

1 **SUPPORTING INFORMATION**

2

3 **Nonadditivity in Public and Inhouse Data –**
4 **Implications for Drug Design**

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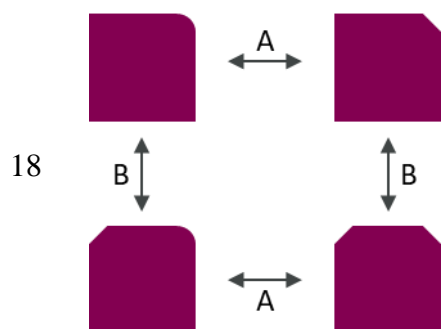
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13 A-B-AB SPLITTING STRATEGY

14 The idea behind this splitting strategy is to show if additive compounds can be predicted more
15 easily based on their matched pair compounds than nonadditive compounds.

16 Due to the random order in the matched square, any of the four compounds can be considered
17 as 'AB'. Within the matched square two transformation are available: A and B.



19 **Figure 1.** Schematic view of a DTC with two transformations indicated as 'A' and 'B'.

20
21 Irrespective of which compound is assigned as 'AB', if two other compounds of the cycle are
22 available, the information about both transformations A and B is included. For the nonadditive
23 compounds, there is a clear classification as test compound. Thus, the following strategy is
24 applied to generate the 'A-B-AB' nonadditive splitting:

- 25 1. Select all compounds with significant NA.
- 26 2. Select all DTC in which the NA compounds from 1. appear.
- 27 3. Selecting the NA compound from 1. as AB if a DTC from 2. is available where at least
28 two compounds are considered additive, i.e. below the significant threshold.
29 Compounds A and B do not need to be unique, i.e. only appearing in one DTC.
30 Information from up to five DTCs was used for constructing test/training data for NA
31 compounds.

32 Pseudo-code for selection of nonadditive AB compounds:

```
33 Get all NA cpds  
34 For each NA cpd:
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```
35     Get all DTC in which it appears
36     DTC_count = 0
37     For each DTC, while DTC_count < 5:
38         Get all 4 cpds and remove the NA cpd
39         Check remaining cpds themselves are additive
40         If  $\geq 2$  cpds remain:
41             Assign NA cpd to test set
42             Assign additive cpds as training
43             DTC_count += 1
```

44 For the additive compounds to be separated into A-B-AB, no clear identification for test is
45 available, since all compounds are additive. Therefore, the following strategy was applied:

- 46 1. Select all additive compounds not yet assigned to nonadditive test or training data.
- 47 2. Select all DTC in which the compounds from 1. appear.
- 48 3. Store compounds from 1. and 2. if a DTC from 2. is available where at least two
49 compounds are considered additive, i.e. below the significant threshold. Compounds A
50 and B do not need to be unique, i.e. only appearing in one DTC.
- 51 4. Randomize the list of compounds.
- 52 5. Assigning compounds to test data if
 - 53 a. The compound is not in the additive training data.
 - 54 b. The compound has at least two additive compounds in a DTC which are not yet
55 assigned to either test or training data.
 - 56 c. If 20 % of the total number of additive compounds, i.e. training set from the
57 selection of nonadditive A-B-AB and all remaining additive compounds, has not
58 been reached.
- 59 6. Assign compounds to training data that are additive and in a DTC selected by 5.
- 60 7. All remaining cpds are considered as training if they have not been assigned as test
61 cases.

62 Pseudo-code for selection of additive AB compounds:

63 Add_cpd_list = []

64 Add_training_set = []

65 Add_test_set = []

66 Get all additive cpds not yet assigned to test or training NA

67 For each additive cpd:

68 Get all DTC in which it appears

69 For each DTC:

70 Get all 4 cpds and remove the additive cpd

71 Check remaining cpds themselves are additive

72 If ≥ 2 cpds remain:

73 Add_cpd_list append cpds

74 Randomize Add_cpd_list

75 For each cpd_X in Add_cpd_list:

76 If cpd_X is not in Add_training_set and

77 If DTC cpds of cpd_X are and

78 If ≥ 2 DTC cpds of cpd_X are additive and

79 not in Add_training_set or Add_test_set and

80 If Add_test_set < 20 % of all additive compounds:

81 Add_test_set append cpd_X

82 Add_training_set append DTC cpds of cpd_X

83 Else:

84 Add_training_set append cpd_X

85 Due to the random selection of compounds (Step 4) to be considered for the additive test set,

86 this randomization is done twice with different random seeds to see any performance difference

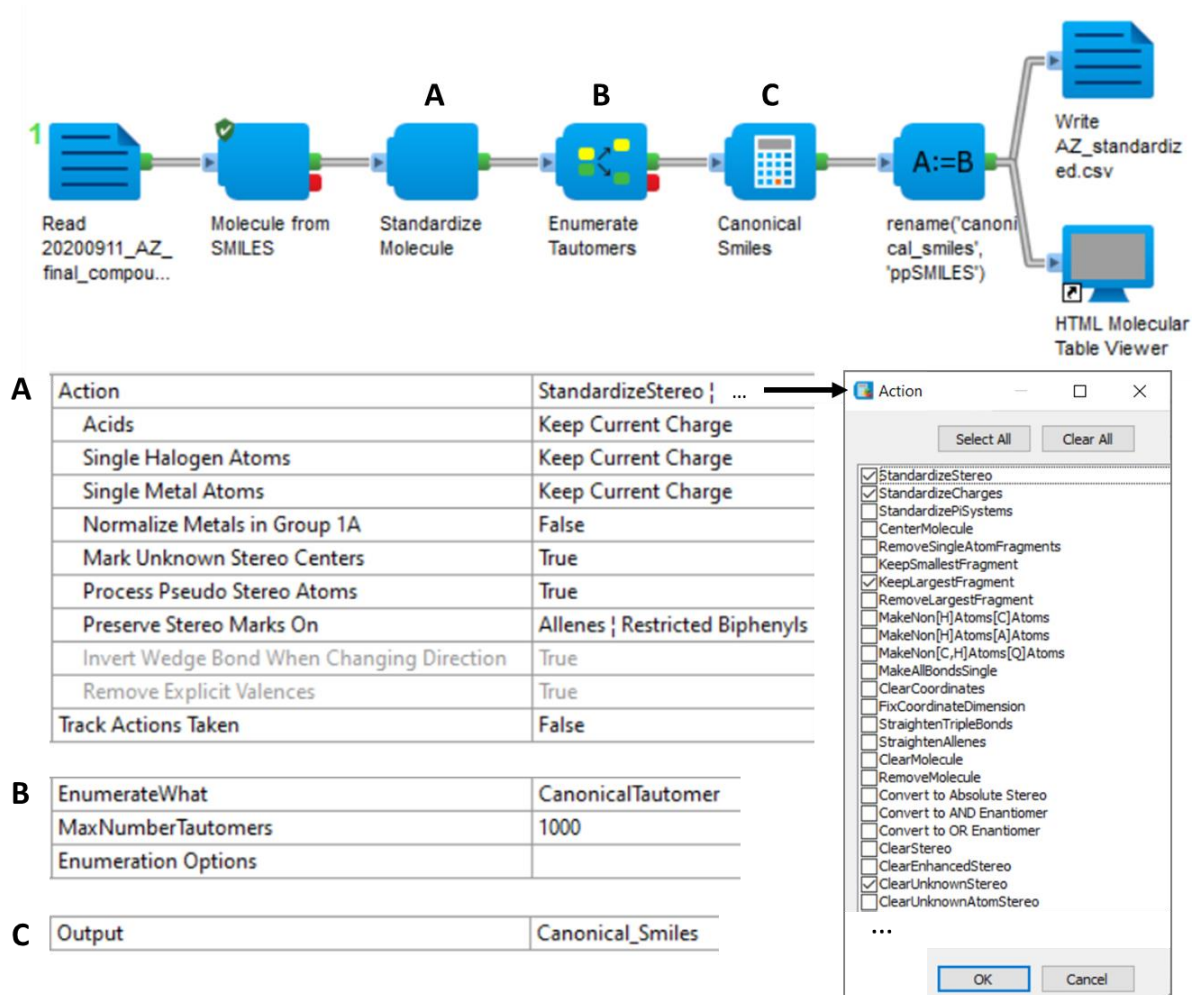
87 just based on splitting.

88 **Table S 1.** Overview of different models trained for each selected ChEMBL data set

| Model ID | Data | Training | Test ID | Test | Rdm seed |
|----------|------|------------------------------|---------|----------------|----------|
| 1 | DTC | 80 % nonsig | a | 20 % nonsig | |
| | | | b | all NA cpds | |
| 2 | DTC | 80 % nonsig + Q1 NA cpds | a | mix in NA cpds | |
| 3 | DTC | 80 % nonsig + median NA cpds | a | mix in NA cpds | |
| 4 | DTC | 80 % nonsig + Q3 NA cpds | a | mix in NA cpds | |
| 5 | all | 80 % nonsig | a | 20 % nonsig | |
| | | | b | all NA cpds | |

| | | | | | |
|----|-----|------------------------------|---|-----------------------|---|
| 6 | all | 80 % nonsig + Q1 NA cpds | a | mix in NA cpds | |
| 7 | all | 80 % nonsig + median NA cpds | a | mix in NA cpds | |
| 8 | all | 80 % nonsig + Q3 NA cpds | a | mix in NA cpds | |
| 9 | DTC | 80 % A-B cpds | a | test additive AB cpds | 4 |
| | | | b | NA AB cpds | |
| | | | c | remaining NA cpds | |
| 10 | DTC | 80 % A-B cpds | a | test additive AB cpds | 7 |
| | | | b | NA AB cpds | |
| | | | c | remaining NA cpds | |
| 11 | all | 80 % A-B cpds + 80 % nonsig | a | test additive AB cpds | 4 |
| | | | b | NA AB cpds | |
| | | | c | remaining NA cpds | |
| | | | d | 20 % nonsig | |
| 12 | all | 80 % A-B cpds + 80 % nonsig | a | test additive AB cpds | 7 |
| | | | b | NA AB cpds | |
| | | | c | remaining NA cpds | |
| | | | d | 20 % nonsig | |

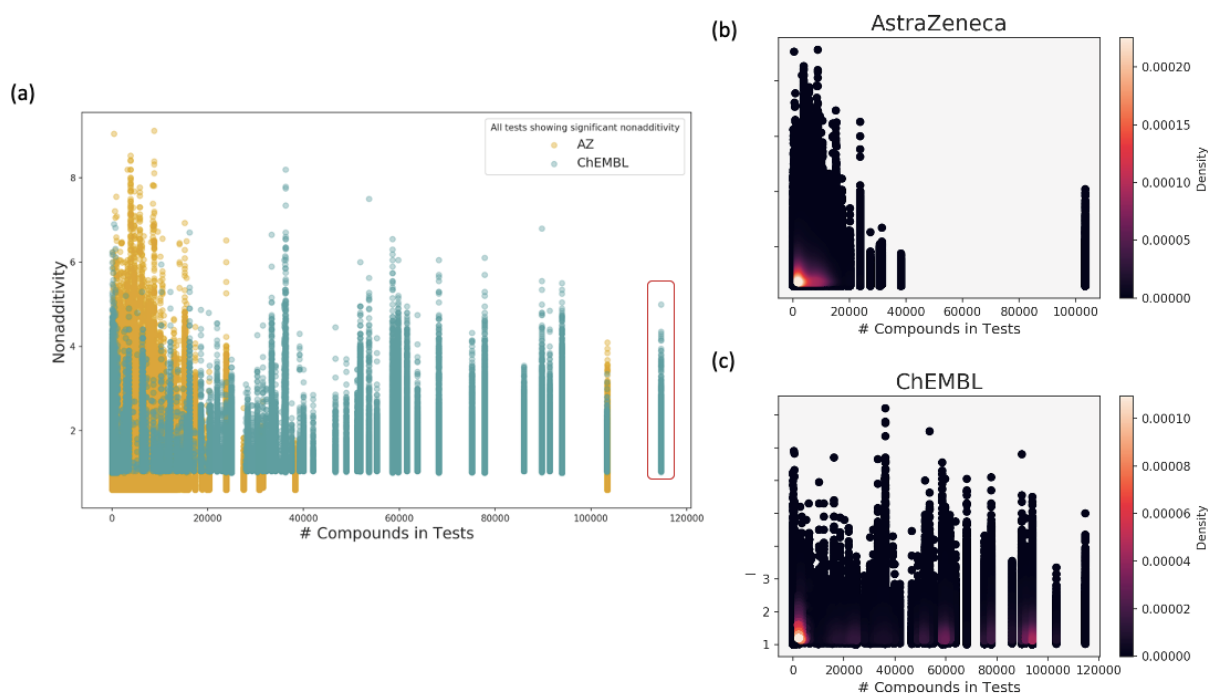
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91 **Figure S 1.** PipelinePilot standardization protocol used for inhouse and ChEMBL SMILES; further options for
 92 components A and B were used as given by default.

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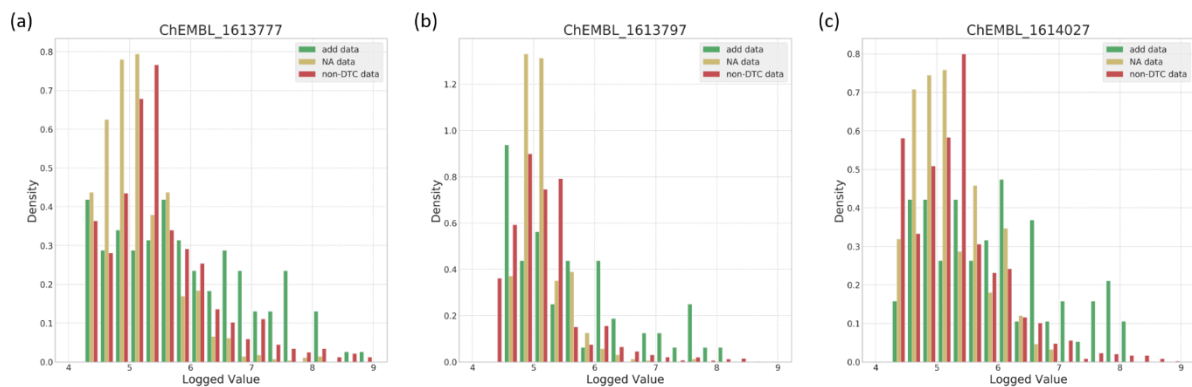


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95 **Figure S 2.** (a) Distribution of the tests from AZ (yellow) and ChEMBL (blue) based on the size of the test and
 96 obtained NA values overlaid. CHEMBL1794483 test is highlighted in red. Density distribution separately for AZ
 97 (b) and ChEMBL (c) tests.

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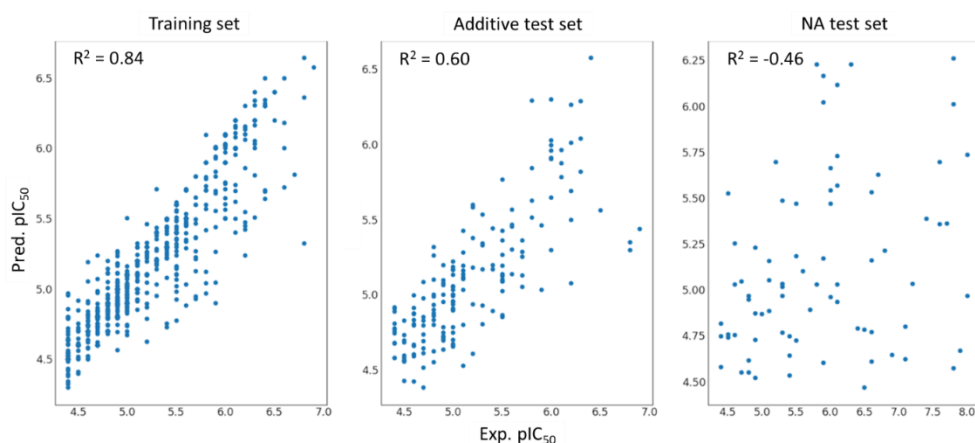
101 **Figure S 3.** pIC₅₀ coverage of selected ChEMBL data sets used for QSAR prediction models. Green: additive
 102 compounds, yellow: nonadditive compounds, red: non-DTC compounds. Nonadditive compounds have a
 103 significant NA value > 1.0 log unit.

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105
106**Table S 2.** Model performance for ChEMBL1614027. Random Forest (RF) and Support Vector Machine (SVM) were trained for models 1-8. A PLS models (model ID 13/14) was trained based on DTC and all data.

| Model ID | Data | Training data | # training | Test ID | Test data | # test | algorithm | R ² (RF/SVM) | RMSE (RF/SVM) | Rdm seed |
|----------|------|------------------------------|------------|---------|-----------------------|--------|-----------|-------------------------|---------------|----------|
| 1 | DTC | 80 % nonsig | 692 | a | 20 % nonsig | 173 | RF/SVM | 0.598 / 0.602 | 0.364 / 0.362 | |
| | | | | b | all NA cpds | 76 | RF/SVM | -0.479 / -0.463 | 1.256 / 1.249 | |
| 2 | DTC | 80 % nonsig + Q1 NA cpds | 697 | a | mixin NA cpds | 58 | RF/SVM | -0.605 / -0.59 | 1.342 / 1.335 | |
| 3 | DTC | 80 % nonsig + median NA cpds | 701 | a | mixin NA cpds | 58 | RF/SVM | -0.561 / -0.569 | 1.323 / 1.327 | |
| 4 | DTC | 80 % nonsig + Q3 NA cpds | 710 | a | mixin NA cpds | 58 | RF/SVM | -0.551 / -0.586 | 1.319 / 1.334 | |
| 5 | all | 80 % nonsig | 2240 | a | 20 % nonsig | 560 | RF/SVM | 0.336 / 0.317 | 0.567 / 0.574 | |
| | | | | b | all NA cpds | 76 | RF/SVM | -0.355 / -0.428 | 1.202 / 1.234 | |
| 6 | all | 80 % nonsig + Q1 NA cpds | 2255 | a | mixin NA cpds | 19 | RF/SVM | -0.446 / -0.747 | 1.27 / 1.396 | |
| 7 | all | 80 % nonsig + median NA cpds | 2269 | a | mixin NA cpds | 19 | RF/SVM | -0.467 / -0.724 | 1.279 / 1.386 | |
| 8 | all | 80 % nonsig + Q3 NA cpds | 2297 | a | mixin NA cpds | 19 | RF/SVM | -0.526 / -0.702 | 1.304 / 1.377 | |
| 9 | DTC | 80 % A-B cpds | 692 | a | test additive AB cpds | 173 | RF | 0.61 | 0.366 | 4 |
| | | | | b | NA AB cpds | 39 | RF | -0.617 | 1.385 | |
| | | | | c | remaining NA cpds | 37 | RF | -0.271 | 1.082 | |
| 10 | DTC | 80 % A-B cpds | 692 | a | test additive AB cpds | 173 | RF | 0.69 | 0.315 | 7 |
| | | | | b | NA AB cpds | 39 | RF | -0.66 | 1.404 | |
| | | | | c | remaining NA cpds | 37 | RF | -0.219 | 1.059 | |
| 11 | all | 80 % A-B cpds + 80 % nonsig | 2240 | a | test additive AB cpds | 173 | RF | 0.589 | 0.379 | 4 |
| | | | | b | NA AB cpds | 39 | RF | -0.514 | 1.34 | |
| | | | | c | remaining NA cpds | 37 | RF | -0.113 | 1.012 | |
| | | | | d | 20 % nonsig | 387 | RF | 0.219 | 0.677 | |
| 12 | all | 80 % A-B cpds + 80 % nonsig | 2240 | a | test additive AB cpds | 173 | RF | 0.63 | 0.344 | 7 |
| | | | | b | NA AB cpds | 39 | RF | -0.578 | 1.368 | |
| | | | | c | remaining NA cpds | 37 | RF | -0.065 | 0.99 | |
| | | | | d | 20 % nonsig | 387 | RF | 0.198 | 0.686 | |
| 13 | DTC | 80 % nonsig | 692 | a | 20 % nonsig | 173 | PLS | 0.537 | 0.39 | |
| | | | | b | all NA cpds | 76 | PLS | -0.6 | 1.306 | |
| 14 | all | 80% nonsig | 2240 | a | 20 % nonsig | 560 | PLS | 0.246 | 0.603 | |
| | | | | b | all NA cpds | 76 | PLS | -0.394 | 1.219 | |

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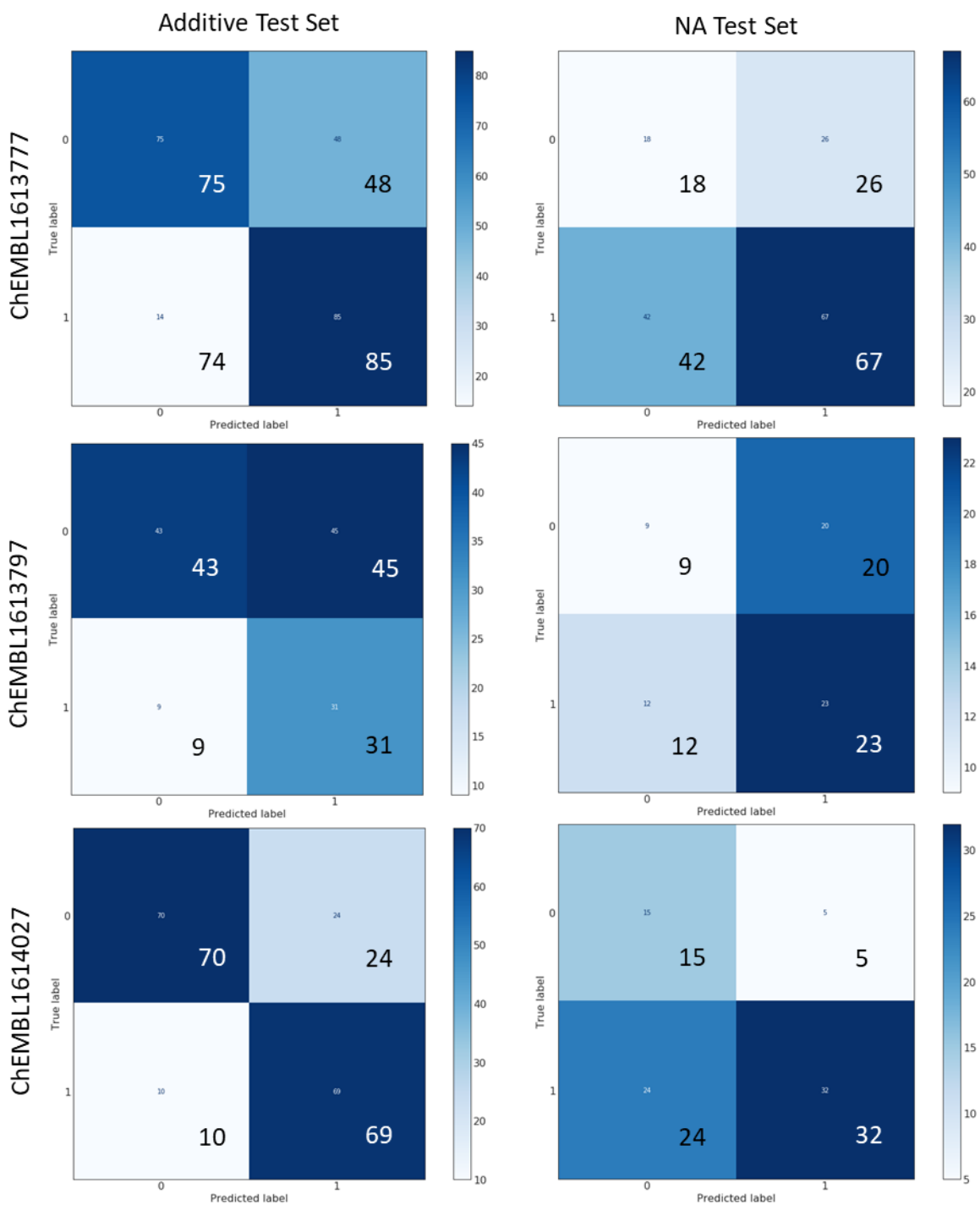
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109**Figure S 4.** SVM correlation plots for ChEMBL1614027.

110 **Table S 3.** Random Forest model performance for ChEMBL1613777.

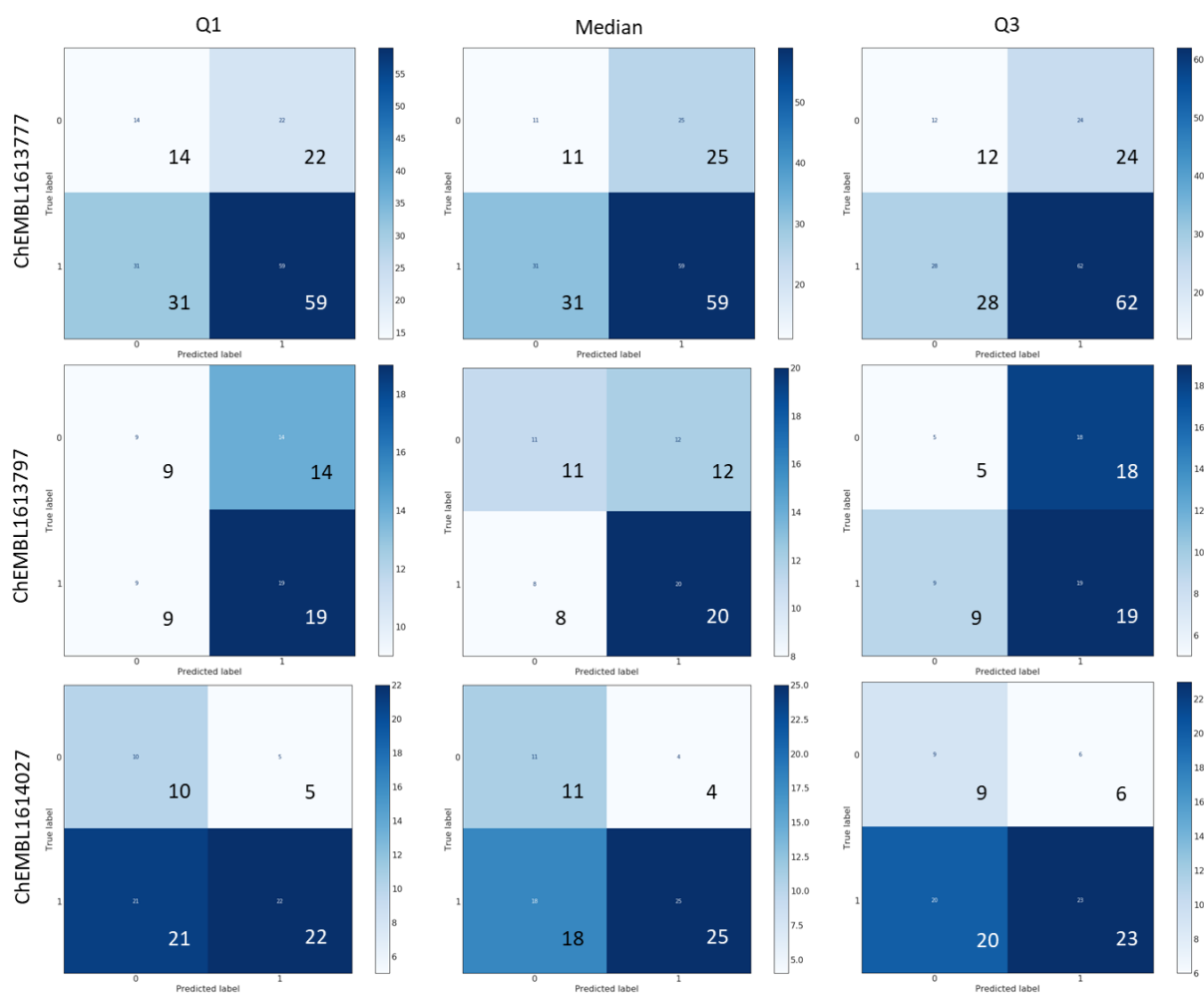
| Model ID | Data | Training data | # training | Test ID | Test data | # test | R ² | RMSE | Rdm seed |
|-----------|------|------------------------------|------------|---------|-----------------------|--------|----------------|--------------|----------|
| 1 | DTC | 80 % nonsig | 886 | a | 20 % nonsig | 222 | 0.564 | 0.442 | |
| | | | | b | all NA cpds | 153 | -0.431 | 1.296 | |
| 2 | DTC | 80 % nonsig + Q1 NA cpds | 893 | a | mixin NA cpds | 126 | -0.443 | 1.29 | |
| 3 | DTC | 80 % nonsig + median NA cpds | 900 | a | mixin NA cpds | 126 | -0.443 | 1.29 | |
| 4 | DTC | 80 % nonsig + Q3 NA cpds | 913 | a | mixin NA cpds | 126 | -0.384 | 1.264 | |
| 5 | all | 80 % nonsig | 2675 | a | 20 % nonsig | 669 | 0.22 | 0.684 | |
| | | | | b | all NA cpds | 153 | -0.339 | 1.254 | |
| 6 | all | 80 % nonsig + Q1 NA cpds | 2694 | a | mixin NA cpds | 80 | -0.234 | 1.203 | |
| 7 | all | 80 % nonsig + median NA cpds | 2712 | a | mixin NA cpds | 80 | -0.218 | 1.195 | |
| 8 | all | 80 % nonsig + Q3 NA cpds | 2748 | a | mixin NA cpds | 80 | -0.168 | 1.17 | |
| 9 | DTC | 80 % A-B cpds | 918 | a | test additive AB cpds | 190 | 0.535 | 0.387 | 4 |
| | | | | b | NA AB cpds | 127 | -0.388 | 1.265 | |
| | | | | c | remaining NA cpds | 26 | -0.423 | 1.318 | |
| 10 | DTC | 80 % A-B cpds | 920 | a | test additive AB cpds | 188 | 0.455 | 0.413 | 7 |
| | | | | b | NA AB cpds | 127 | -0.394 | 1.268 | |
| | | | | c | remaining NA cpds | 26 | -0.405 | 1.31 | |
| 11 | all | 80 % A-B cpds + 80 % nonsig | 2706 | a | test additive AB cpds | 190 | 0.433 | 0.428 | 4 |
| | | | | b | NA AB cpds | 127 | -0.383 | 1.263 | |
| | | | | c | remaining NA cpds | 26 | -0.236 | 1.229 | |
| | | | | d | 20 % nonsig | 448 | 0.11 | 0.806 | |
| 12 | all | 80 % A-B cpds + 80 % nonsig | 2708 | a | test additive AB cpds | 188 | 0.439 | 0.419 | 7 |
| | | | | b | NA AB cpds | 127 | -0.329 | 1.238 | |
| | | | | c | remaining NA cpds | 26 | -0.261 | 1.241 | |
| | | | | d | 20 % nonsig | 448 | 0.129 | 0.797 | |

111 **Table S 4** Random forest model performance for ChEMBL1613797.

| Model ID | Data | Training data | # training | Test ID | Test data | # test | R ² | RMSE | Rdm seed |
|-----------|------|------------------------------|------------|---------|-----------------------|--------|----------------|-------|----------|
| 1 | DTC | 80 % nonsig | 509 | a | 20 % nonsig | 128 | 0.047 | 0.407 | |
| | | | | b | all NA cpds | 64 | -0.286 | 1.142 | |
| 2 | DTC | 80 % nonsig + Q1 NA cpds | 513 | a | mixin NA cpds | 51 | -0.237 | 1.179 | |
| 3 | DTC | 80 % nonsig + median NA cpds | 516 | a | mixin NA cpds | 51 | -0.226 | 1.174 | |
| 4 | DTC | 80 % nonsig + Q3 NA cpds | 522 | a | mixin NA cpds | 51 | -0.25 | 1.185 | |
| 5 | all | 80 % nonsig | 4924 | a | 20 % nonsig | 1231 | 0.05 | 0.578 | |
| | | | | b | all NA cpds | 64 | -0.212 | 1.109 | |
| 6 | all | 80 % nonsig + Q1 NA cpds | 4940 | a | mixin NA cpds | 3 | -0.233 | 0.499 | |
| 7 | all | 80 % nonsig + median NA cpds | 4955 | a | mixin NA cpds | 3 | -0.429 | 0.538 | |
| 8 | all | 80 % nonsig + Q3 NA cpds | 4985 | a | mixin NA cpds | 3 | -0.143 | 0.481 | |
| 9 | DTC | 80 % A-B cpds | 515 | a | test additive AB cpds | 122 | 0.025 | 0.385 | 4 |
| | | | | b | NA AB cpds | 28 | -0.554 | 1.259 | |
| | | | | c | remaining NA cpds | 36 | -0.123 | 0.983 | |
| 10 | DTC | 80 % A-B cpds | 510 | a | test additive AB cpds | 122 | 0.102 | 0.331 | 7 |
| | | | | b | NA AB cpds | 28 | -0.6 | 1.277 | |
| | | | | c | remaining NA cpds | 36 | -0.103 | 0.974 | |
| 11 | all | 80 % A-B cpds + 80 % nonsig | 4929 | a | test additive AB cpds | 122 | 0.035 | 0.383 | 4 |
| | | | | b | NA AB cpds | 28 | -0.607 | 1.28 | |
| | | | | c | remaining NA cpds | 36 | -0.117 | 0.981 | |
| | | | | d | 20 % nonsig | 1104 | 0.048 | 0.595 | |
| 12 | all | 80 % A-B cpds + 80 % nonsig | 4924 | a | test additive AB cpds | 122 | 0.039 | 0.342 | 7 |
| | | | | b | NA AB cpds | 28 | -0.574 | 1.267 | |
| | | | | c | remaining NA cpds | 36 | -0.119 | 0.981 | |
| | | | | d | 20 % nonsig | 1104 | 0.046 | 0.595 | |



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 113 **Figure S 5.** Confusion matrices for the binary classification of additive and nonadditive test sets. Predictions were
 114 done using RF models, binary classification was based on $pIC_{50} = 5$.
 115



116

117 **Figure S 6.** Confusion matrices for binary classification for the ‘mixin’ data sets. Predictions were done using RF
 118 models, binary classification was based on $pIC_{50} = 5$.
 119