

High throughput tight binding calculation of electronic HOMO-LUMO gaps and its prediction for natural compounds

Sascha Thinius^[a]

Correspondence: sascha.thinius@ifam.fraunhofer.de; sascha.thinius.87@gmail.com

Hyperparameter optimization - optimized set of parameters for randomized search:

GBR: {'alpha': 0.9, 'ccp_alpha': 0.0, 'criterion': 'friedman_mse', 'init': None, 'learning_rate': 0.0321079969138713, 'loss': 'squared_error', 'max_depth': 12, 'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 1171, 'n_iter_no_change': None, 'random_state': None, 'subsample': 0.6917115704474215, 'tol': 0.0001, 'validation_fraction': 0.1, 'verbose': 0, 'warm_start': False}

MLPR: {'activation': 'relu', 'alpha': 0.00013539468639451956, 'batch_size': 'auto', 'beta_1': 0.9055614316573964, 'beta_2': 0.999, 'early_stopping': False, 'epsilon': 1e-08, 'hidden_layer_sizes': (300, 200, 100, 50), 'learning_rate': 'constant', 'learning_rate_init': 0.001, 'max_fun': 15000, 'max_iter': 500, 'momentum': 0.9, 'n_iter_no_change': 5, 'nesterovs_momentum': True, 'power_t': 0.5, 'random_state': None, 'shuffle': True, 'solver': 'adam', 'tol': 0.0005, 'validation_fraction': 0.1, 'verbose': False, 'warm_start': False}

GBR Model Feature Importance:

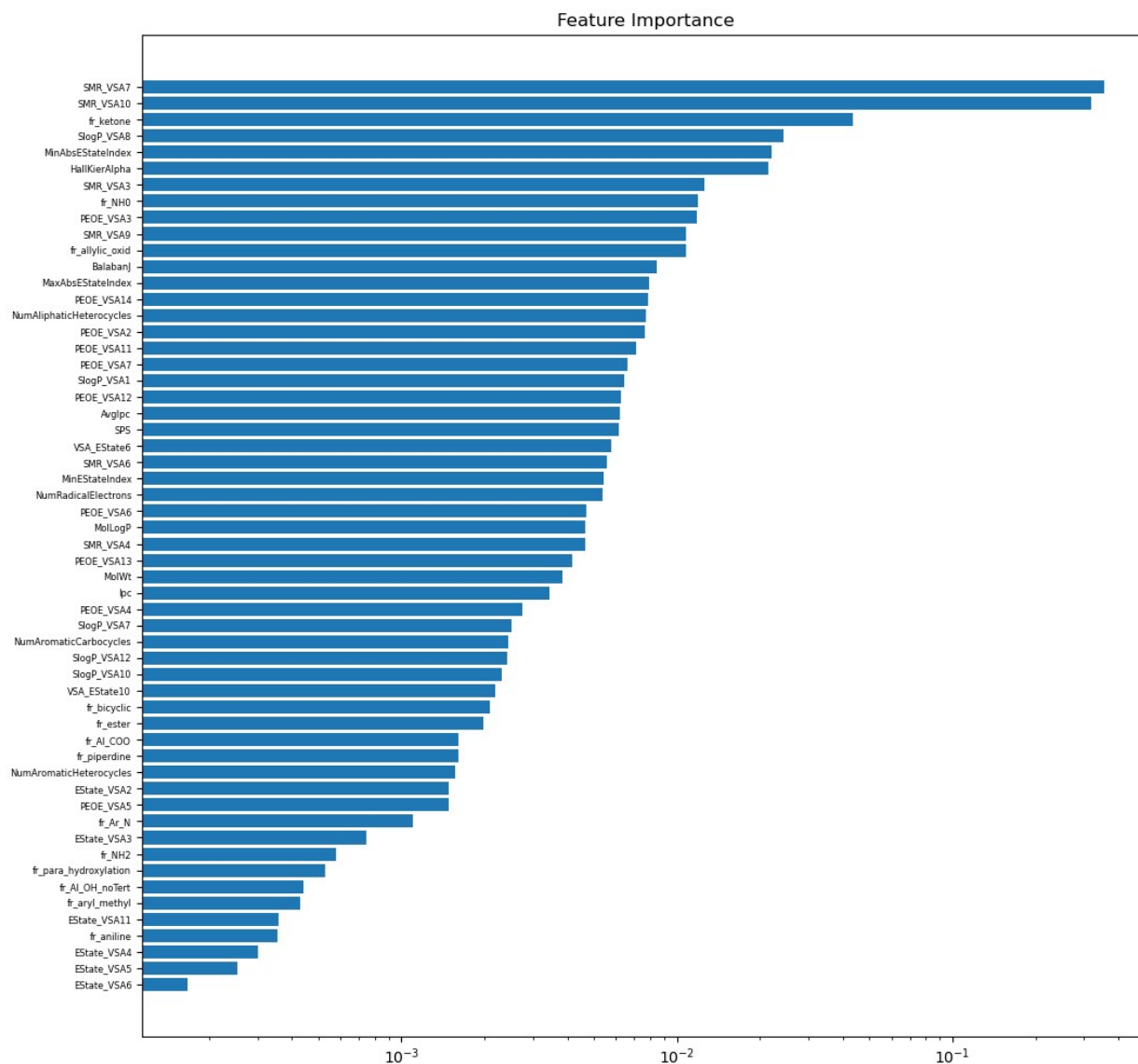


Figure S1: The relative importance of each molecular descriptor for the Gradient Boosting Regressor (GBR) model, sorted in descending order. The importance metric indicates the contribution of each feature to the model's predictions. The logarithmic scale on the x-axis highlights that the model's predictions are dominated by a few key features, primarily those related to molecular polarizability (SMR_VSA7, SMR_VSA10) and the presence of ketone fragments (fr_ketone).



table of the single descriptor contribution for the GBR model:

Table S1: The complete list of all molecular descriptors and their corresponding feature importance values for the Gradient Boosting Regressor (GBR) model, sorted in descending order.

descriptor	feature importance
SMR_VSA7	0.3545370506427196
SMR_VSA10	0.3189477603409475
fr_ketone	0.043355946009772654
SlogP_VSA8	0.024361114189223737
MinAbsEStateIndex	0.022079855516308193
HallKierAlpha	0.02142998649717104
SMR_VSA3	0.012575480656202306
fr_NH0	0.011926842442014604
PEOE_VSA3	0.011765650842991669
SMR_VSA9	0.010827996870413808
fr_allylic_oxid	0.010791493260704166
BalabanJ	0.008404100322501391
MaxAbsEStateIndex	0.007901535542237765
PEOE_VSA14	0.007843345900954273
NumAliphaticHeterocycles	0.007689300322622823
PEOE_VSA2	0.0076543614597266605
PEOE_VSA11	0.007132292603300951
PEOE_VSA7	0.006611842332520015
SlogP_VSA1	0.006409881164823698
PEOE_VSA12	0.00625829887237445
AvgIpc	0.006201809042991263
SPS	0.0061684746614582555
VSA_EState6	0.005771194866363084
SMR_VSA6	0.005542426338198005
MinEStateIndex	0.0054140764606567925
NumRadicalElectrons	0.00537131165165876
PEOE_VSA6	0.004669820678690445
MolLogP	0.004635016029957915
SMR_VSA4	0.00463256729367672
PEOE_VSA13	0.0041621834497876
MolWt	0.0038454106803835876
Ipc	0.0034334748375035337
PEOE_VSA4	0.0027347392046638535
SlogP_VSA7	0.002516851429005792
NumAromaticCarbocycles	0.0024361194223689506
SlogP_VSA12	0.0024094972964538723
SlogP_VSA10	0.0023022699682205545
VSA_EState10	0.002183400973898018
fr_bicyclic	0.0020944360754341315
fr_ester	0.0019736029426533157
fr_Al_COO	0.0016084339785770738
fr_piperdine	0.0016024953385289705
NumAromaticHeterocycles	0.0015646714728290855
EState_VSA2	0.0014830882240174821
PEOE_VSA5	0.001480804233055884
fr_Ar_N	0.001104413402410501
EState_VSA3	0.0007431130195376715
fr_NH2	0.0005780459353178737
fr_para_hydroxylation	0.0005277236836350452
fr_Al_OH_noTert	0.0004398099196385116
fr_aryl_methyl	0.0004306268701694323

EState_VSA11	0.0003571689919175693
fr_aniline	0.00035546111272848237
EState_VSA4	0.00030027576683221797
EState_VSA5	0.0002533586761247892
EState_VSA6	0.00016769028112372864

2D histogram plots for molecular subsets of chemical motifs (see table 3 in publication):

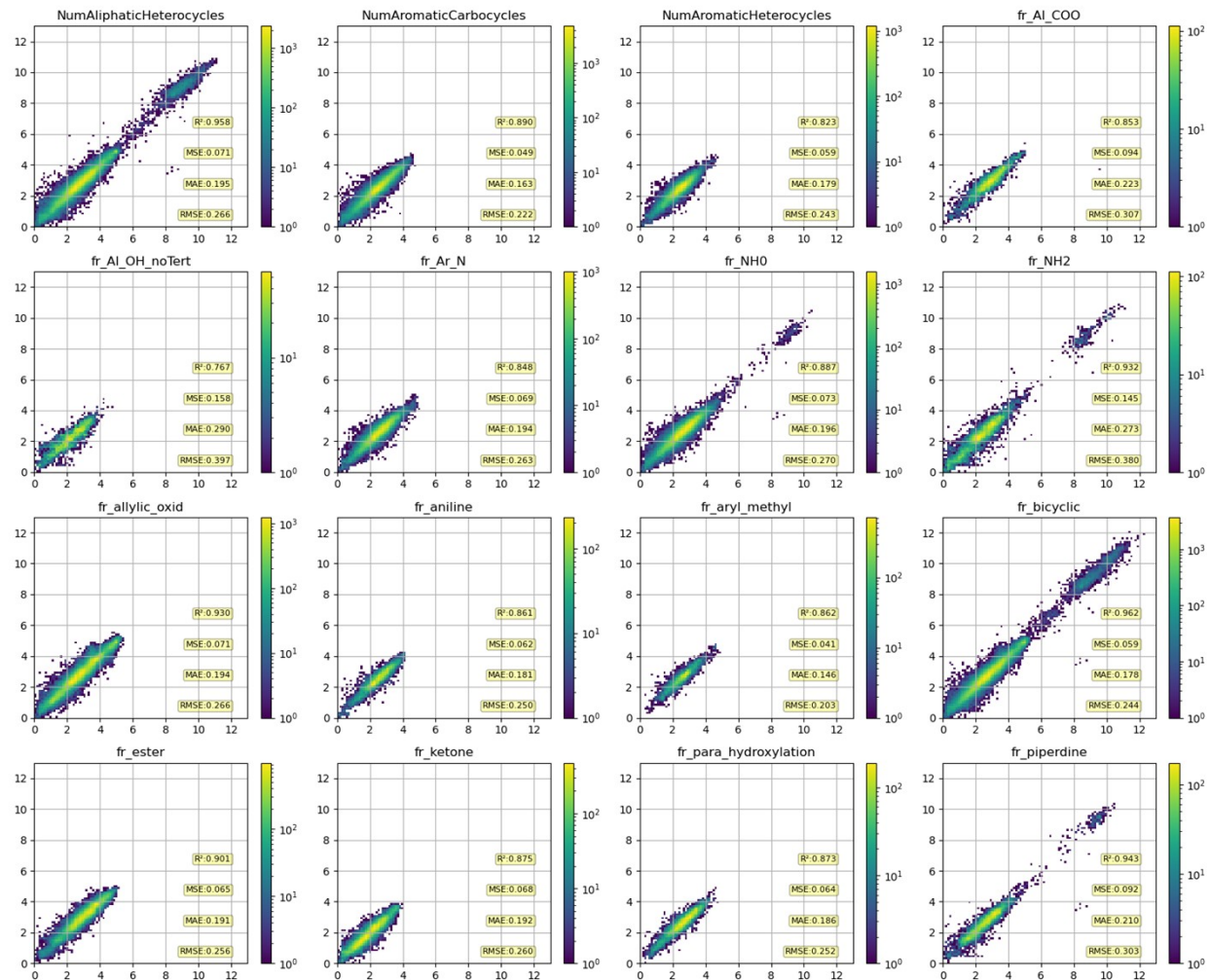


Figure S2: The provided scatterplot grid visualizes the relationship between predicted and actual HL-Gap values for various molecular subsets, each defined by a specific molecular descriptor or fragment count. Each plot displays predicted HL-Gap (GAP_P) on the x-axis and actual HL-Gap (GAP) on the y-axis, with color representing the density of molecules in each bin, where warmer colors indicate higher density.

Verification of Data Split Consistency:

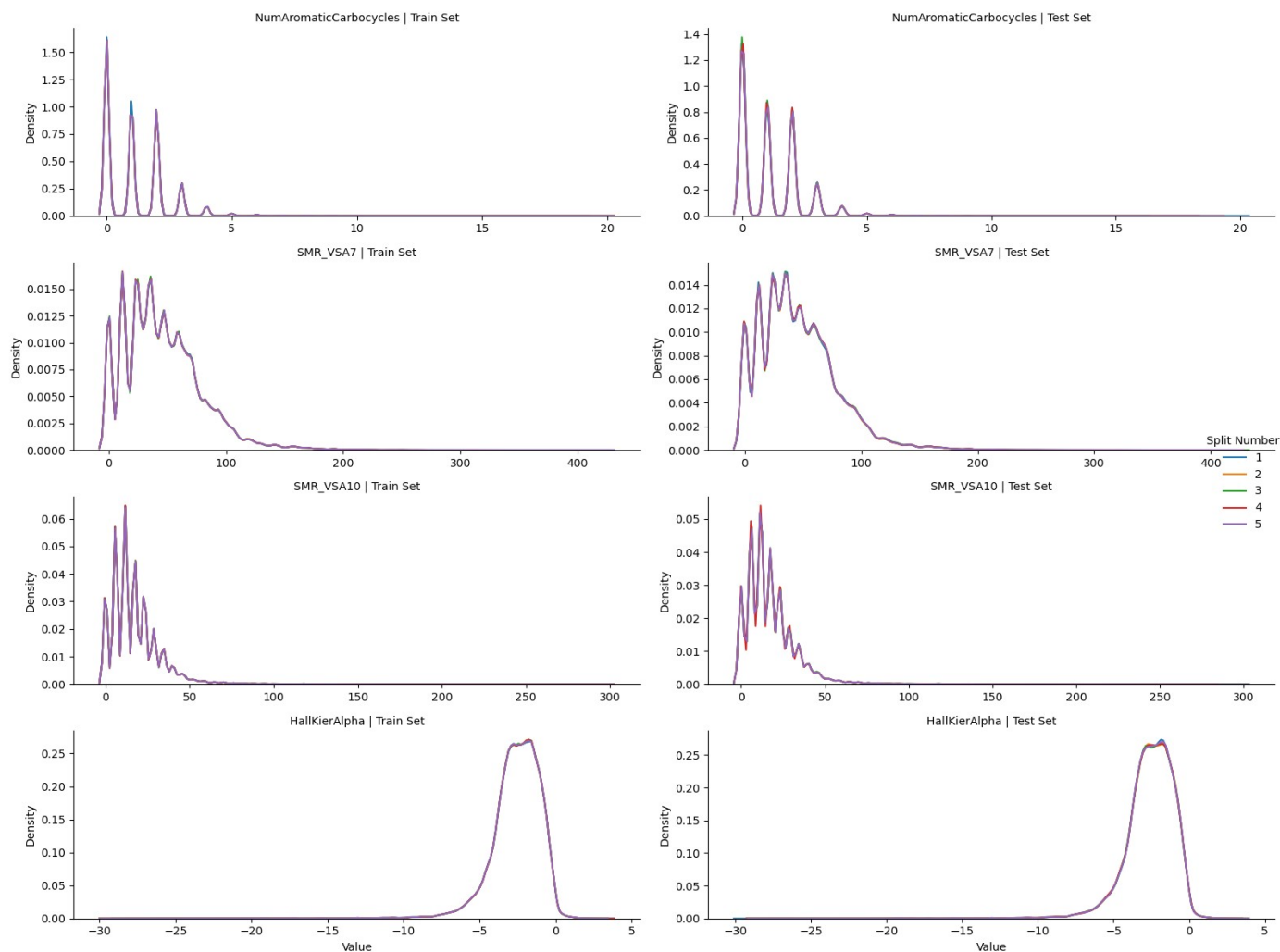


Figure S3: This grid of Kernel Density Estimate (KDE) plots visualizes the statistical distribution of four key molecular descriptors. Each row corresponds to a specific descriptor, and each column represents either the training (70%) or testing (30%) subset. Within each subplot, the five overlapping curves represent the data distribution from five independent, random splits. The high degree of overlap between the curves demonstrates that the data distributions are highly consistent and stable, validating that the random splitting methodology is robust and unbiased.