Table S6 Utilization of one-class SVM in the selection of negative samples
(A) One-class SVM models constructed from the DrugBank dataset.

| ${ }^{1}$ kernel | 10-fold cross validation accuracy (\%) | ${ }^{2}$ self-prediction accuracy |
| :---: | :---: | :---: |
| sigmoid | 87.2 | 92.1 |
| RBF | 50.1 | 50.0 |
| polynomial | 50.0 | 50.0 |

(B) Results of comprehensive prediction

| ${ }^{3}$ kernel | ${ }^{4}$ rule | ${ }^{5}$ accuracy | ${ }^{6} \mathrm{P} 10275$ | ${ }^{6} \mathrm{P} 11229$ | ${ }^{6} \mathrm{P} 35367$ | ${ }^{7}$ evaluation |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RBF | min | 99.9 | 81317 | 40897 | 35466 | 27.2 |
| RBF | mle | 99.9 | 4470 | 10977 | 22240 | 61.7 |
| sigmoid | min | 99.8 | 79553 | 54180 | 48262 | 11.9 |
| sigmoid | mle | 97.8 | 16194 | 3316 | 392 | 13.5 |

${ }^{1}$ : Kernel functions used to train one-class SVM models. $\operatorname{RBF}\left(f\left(\boldsymbol{x}, \boldsymbol{y}=\exp \left(-\gamma|\boldsymbol{x}-\boldsymbol{y}|^{2}\right)\right), \operatorname{sigmoid}\left(f(\boldsymbol{x}, \boldsymbol{y})=\tanh \left(\gamma \boldsymbol{x}^{t} \boldsymbol{y}+c\right)\right)\right.$, and polynomial $\left(f(\boldsymbol{x}, \boldsymbol{y})=\left(\gamma \boldsymbol{x}^{t} \boldsymbol{y}+c\right)^{d}\right)$. Here, $\gamma, c$ and $d$ are constants.
${ }^{2}$ : prediction accuracy when a prediction model was constructed from the whole DrugBank dataset and applied to the DrugBank dataset.
3: kernel functions used to train the second-layer SVM model.
4: selection rule of candidates for negative data. The one-class SVM model using the sigmoid kernel (A) was applied to all the combinations of proteins and chemical compounds in DrugBank dataset except positives, which were represented as described in Sec. 2.3 in Supplementary Materials, and negative samples were selected according to the following selection rules.
min: Top $n$ samples in the ascending order of the decision values.
$m l e$ : Top $n$ samples in the descending order of the decision values whose decision values were under 0 .
Here, if the decision value for a sample was above 0 , the sample was supposed to be included in the high-density region which was estimated from positive samples. There existed no samples whose decision value equaled to 0 .
5: 10-fold cross-validation accuracy $(=(T P+T N) /(T P+F N+T N+F P))$ of the second-layer SVM. 24,500 negatives and 10 subpos first-layer SVM models were used to train the second-layer SVM model. TP: true positives, TN: true negatives, FN: false negatives, FP: false positives.
${ }^{6}$ : target proteins whose ligands were predicted on the basis of 109,841 compounds. The number of predicted binding compounds is shown.
7:
evaluation $=100 \times\left(\frac{1}{2}\left[\operatorname{rec}_{0.5}+\frac{\operatorname{rec}_{0.95}+\operatorname{prec}_{0.95}}{2\left\{1+\left(1-\operatorname{rec}_{0.95}\right)\left(1-\operatorname{prec}_{0.95}\right)\right\}}\right]-\frac{\text { total \# of predicted positives }- \text { \# of known positives }}{\text { total \# of prediction targets }- \text { \# of known positives }}\right)$,
where $\operatorname{rec}_{x}$ is the recall rate $(=\mathrm{TP} /(\mathrm{TP}+\mathrm{FN}))$ at the threshold $x$, ranging from 0 to 1.0 .5 is the threshold following the definition of SVM. TP: true positives, FN: false negatives.

