Supplementary Material

Using the Gini coefficient to characterize the shape of computational chemistry error distributions

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Case	Property (units)	N	K	Source	Figure
BOR2019	Band gaps (eV)	471	15	[1]	1
NAR2019	Enthalpies of formation (kcal/mol)	469	4	[2]	2
PER2018	Intensive atomization energies (kcal/mol)	222	9	[3]	3
SCH2018	Chemisorption energies (eV)	195	7	[4]	4
THA2015	Polarizability (relative errors, in $\%$)	135	7	[5]	5
WU2015	Polarizability (relative errors, in $\%$)	145	36	[6]	6, 7
ZAS2019	Effective atomization energies (kcal/mol)	6211	3	[7]	8
ZHA2018	Solid formation enthalpies (kcal/mol)	196	2	[8]	9

Table 1: Case studies: N is the number of systems in the dataset and K is the number of methods.

1 Statistics

Statistics for the datasets listed in Table 1 are provided in the companion file "allStats.csv" for four combinations of the correction level (ctd = -1/1) and outliers treatment (out = FALSE/TRUE). The headers in the table are defined as follows (prefix 'u_' refers to uncertainty, obtained by bootstrapping with 1000 samples):

Dataset name of the dataset

Methods name of the method

ctd -1 = raw data; 1 = linear correction

out FALSE = raw data; TRUE = removal of global outliers

mue mean unsigned error

mse mean signed error

rmsd root mean squared deviation

q95hd 95th quantile of the absolute errors Q_{95} (Harrell-Davis estimator [9])

hrmode mode of the errors distribution (HRM estimator [10])

skew skewness (moments-based formula)

skewgm robust skewness (Groeneveld and Meeden estimator [11])

skewgm_mcf robust skewness of mode-centered errors

kurt kurtosis (moments-based formula)

kurtcs robust kurtosis excess [12]

gini Gini coefficient of the absolute errors G_F

gimc Gini coefficient of the mode-centered error distributionbmax value of the error bias maximizing the Gini coefficientgmax maximal value of the Gini coefficient (data centered on bmax)



2 ECDF and Lorenz curves

Figure 1: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from BOR2019.



Figure 2: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from NAR2019.



Figure 3: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from PER2018.



Figure 4: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from SCH2018.



Figure 5: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from THA2015.



Figure 6: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from WU2015 (1/2).



Figure 7: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from WU2015 (2/2).



Figure 8: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from ZAS2019.



Figure 9: Empirical cumulative distribution functions (ECDF) and Lorenz curves for absolute error sets from ZHA2018.

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