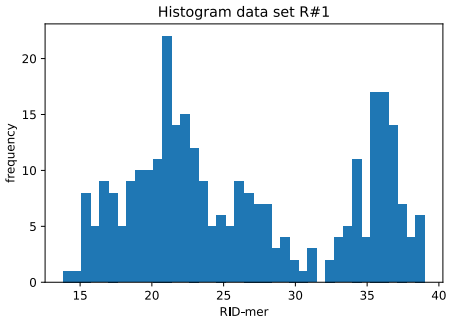


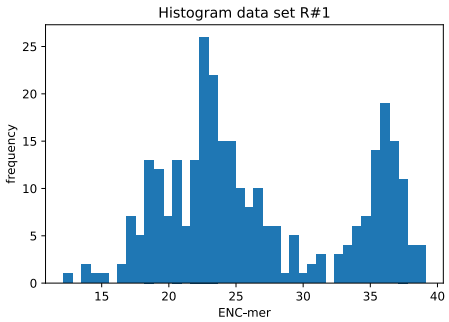
Figure A.7: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.7 and data set C#7.

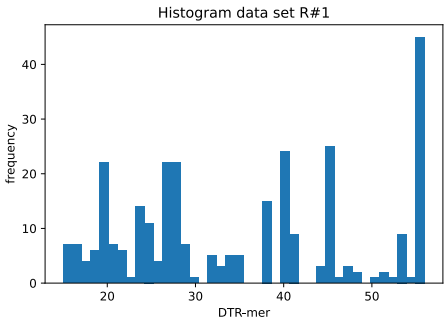

Histogram data set R#1
frequency
LIR-mer

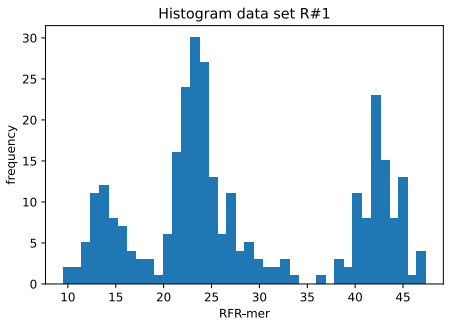

Histogram data set R#1
frequency
LAS-mer

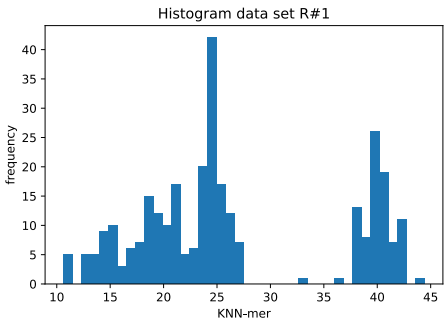

Histogram data set R#1
frequency
SVR-mer

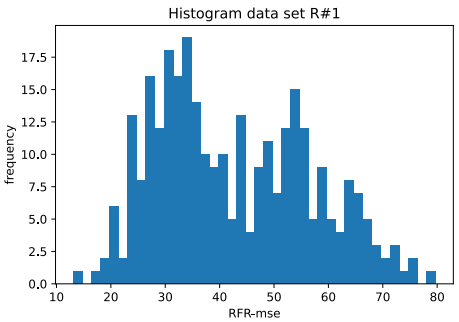

Histogram data set R#1
frequency
RID-mer

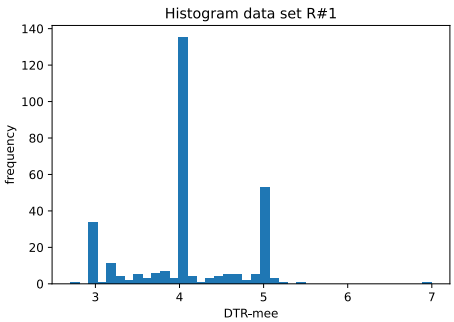

Histogram data set R#1
frequency
ENC-mer


Histogram data set R#1
frequency
DTR-mer


Histogram data set R#1
frequency
RFR-mer


Histogram data set R#1
frequency
KNN-mer


Histogram data set R#1
frequency
RFR-mse


Histogram data set R#1
frequency
DTR-mee

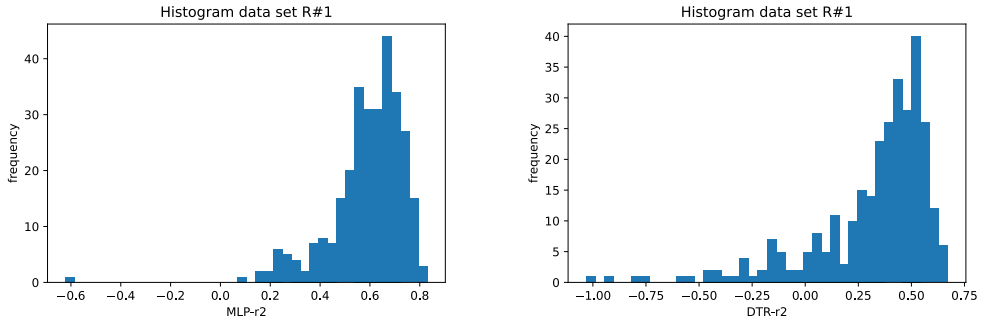
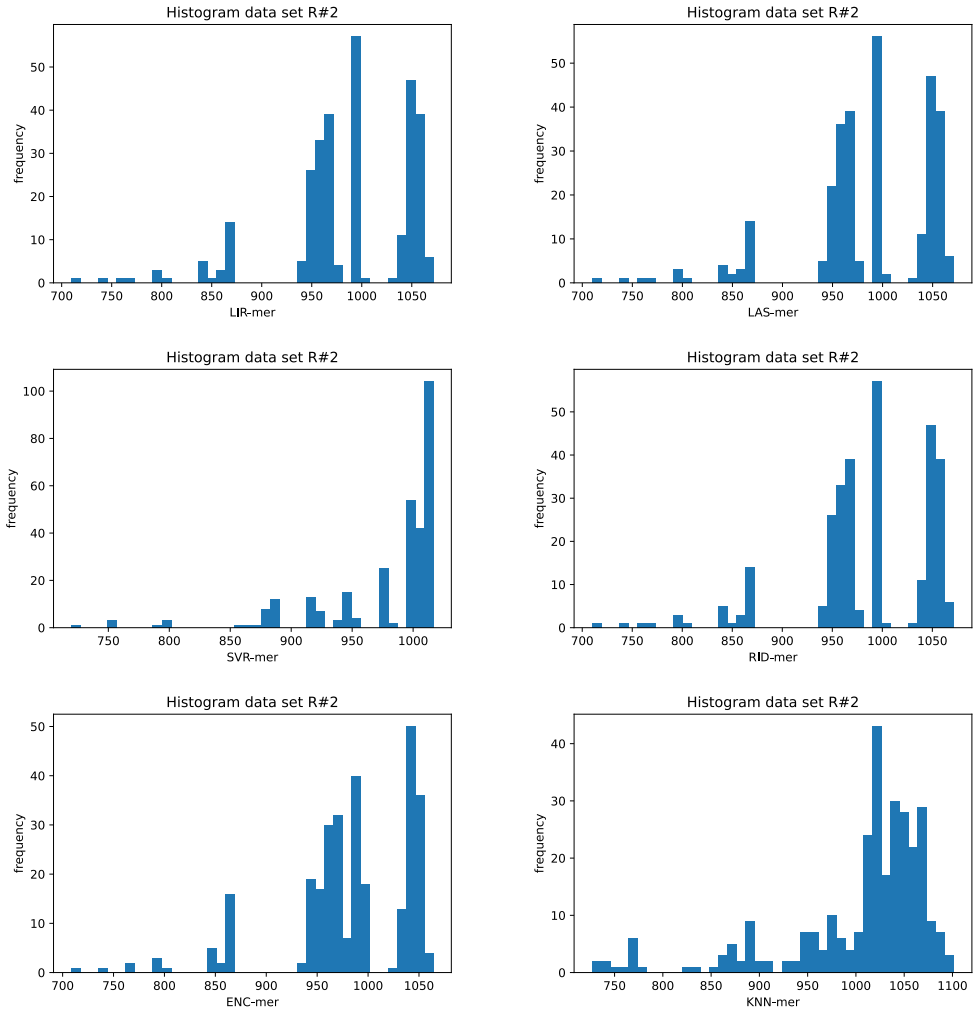


Figure A.8: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.8 and data set R#1.



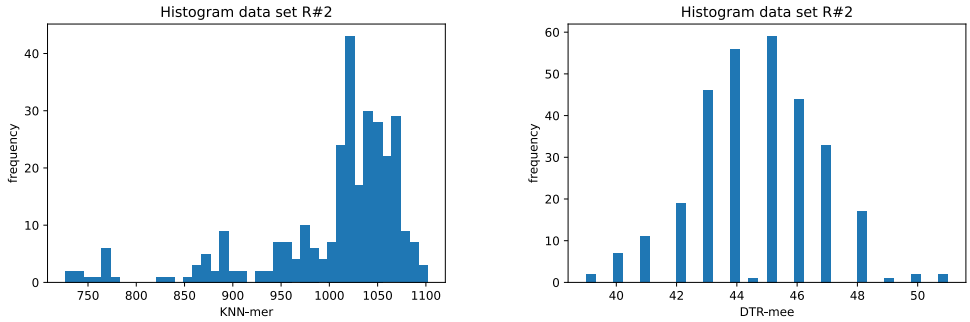
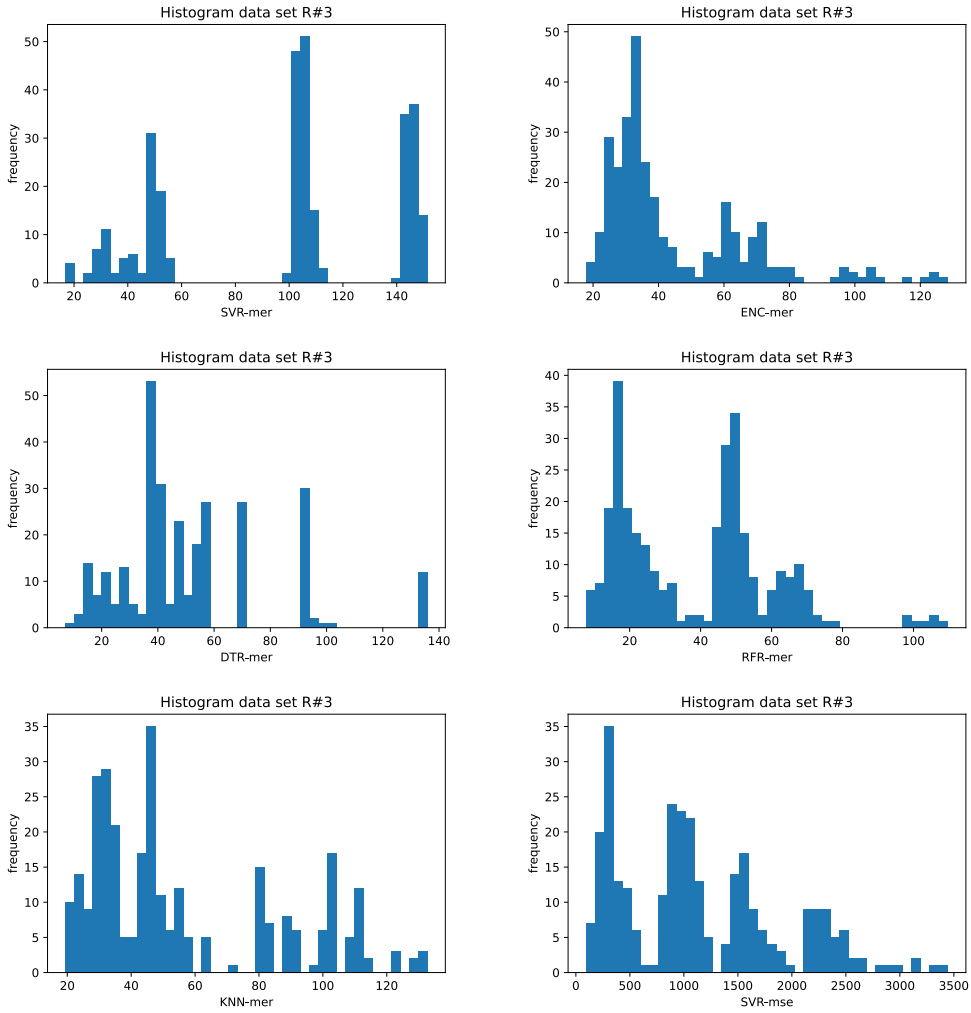


Figure A.9: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.9 and data set R#2.



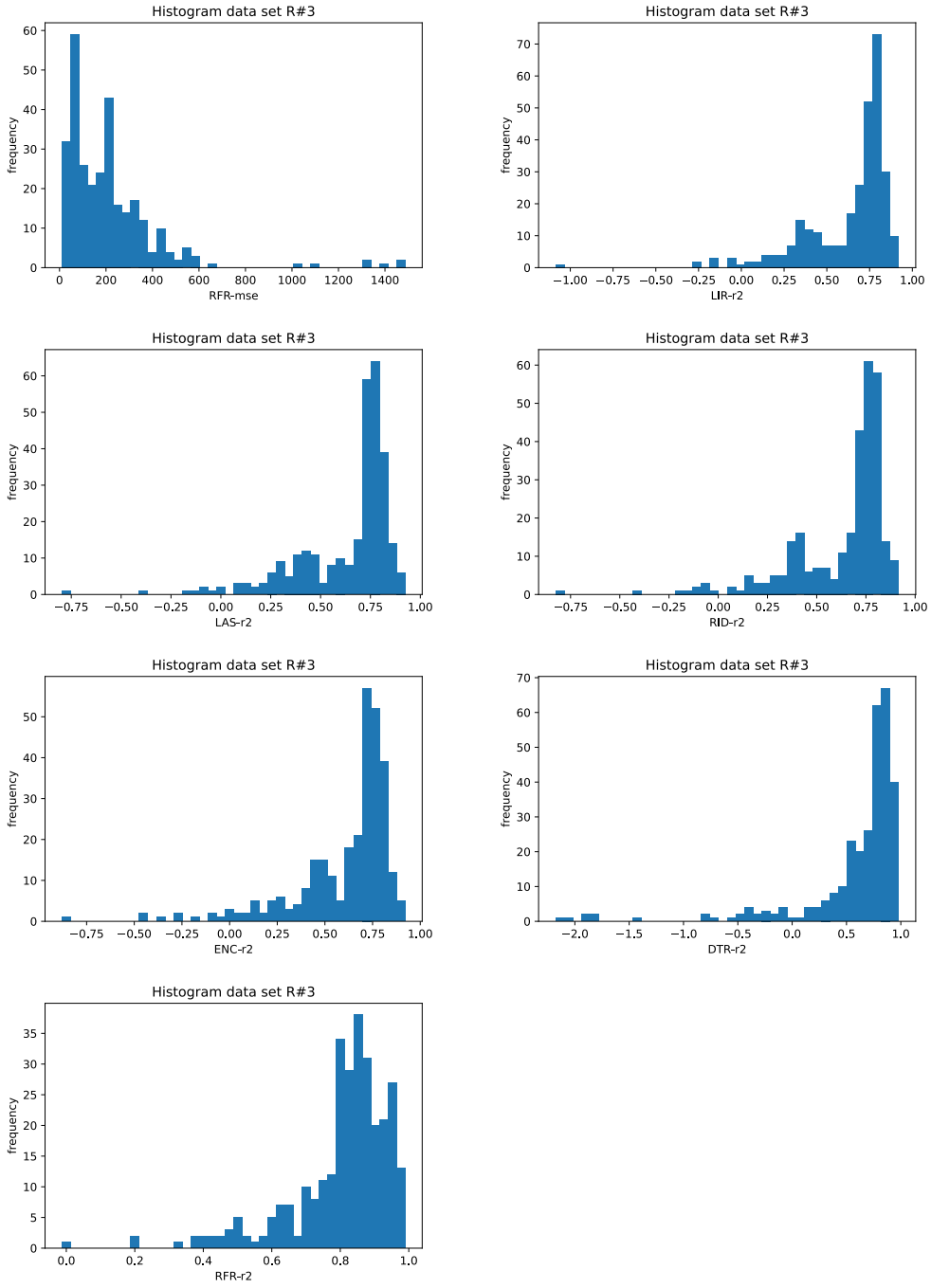
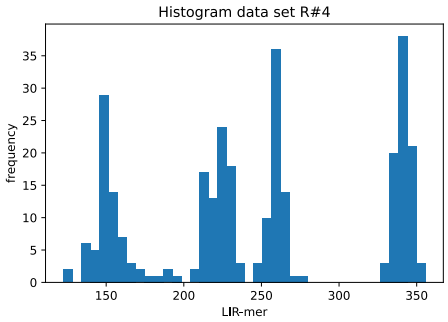
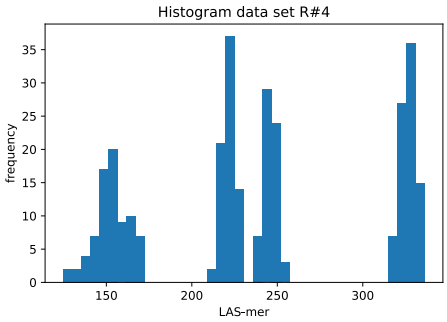
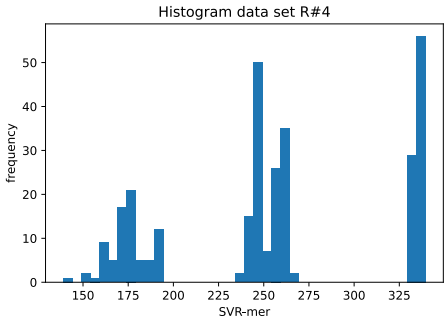
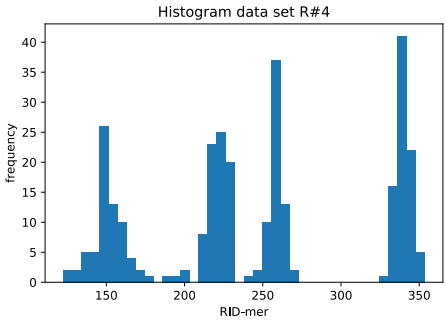


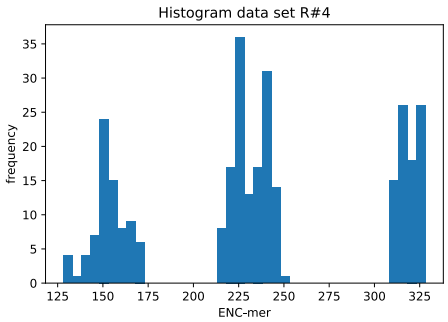
Figure A.10: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.10 and data set R#3.

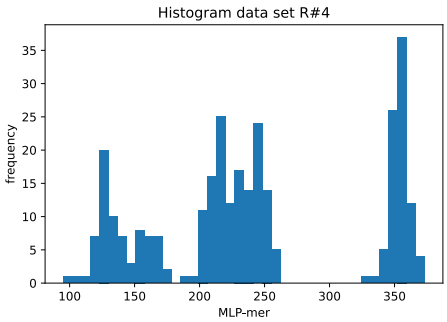

Histogram data set R#4
frequency
LIR-mer

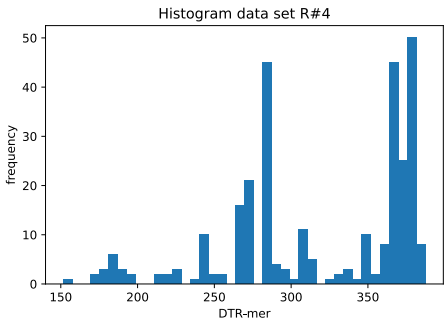

Histogram data set R#4
frequency
LAS-mer

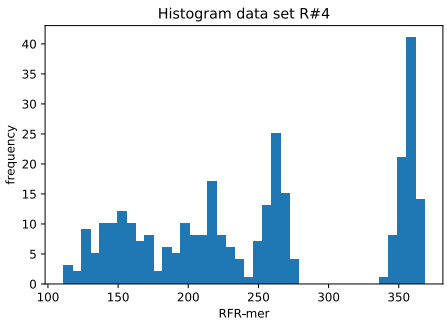

Histogram data set R#4
frequency
SVR-mer


Histogram data set R#4
frequency
RID-mer


Histogram data set R#4
frequency
ENC-mer


Histogram data set R#4
frequency
MLP-mer


Histogram data set R#4
frequency
DTR-mer


Histogram data set R#4
frequency
RFR-mer

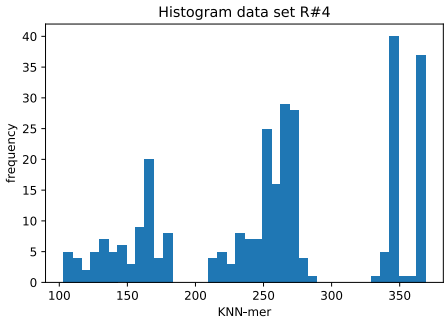
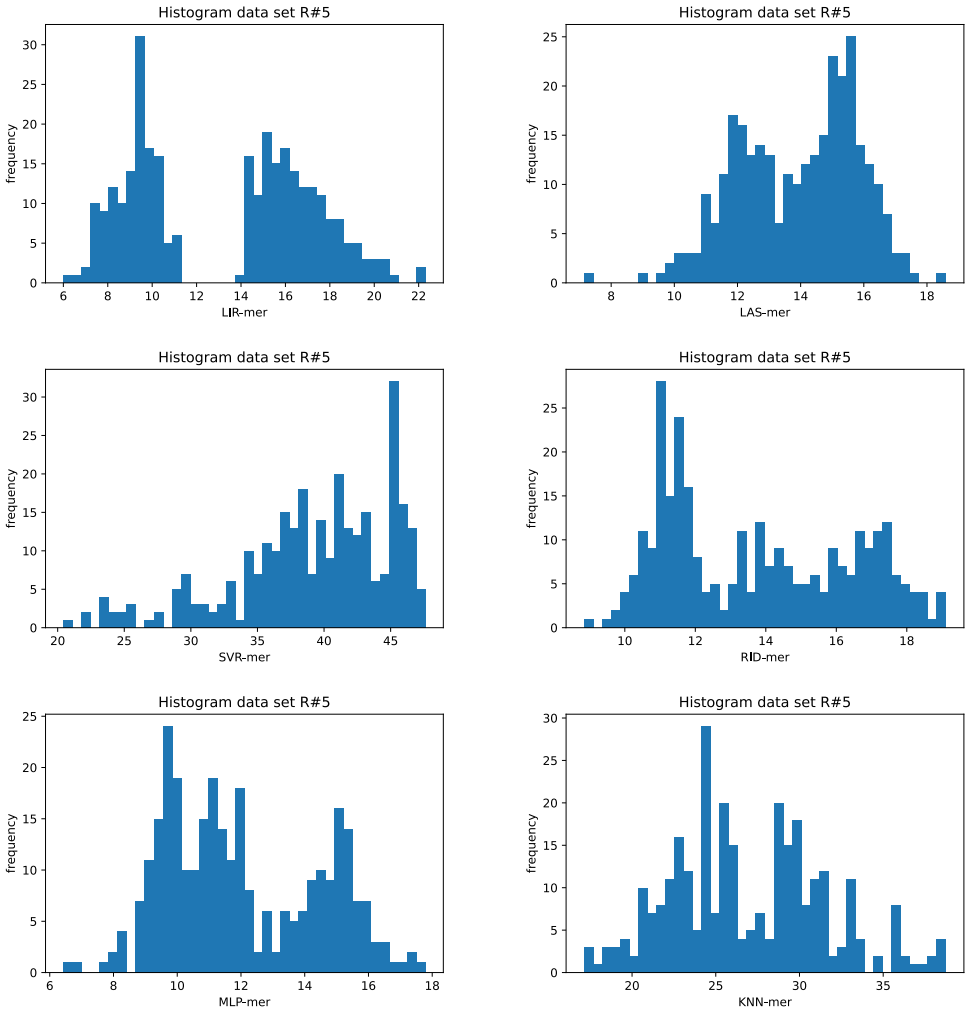


Figure A.11: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.11 and data set R#4.



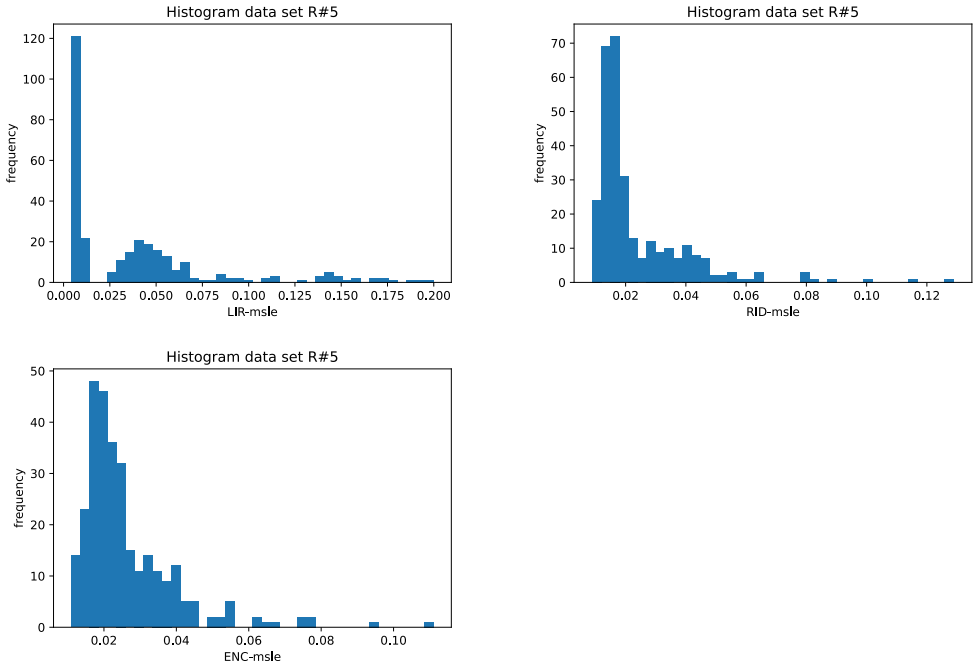
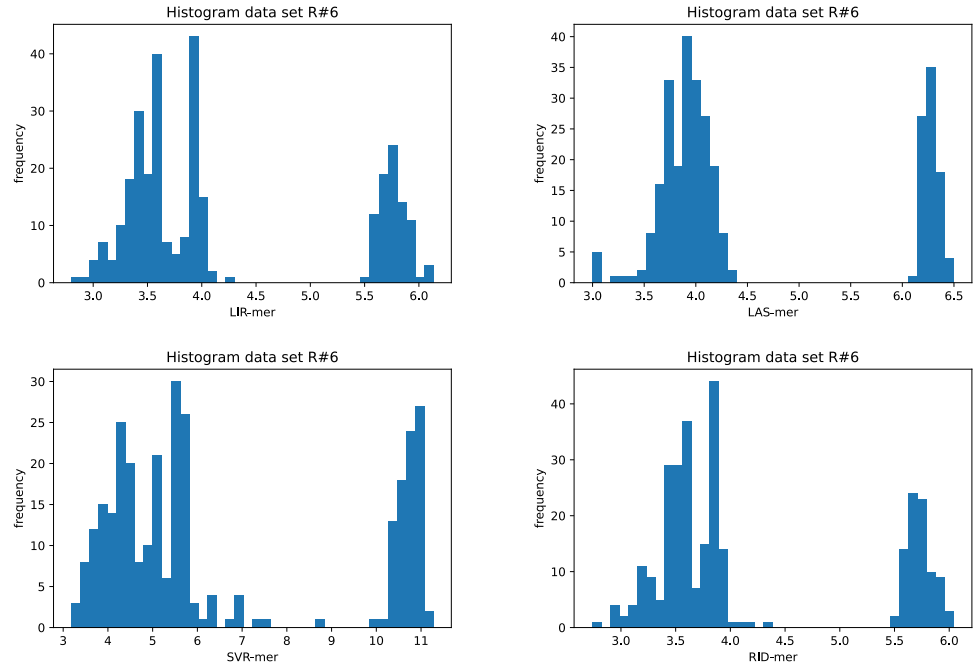


Figure A.12: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.12 and data set R#5.



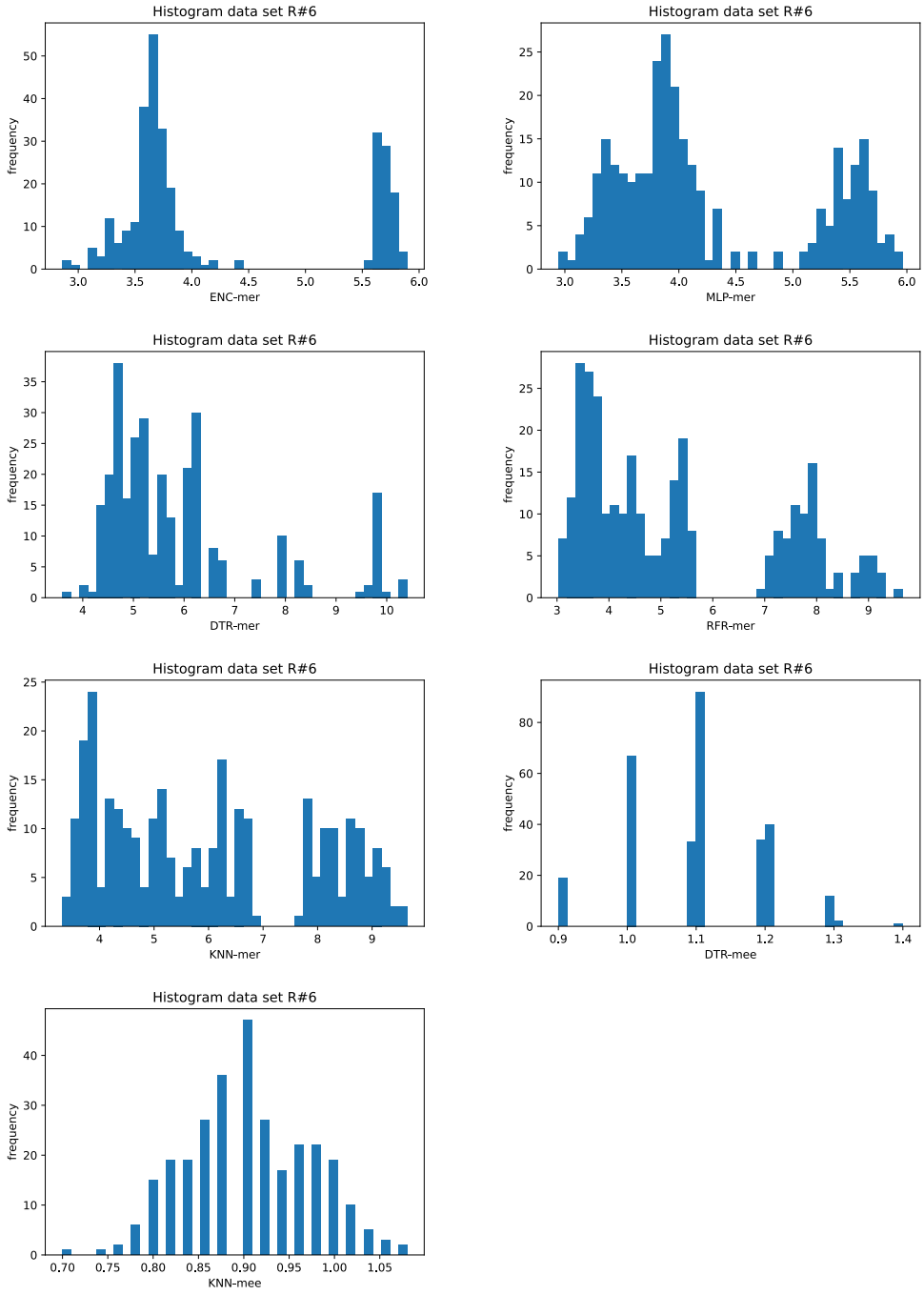


Figure A.13: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.13 and data set R#6.

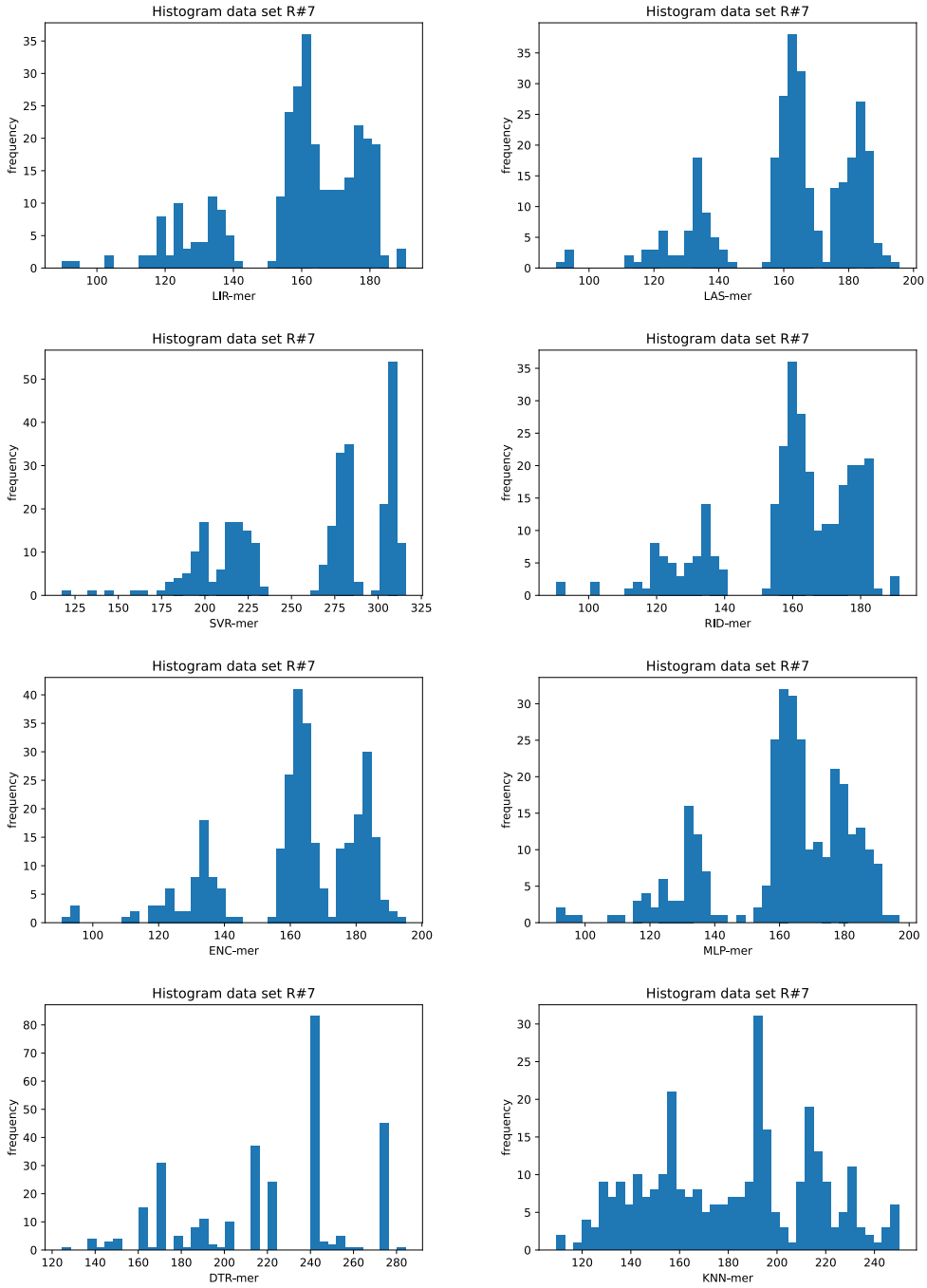
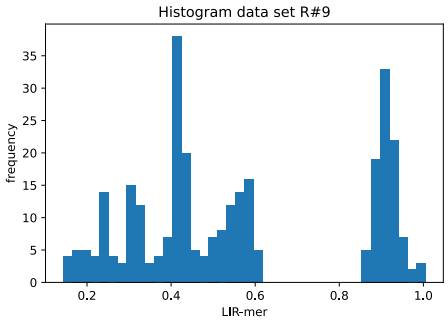
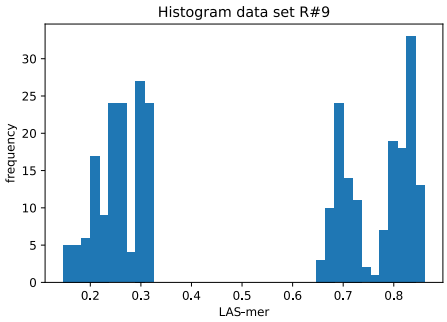
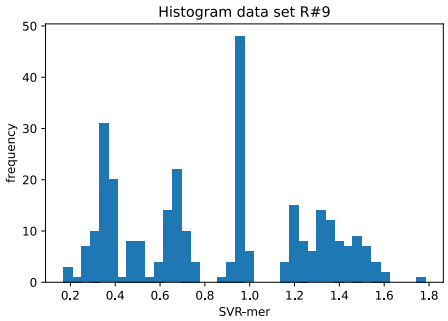
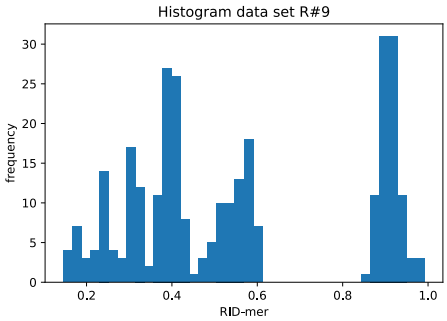


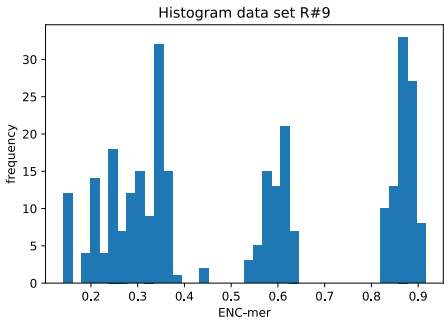
Figure A.14: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.14 and data set R#7.

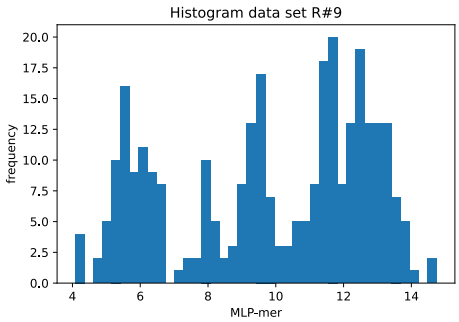

Histogram data set R#9
frequency
LIR-mer

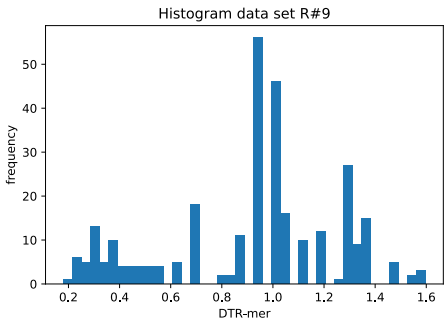

Histogram data set R#9
frequency
LAS-mer

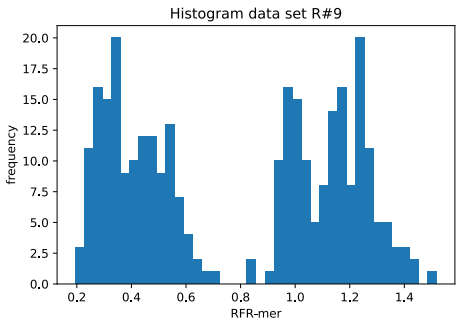

Histogram data set R#9
frequency
SVR-mer

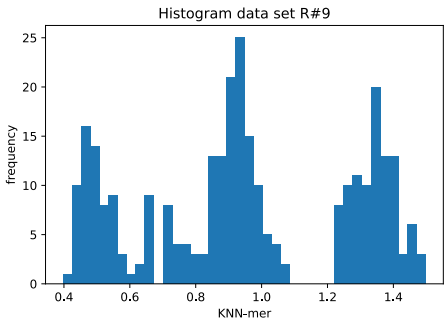

Histogram data set R#9
frequency
RID-mer

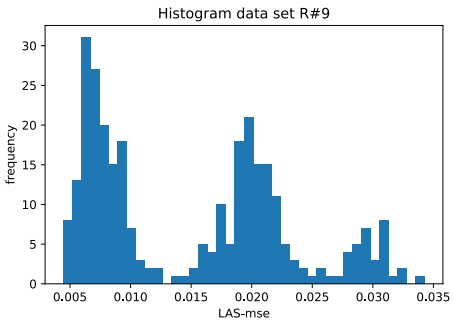

Histogram data set R#9
frequency
ENC-mer

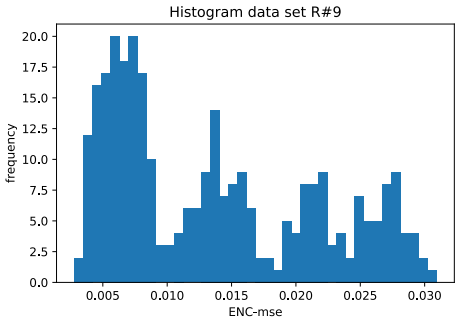

Histogram data set R#9
frequency
MLP-mer

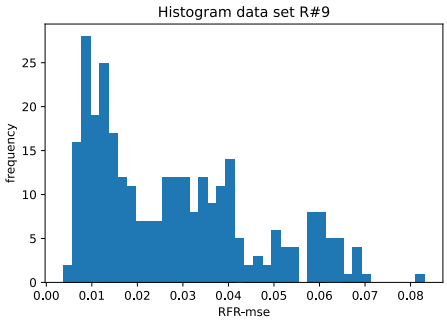

Histogram data set R#9
frequency
DTR-mer

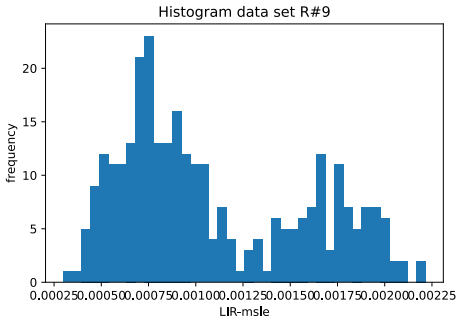

Histogram data set R#9
frequency
RFR-mer

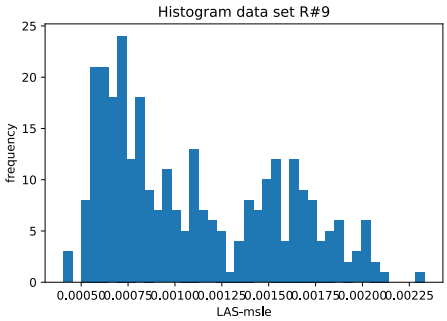

Histogram data set R#9
frequency
KNN-mer

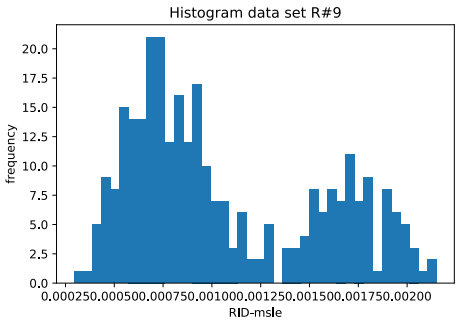

Histogram data set R#9
frequency
LAS-mse

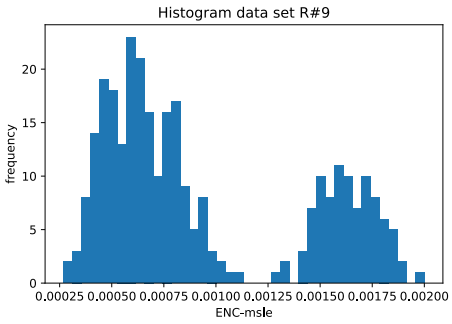

Histogram data set R#9
frequency
ENC-mse

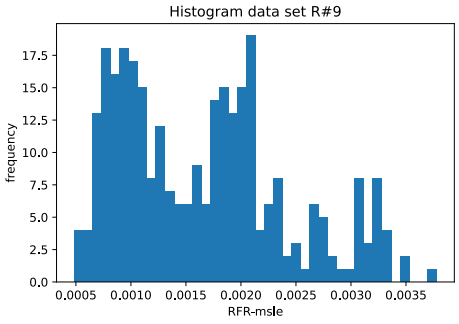

Histogram data set R#9
frequency
RFR-mse

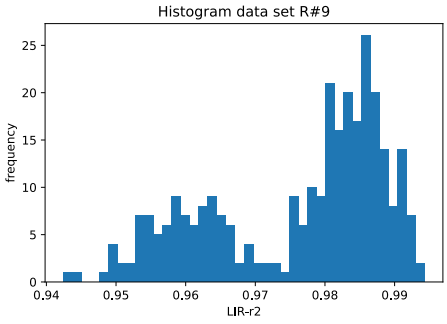

Histogram data set R#9
frequency
LIR-msle

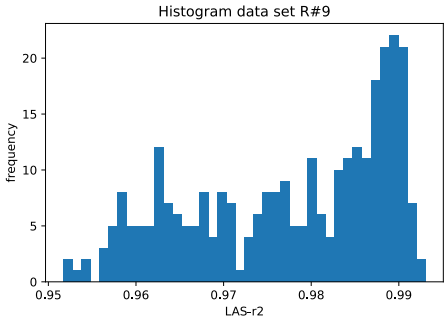

Histogram data set R#9
frequency
LAS-msle

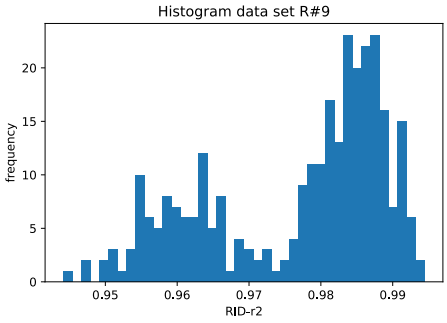

Histogram data set R#9
frequency
RID-msle


Histogram data set R#9
frequency
ENC-msle


Histogram data set R#9
frequency
RFR-msle


Histogram data set R#9
frequency
LIR-r2


Histogram data set R#9
frequency
LAS-r2


Histogram data set R#9
frequency
RID-r2

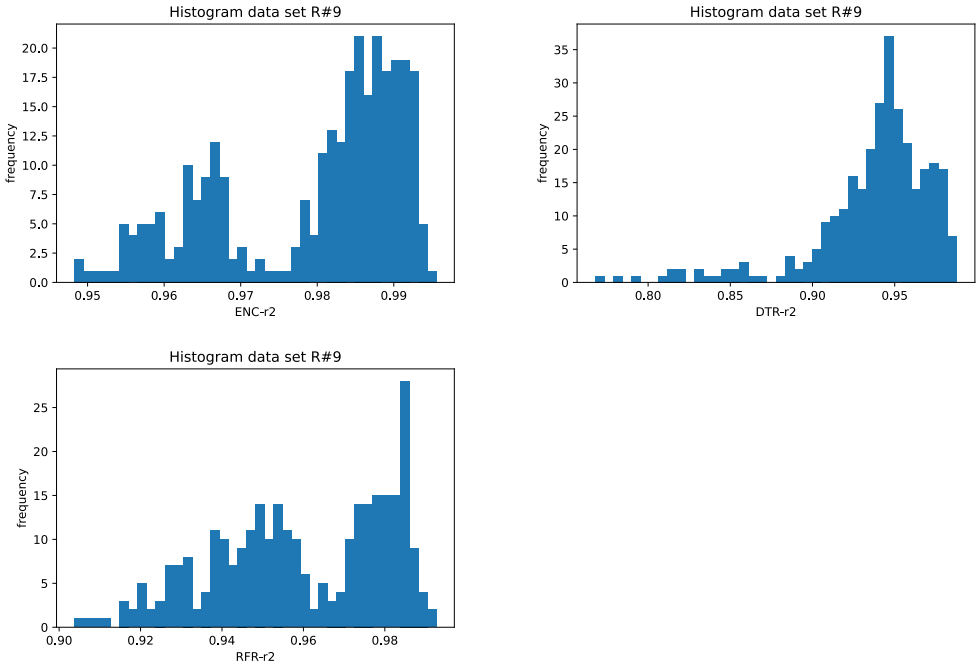


Figure A.15: Histograms of the algorithm-metrics distribution, which do not reach the p-value criteria; related to Table 2.16 and data set R#9.