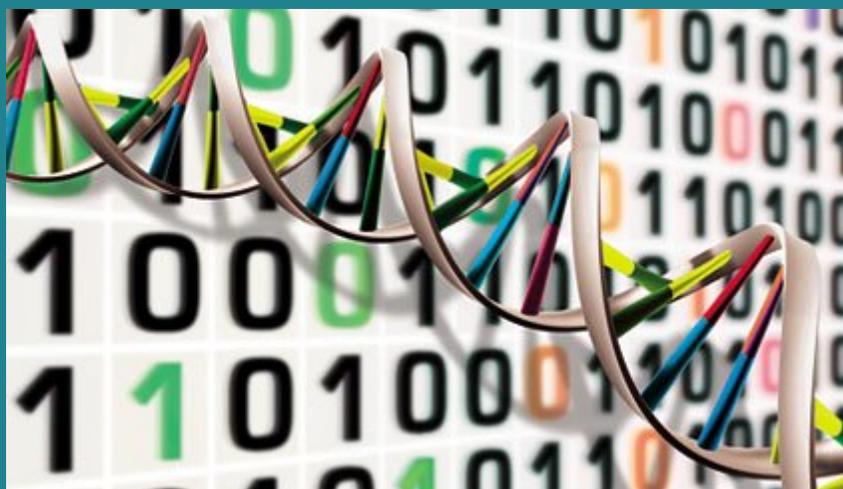https://comptox.epa.gov/dashboard/web-test/

User's Guide for WebTEST (version 1.0) (Web-services Toxicity Estimation Software Tool)

A Web-Services Program to Estimate Toxicity from Molecular Structure

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User's Guide for T.E.S.T.
(Toxicity Estimation Software Tool)

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The U.S. Environmental Protection Agency, through its Office of Research and Development, funded and conducted the research described herein under an approved Quality Assurance Project Plan (Quality Assurance Identification Number G-STD-0013882-QP-1-3). It has been subjected to the Agency's peer and administrative review and has been approved for publication as an EPA document. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

Foreword

The U.S. Environmental Protection Agency (US EPA) is charged by Congress with protecting the Nation's land, air, and water resources. Under a mandate of national environmental laws, the Agency strives to formulate and implement actions leading to a compatible balance between human activities and the ability of natural systems to support and nurture life. To meet this mandate, US EPA's research program is providing data and technical support for solving environmental problems today and building a science knowledge base necessary to manage our ecological resources wisely, understand how pollutants affect our health, and prevent or reduce environmental risks in the future.

The National Risk Management Research Laboratory (NRMRL) within the Office of Research and Development (ORD) is the Agency's center for investigation of technological and management approaches for preventing and reducing risks from pollution that threaten human health and the environment. The focus of the Laboratory's research program is on methods and their cost-effectiveness for prevention and control of pollution to air, land, water, and subsurface resources; protection of water quality in public water systems; remediation of contaminated sites, sediments and ground water; prevention and control of indoor air pollution; and restoration of ecosystems. NRMRL collaborates with both public and private sector partners to foster technologies that reduce the cost of compliance and to anticipate emerging problems. NRMRL's research provides solutions to environmental problems by: developing and promoting technologies that protect and improve the environment; advancing scientific and engineering information to support regulatory and policy decisions; and providing the technical support and information transfer to ensure implementation of environmental regulations and strategies at the national, state, and community levels.

Abstract

This guide provides an introduction into QSAR (Quantitative Structure Activity Relationship) models, a detailed description of the QSAR methodologies in TEST, a description of the experimental datasets, a detailed analysis of the validation results for the external test sets, and step-by-step instructions for using the software.

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1. Introduction

Quantitative Structure Activity Relationships (QSARs) are mathematical models that are used to predict measures of toxicity from physical characteristics of the structure of chemicals (known as molecular descriptors). Acute toxicities (such as the concentration, which causes half of fish to die) are one example of toxicity measures, which may be predicted from QSARs. Simple QSAR models calculate the toxicity of chemicals using a simple linear function of molecular descriptors:

$$Toxicity = ax_1 + bx_2 + c$$

where x_1 and x_2 are the independent descriptor variables and *a*, *b*, and *c* are fitted parameters. The molecular weight and the octanol-water partition coefficient are examples of molecular descriptors.

QSAR toxicity predictions may be used to screen untested compounds in order to establish priorities for expensive and time-consuming traditional bioassays designed to establish toxicity levels. When conditions do not permit traditional bioassays, QSARs are an alternative to bioassays for estimating toxicity. In addition, QSAR models are useful for estimating toxicities needed for green process design algorithms such as the Waste Reduction Algorithm [1].

The Toxicity Estimation Software Tool (T.E.S.T.) has been developed to allow users to easily estimate toxicity using a variety of QSAR methodologies. T.E.S.T allows a user to estimate toxicity without requiring any external programs. Users can input a chemical to be evaluated by drawing it in an included chemical sketcher window, entering a structure text file, or importing it from an included database of structures. Once a chemical has been entered, its toxicity can be estimated using one of several advanced QSAR methodologies. The program does not require molecular descriptors from external software packages (the required descriptors are calculated within T.E.S.T.).

1.1. Toxicity Endpoints

T.E.S.T allows you to estimate the value for several toxicity end points:
1. 96 hour fathead minnow LC_{50} (concentration of the test chemical in water in mg/L that causes 50% of fathead minnow to die after 96 hours)
2. 48 hour *Daphnia magna* LC_{50} (concentration of the test chemical in water in mg/L that causes 50% of *Daphnia magna* to die after 48 hours)
3. 48 hour *Tetrahymena pyriformis* IGC_{50} (concentration of the test chemical in water in mg/L that causes 50% growth inhibition to *Tetrahymena pyriformis* after 48 hours)
4. Oral rat LD_{50} (amount of chemical in mg/kg body weight that causes 50% of rats to die after oral ingestion)
5. Bioaccumulation factor (ratio of the chemical concentration in fish as a result of absorption via the respiratory surface to that in water at steady state)
6. Developmental toxicity (whether or not a chemical causes developmental toxicity

effects to humans or animals)

7. Ames mutagenicity (a compound is positive for mutagenicity if it induces revertant colony growth in any strain of *Salmonella typhimurium*)

T.E.S.T. allows you estimate several physical properties:

1. Normal boiling point (the temperature in °C at which a chemical boils at atmospheric pressure)
2. Density (the density in g/cm³)
3. Flash point (the lowest temperature in °C at which it can vaporize to form an ignitable mixture in air)
4. Thermal conductivity (the property of a material in units of mW/mK reflecting its ability to conduct heat)
5. Viscosity (a measure of the resistance of a fluid to flow in cP defined as the proportionality constant between shear rate and shear stress)
6. Surface tension (a property of the surface in dyn/cm of a liquid that allows it to resist an external force)
7. Water solubility (the amount of a chemical in mg/L that will dissolve in liquid water to form a homogeneous solution)
8. Vapor pressure (the pressure of a vapor in mmHg in thermodynamic equilibrium with its condensed phases in a closed system)
9. Melting point (the temperature in °C at which a chemical in the solid state changes to a liquid state)

1.2. QSAR Methodologies

T.E.S.T allows you to estimate toxicity values using several different advanced QSAR methodologies [2]:

- **Hierarchical method:** The toxicity for a given query compound is estimated using the weighted average of the predictions from several different models. The different models are obtained by using Ward's method to divide the training set into a series of structurally similar clusters. A genetic algorithm based technique is used to generate models for each cluster. The models are generated prior to runtime.
- **Single model method**: Predictions are made using a multilinear regression model that is fit to the training set (using molecular descriptors as independent variables) using a genetic algorithm based approach. The regression model is generated prior to runtime.
- **Group contribution method**: Predictions are made using a multilinear regression model that is fit to the training set (using molecular fragment counts as independent variables). The regression model is generated prior to runtime.
- **Nearest neighbor method**: The predicted toxicity is estimated by taking an average of the 3 chemicals in the training set that are most similar to the test chemical.
- **Consensus method**: The predicted toxicity is estimated by taking an average of the predicted toxicities from the above QSAR methods (provided the predictions

are within the respective applicability domains).

T.E.S.T provides multiple prediction methodologies so one can have greater confidence in the predicted toxicities (assuming the predicted toxicities are similar from different methods). In addition, some researchers may have more confidence in particular QSAR approaches based on personal experience. The QSAR methodologies above are described in more detail in the Theory section. The advantages and disadvantages of the different QSAR methods are given in Table 1.2.

Table 1.2. Advantages and disadvantages of the QSAR methods in T.E.S.T.

Method	Advantages	Disadvantages
Hierarchical	• Can produce more reliable predictions since predictions are made from multiple models	• Cannot provide external estimates of toxicity for compounds in the training set
Single model	• Single transparent model can be easily viewed/exported • The model does not need to rely on clustering the chemicals correctly	• Since the model is fit to the entire dataset it may incorrectly predict the trends in toxicity for certain chemical classes • Cannot provide external estimates of toxicity for compounds in the training set
Group contribution	• Single transparent model can be easily viewed/exported • Estimates of toxicity can be made without using a computer program	• The model doesn't correct for the interactions of adjacent fragments • Since the model is fit to the entire dataset it may incorrectly predict the trends in toxicity for certain chemical classes • Cannot provide external estimates of toxicity for compounds in the training set
Nearest neighbor	• Provides a quick estimate of toxicity • Allows one to determine structural analogs for a given test compound • Always provide an external prediction of toxicity	• It does not use a QSAR model to correlate the differences between the test compound and the nearest neighbors • Was shown to achieve the worst prediction results during external validation
Consensus	• Was shown to achieve the best prediction results during external validation	• Cannot provide external estimates of toxicity for compounds in the training set

2. THEORY

2.1. Molecular Descriptors

Molecular descriptors are physical characteristics of the structure of chemicals such as the molecular weight or the number of benzene rings. The overall pool of descriptors in the software contains 797 2-dimensional descriptors. The descriptors include the following classes of descriptors: E-state values and E-state counts, constitutional descriptors, topological descriptors, walk and path counts, connectivity, information content, 2d autocorrelation, Burden eigenvalue, molecular property (such as the octanol-water partition coefficient), Kappa, hydrogen bond acceptor/donor counts, molecular distance edge, and molecular fragment counts. *The complete list of descriptors and their sources from the literature are described in the Molecular Descriptors Guide.*

The descriptors were calculated using computer code written in Java. The basis of the molecular calculations was the Chemistry Development Kit [3]. The Chemistry Development Kit (CDK) is a Java library for structural chemo- and bioinformatics [4]. The descriptor values were validated using MDL QSAR [5], Dragon [6], and Molconn-z [7]. The descriptor values were generally in good agreement (aside from small differences in the descriptor definitions for descriptors such as the number of hydrogen bond acceptors).

2.2. QSAR Methodologies

2.2.1. Hierarchical Clustering

The hierarchical clustering method utilizes a variation of Ward's Method [8] to produce a series of clusters from the training set. Clusters are subsets of chemicals from the overall set, which possess similar properties. An example of a hierarchical clustering for a hypothetical training set with five chemicals is given in Figure 2.2.1.
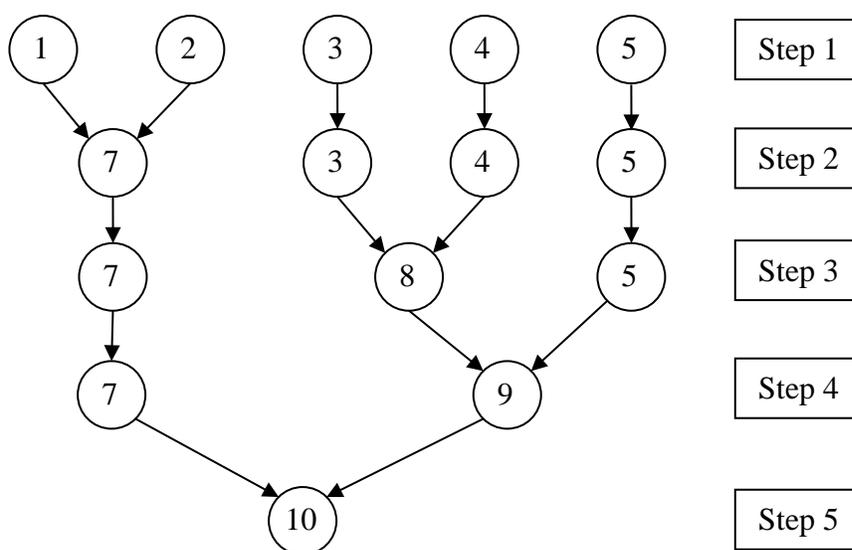
Figure 2.1.1. Hierarchical clustering with five chemicals

For a training set of n chemicals, initially there will be n clusters (each cluster contains one chemical). The overall variance in the system at a given step l is defined to be the sum of the variances of the individual clusters:

$$V(l) \equiv \sum_{k=1}^{m} v(k,l) \tag{1}$$

where $v(k,l)$ is the variance (in terms of the molecular descriptors) for cluster k at step l:

$$v(k,l) \equiv \sum_{i=1}^{n_k} \sum_{j=1}^{d} (x_{ij} - C_j)^2 \tag{2}$$

where n_k is the number of chemicals in the kth cluster, d is the number of descriptors in the overall descriptor pool, x_{ij} is the normalized descriptor j for chemical i, and C_j is the centroid or average value for descriptor j for cluster k:

$$C_j = \frac{1}{n_k} \sum_{i=1}^{n_k} x_{ij} \tag{3}$$

Each step of the method adds two of the clusters together into one cluster so that the increase in variance over all clusters in the system is minimized:
$$\min \Delta V(l+1) \equiv V(l+1) - V(l) = v(k',l+1) - v(k_1,l) - v(k_2,l) \tag{4}$$

where clusters k_1 and k_2 join together at step l to make cluster k' at step $l+1$. The process of combining clusters continues until all of the chemicals are lumped into a single cluster.

After the clustering is complete, each cluster is analyzed to determine if an acceptable QSAR can be developed. Each cluster undergoes evaluation using a genetic algorithm technique to determine an optimal descriptor set for characterizing the toxicity values of the chemicals within that cluster. The maximum number of descriptors allowed for a given cluster will be $n_k/5$ because the recommended ratio of compounds to variables should be at least 5 [9, 10] for reasonably small probability for chance correlations. The genetic algorithm used in this study was taken from the Weka statistical package, version 3.5.1 [11, 12].

The genetic algorithm is used to maximize the adjusted fivefold leave many out cross validation coefficient ($q^2_{adj,LMO}$):

$$q^2_{adj,LMO} = 1 - \left[\frac{\sum_{i=1}^{n_k}\left(\hat{y}_i - y_{exp,i}\right)^2 \big/ \left(n_k - p - 1\right)}{\sum_{i=1}^{n_k}\left(y_{exp,i} - \bar{y}_{exp}\right)^2 \big/ \left(n_k - 1\right)} \right] \tag{5}$$

where $\hat{y}_i$ and $y_{exp,i}$ are the predicted and experimental toxicity values for chemical i, $\bar{y}_{exp}$ is the average experimental toxicity for the chemicals in the cluster, and p is the number of parameters in the model. The predicted toxicity values are calculated by dividing the dataset into five folds (a fold is a subset of the training set). The toxicities of the chemicals in each fold ($\hat{y}_i$) are predicted using a multiple linear regression model fit to the chemicals in the other folds. The five fold q^2 was used instead of the traditional q^2 LOO (leave-one-out) inside the genetic algorithm because it yields a significant degree of computational savings for large cluster sizes. The $n_k - p - 1$ term penalizes models that include extra parameters that do not significantly increase the predictive power of the model (by decreasing the value of $q^2_{adj,LMO}$).

During the optimization process the models are checked for outliers. A chemical is determined to be an outlier if at least two statistical tests (e.g., DFFITS, leverage, Cook's distance, and covariance ratio) indicate that the chemical represents an influential data point and if the chemical represents an outlier in terms of the studentized deleted residual [13]. If a chemical is determined to be an outlier, the chemical is deleted from the cluster and the genetic algorithm descriptor selection is repeated. The process of model building via the genetic algorithm and outlier removal is repeated until no outliers are detected in the optimized model. *For binary endpoints such as Ames mutagenicity, outliers were not removed because this had the potential to produce clusters with all positive or all negative chemicals. In addition, the outlier statistical tests described above may not apply to binary endpoints.*

Once the iteration for the optimum model has been completed, the q^2 LOO value for the model is calculated. If the q^2 LOO is greater than or equal to 0.5, the model is

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considered to be valid (see pg 67 of Erikkson et al. [14]). If the q^2 LOO is less than 0.5, the model from the cluster is not used to make predictions for test compounds. For binary endpoints, the validity of a model is determined from the concordance LOO instead of q^2 LOO. Concordance is the fraction of all compounds that are predicted correctly (i.e., experimentally active compounds that are predicted to be active and experimentally inactive compounds that are predicted to be inactive). If the concordance LOO is greater than or equal to 0.8, the model is considered to be valid. In addition, both the leave-one-out sensitivity and specificity must be at least 0.5 to avoid using models which are heavily biased to predict either active or inactive scores. Sensitivity is the fraction of experimentally active compounds that are predicted to be active. Specificity is the fraction of experimentally inactive compounds that are predicted to be inactive.

The predicted toxicity ($\hat{y}$) for a test chemical is given by the weighted average for all the valid predictions [15]:

$$\hat{y} = \frac{\sum_{j=1}^{nvc} w_j \hat{y}_j}{\sum_{j=1}^{\#valid\ clusters} w_j} \tag{6}$$

where $\hat{y}_j$ and w_j are prediction and weight for the jth model and nvc is the number of valid cluster model predictions. If the mean toxicity is given by the maximum likelihood estimator of the mean of the probability distributions, the weight values are given by [15]

$$w_j = \frac{1}{se_j^{\ 2}} \tag{7}$$

where se_j is the standard error for the jth prediction given by

$$se_j = \sqrt{\sigma_j^{\ 2}\left(1 + h_{00}\right)} \tag{8}$$

where $\sigma_j^{\ 2}$ is given by

$$\sigma_j^{\ 2} = \frac{\sum_{i=1}^{n_j}\left(\hat{y}_i - y_{\exp,i}\right)^2}{n_j - p_j - 1} \tag{9}$$

where n_j is the number of chemicals in cluster model j and p_j is the number of model parameters for model j. h_{00}, the leverage for the test chemical, is given by

$$h_{00} = X_o^T\left(X^T X\right)^{-1} X_0 \tag{10}$$

where X_0 is the vector of model descriptor values for the test compound. *For binary endpoints such as Ames mutagenicity, the predictions were made using equal weighting of the individual predictions (i.e. $w_j = 1$ in equation 6) because weighting by the standard error (see equation 7) did not improve the external prediction accuracy.*

The square of the standard deviation for the prediction from multiple models ($\sigma_\mu^{\ 2}$)

can be approximated as

$$\sigma_\mu^{\,2} = \frac{\overline{\sigma^2}}{nvc} = \left(\frac{1}{nvc}\right)\frac{\sum\limits_{j=1}^{nvc} w_j se_j^{\,2}}{\sum\limits_{j=1}^{nvc} w_j} = \left(\frac{1}{nvc}\right)\frac{\sum\limits_{j=1}^{nvc}\left(\frac{1}{se_j^{\,2}}\right) se_j^{\,2}}{\sum\limits_{j=1}^{nvc}\left(\frac{1}{se_j^{\,2}}\right)} = \frac{1}{\sum\limits_{j=1}^{nvc}\left(\frac{1}{se_j^{\,2}}\right)} \qquad (11)$$

The uncertainty ($\hat{u}$) in the overall prediction for the test chemical is given by

$$\hat{u} = t_{1-\alpha/2,nvc}\,\sigma_\mu = t_{1-\alpha/2,\,nvc-1}\sqrt{1/\sum\limits_{j=1}^{nvc}\frac{1}{se_j^{\,2}}} \qquad (12)$$

where t is the t-statistic, $\alpha = 0.1$ (90% confidence interval), and se_j is the standard error for the jth prediction. The prediction interval is obtained by adding and subtracting the uncertainty from the predicted toxicity:

$$\hat{y} - \hat{u} \le Toxicity \le y + \hat{u} \qquad (13)$$

The prediction interval indicates that one is 90% confident that the actual toxicity is between $\hat{y} - \hat{u}$ and $\hat{y} + \hat{u}$.

The prediction uncertainty for a given cluster model is given by [16]

$$u_j = t_{1-\alpha/2,\,n_j-p-1}\sqrt{\sigma^2\left(1+h_{00}\right)} \qquad (14)$$

The uncertainty is a function of the quality of the regression model (from the σ^2 parameter) and the distance (in the descriptor space of the model) between the test chemical and the chemicals in the cluster used to build the model (from the h_{00} parameter).

Before any cluster model can be used to make a prediction for a test chemical, it must be determined whether the test chemical falls within the domain of applicability for the model. The applicability domain is defined using several different constraints. The first constraint, the model ellipsoid constraint, checks if the test chemical is within the multidimensional ellipsoid defined by the ranges of descriptor values for the chemicals in the cluster (for the descriptors appearing the cluster model). The model ellipsoid constraint is satisfied if the leverage of the test compound (h_{00}) is less than the maximum leverage value for all the compounds used in the model [16]. The second constraint, the Rmax constraint, checks if the distance from the test chemical to the centroid of the cluster is less than the maximum distance for any chemical in the cluster to the cluster centroid. The distance is defined in terms of the entire pool of descriptors (instead of just the descriptors appearing in the model):

$$distance_i = \sum\limits_{j=1}^{d}\left(x_{ij} - C_j\right)^2 \qquad (15)$$

where $distance_i$ is the distance of chemical i to the centroid of the cluster.
The last constraint, the fragment constraint, is that the compounds in the cluster have to have at least one example of each of the fragments contained in the test chemical. For example, if one was trying to make a prediction for ethanol, the cluster must contain at least one compound with a methyl fragment (-CH_3 [aliphatic attach]), one compound with a methylene fragment (-CH_2 [aliphatic attach]), and one compound

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with a hydroxyl fragment (-OH [aliphatic attach]). This constraint was added to avoid situations where a chemical might have a similar backbone structure to the chemicals in a given cluster but has a different functional group attached. For example, if a given cluster contained only short-chained aliphatic amines one would not want to use it to predict the toxicity of ethanol. If a chemical contains a fragment that is not present in the training set, the toxicity cannot be predicted. The fragment constraint can be removed by checking the **Relax fragment constraint** checkbox. *For binary endpoints such as Ames mutagenicity, the fragment constraint was not employed since it did not improve the external prediction accuracy and decreased the prediction coverage.*

In the current version of the software, the predictions are made using the closest cluster from each step in the hierarchical clustering (in terms of the distance of the chemical to the centroid of the cluster defined above). The rationale behind this approach is that one would like to follow the hierarchical clustering process, selecting the best model from each step. In order for the prediction from the model to be used it must be statistically valid and meet the constraints defined above. If the closest cluster for a given step does not have a statistically valid model (or violates any of the constraints), no prediction is used from that step. If the closest cluster for a given step in the clustering process is the same as the closest cluster from a previous step, it is not used again in the prediction of toxicity.

2.2.2. Single model

In the single model approach, a single multiple linear regression model is fit to the entire training set. The model is generated using techniques and constraints similar to those for the hierarchical method (except that the training cluster contains the entire training set). The advantage of this approach is that a simple transparent model can be developed which does not rely on clustering the chemicals correctly. The disadvantage of this approach is that sometimes an overall model cannot correctly correlate the toxicity for every chemical class [17]. For example, the single model might be able to correctly describe the trend of linearly increasing toxicity for a series of normal alcohols (i.e. 1-propanol, 1-butanol,1-pentanol, …), but it may incorrectly describe the trend for a series of normal acids (i.e. propanoic acid, butanoic acid, pentanoic acid, …) that does not increase linearly.

2.2.3. Group contribution

The group contribution approach is based on the group contribution approach of Martin and Young [18]. Fragment counts (such as the number of methyl and hydroxyl groups in a compound) are used to fit a multiple linear regression model to the entire data set. A genetic algorithm approach is not used to reduce the number of parameters in the model because the approach tries to characterize the contribution from all the fragments appearing in the training set. The only constraint on the fragments appearing in the final model is that there must be at least three molecules in the training set that contain each fragment. If a fragment appears less than three

times in the training set, it is deleted from the list of fragments and all the chemicals containing this fragment are removed from the training set. After the multiple linear regression is performed, the model is checked for outliers. If outliers are detected, they are removed and the regression is performed again. The process is repeated until no more outliers are found. Similar to the hierarchical methodology, predictions are made using the model ellipse and fragment constraints.

The advantage of this approach is a single transparent model can be developed whose descriptors can be determined from visual inspection of the molecular structure of the test compound. The disadvantage of this approach is that it assumes that the contribution of each fragment does not depend on the presence of nearby fragments in the molecule.

2.2.4. Nearest neighbor

In the nearest neighbor approach, the predicted toxicity is simply the average of the toxicities of the three most similar chemicals (structural analogs) in the training set. In order to make a prediction, each of the structural analogs must exceed a certain minimum cosine similarity coefficient (SCmin). SCmin was set at 0.5 so that the prediction coverage was similar to the other QSAR methods [2]. The nearest neighbor method provides a quick external estimate of toxicity (the test chemical is never present in the selected set of analogs). The disadvantage of the nearest neighbor method is that the structural differences between the test chemical and its structural analogs are not accounted for.

2.2.5. Consensus

In the consensus method, the predicted toxicity is simply the average of the predicted toxicities from the other QSAR methodologies (taking into account the applicability domain of each method)[19]. If only a single QSAR methodology can make a prediction, the predicted value is deemed unreliable and not used. This method typically provides the highest prediction accuracy since errant predictions are dampened by the predictions from the other methods. In addition, this method provides the highest prediction coverage because several methods with slightly different applicability domains are used to make a prediction.

2.3. Validation Methods

2.3.1. Statistical external validation

The predictive ability of each of the QSAR methodologies was evaluated using statistical external validation [20]. In version 2.0 of the TEST software, the data set was divided into training and test sets using the Kennard-Stone rational design

algorithm [21-24]. Starting in version 3.0, random selection was used to develop the training and test sets because it was felt that using Kennard-Stone method yields an overly optimistic estimate of predictive ability (because the test compounds are always within the model calibration domain). *For the developmental toxicity endpoint, however, the training and test sets were taken from the datasets used in CAESAR [25]. This was done for comparison purposes.*

A QSAR model has acceptable predictive power if the following conditions are satisfied [26]:

$$q^2 > 0.5; \tag{17}$$

$$R^2 > 0.6; \tag{18}$$

$$\frac{\left(R^2 - R_o^2\right)}{R^2} < 0.1 \text{ and } 0.85 \le k \le 1.15 \tag{19}$$

where q^2 is the leave one out correlation coefficient for the training set, R^2 is correlation coefficient between the observed and predicted toxicities for the test set, R_o^2 is correlation coefficient between the observed and predicted toxicities for the test set with the Y-intercept set to zero (where the regression line is given by Y=kX).

The prediction accuracy will be evaluated in terms of equations 18 and 19. In addition the accuracy will be evaluated in terms of the RMSE (root mean square error), and the MAE (mean absolute error) for the test set. It has been demonstrated that q^2 (the leave one out correlation coefficient for the training set) is not correlated with R^2 for the test set [27]. The prediction coverage (fraction of chemicals predicted) must be considered because the prediction accuracy (in terms of R^2 and RMSE) can sometimes be improved at the sacrifice of the prediction coverage.

For binary (active/inactive) toxicity endpoints such as developmental toxicity, the prediction accuracy is evaluated in terms of the fraction of compounds that are predicted accurately. The prediction accuracy is evaluated in terms of three different statistics: concordance, sensitivity, and specificity. Concordance is the fraction of all compounds that are predicted correctly (i.e. experimentally active compounds that are predicted to be active and experimentally inactive compounds that are predicted to be inactive). Sensitivity is the fraction of experimentally active compounds that are predicted to be active. Specificity is the fraction of experimentally inactive compounds that are predicted to be inactive.

3. EXPERIMENTAL DATA SETS

3.1. 96 hour fathead minnow LC$_{50}$ data set

The fathead minnow LC$_{50}$ endpoint represents the concentration in water, which kills

half of fathead minnow (*Pimephales promelas*) in 4 days (96 hours). The data set for this endpoint was obtained by downloading the ECOTOX aquatic toxicity database[28].

The database was then filtered using the following criteria:
- The ECOTOX "Media Type" field = "FW" (fresh water)
- The ECOTOX "Test Location" field = "Lab" (laboratory)
- The ECOTOX "Conc 1 Op (ug/L)" field cannot be <, >, or ~ (i.e. use only discrete LC_{50} values)
- The ECOTOX "Effect" field = "Mor" (mortality)
- The ECOTOX "Effect Measurement" field = "MORT" (mortality)
- The ECOTOX "Exposure Duration" field = "4" (4 days or 96 hours)
- Compounds can only contain the following element symbols: C, H, O, N, F, Cl, Br, I, S, P, Si, As
- Compounds must represent a single pure component (i.e. salts, undefined isomeric mixtures, polymers, or mixtures were removed)

The LC_{50} values were taken from the "Conc 1 (ug/L)" field in ECOTOX. For chemicals with multiple LC_{50} values, the median value was used.

In version 2.0 of T.E.S.T., 10 compounds in this dataset possessed 2d isomers (the structures were equivalent in terms of their molecular connectivity). In version 3.0, only one isomer was kept, using the average toxicity value. In version 4.0, all isomers were kept since the presence of the isomers had negligible impact on the external prediction statistics. The final fathead minnow LC_{50} data set contained 823 chemicals. For use in QSAR modeling, the experimental values in μg/L were converted to $-Log_{10}$ (LC_{50} mol/L).
For the hierarchical, single model, group contribution, Nearest neighbor, and Consensus methods, the data set were divided randomly into a training set (80% of the overall set) and a test set (20% of the overall set).

3.2. 48 hour *Daphnia magna* LC_{50} data set

The *Daphnia magna* LC_{50} endpoint represents the concentration in water, which kills half of *D. magna* (a water flea) in 48 hours. The data set for this endpoint was obtained from the ECOTOX aquatic toxicity database[28]. The database was filtered using the same criteria as those for the 96 hour fathead minnow LC_{50}. The final *D. magna* LC_{50} data set contained 541 chemicals. The modeled endpoint was $-Log_{10}$ (LC_{50} mol/L).

3.3. 40 hour *Tetrahymena pyriformis* IGC_{50} data set

The *Tetrahymena pyriformis* IGC_{50} endpoint represents the 50% growth inhibitory concentration of the *T. pyriformis* organism (a protozoan ciliate) after 40 hours. The IGC_{50} training set was obtained from Schultz and coworkers [19, 29-66]. The final *T. pyriformis IGC_{50}* data set contained 1792 chemicals. The modeled endpoint was $-Log_{10}$

(IGC$_{50}$ mol/L).

3.4. Oral rat LD$_{50}$ data set

The oral rat LD$_{50}$ endpoint represents the amount of the chemical (mass of the chemical per body weight of the rat) which when orally ingested kills half of rats. The dataset for this endpoint was obtained by downloading records from the ChemIDplus database [67]. 13548 records were obtained by using the following search criteria:
- "Test" = LD50
- "Species" = rat
- "Route" = oral

The list of chemicals was filtered using the following criteria:
- Only chemicals with discrete LD$_{50}$ values were used (i.e. chemicals with LD$_{50}$ values with ">" or "<" were removed)
- Compounds can only contain the following element symbols: C, H, O, N, F, Cl, Br, I, S, P, Si, or As
- Compounds must represent a single pure component (i.e. salts, undefined isomeric mixtures, polymers, or mixtures were removed)

In version 2.0 of T.E.S.T., the final dataset consisted of 7392 chemicals. 87 compounds in this dataset possessed 106 2d isomers. In version 3.0, only one isomer was kept, using the average toxicity value. In version 4.0 and greater, all isomers were kept because the presence of the isomers had negligible impact on the external prediction statistics. The final oral rat LD$_{50}$ data set contained 7413 chemicals. The modeled endpoint was the – Log$_{10}$ (LD$_{50}$ mol/kg).

3.5. Bioconcentration factor data set

The bioconcentration factor (BCF) is defined as the ratio of the chemical concentration in biota as a result of absorption via the respiratory surface to that in water at steady state [68]. Data were compiled from several different databases [69-72]. The final dataset consists of 676 chemicals (after removing salts, mixtures, and ambiguous compounds). The modeled endpoint was the Log$_{10}$(BCF).

3.6. Developmental toxicity data set

The developmental toxicity is defined as whether or not a chemical causes developmental toxicity effects in humans and animals. Developmental toxicity includes any effect interfering with normal development, both before and after birth. A dataset of 293 chemicals was created by Arena and Coworkers [73, 74] by combining data from the Teratogen Information System (TERIS) [75] and FDA guidelines [76]. The developmental toxicity values were taken from the revised binary toxicity values developed for the CAESAR project [25]. One chemical, Azatguiorube, was removed because structural information could not be found for this chemical. The final dataset

consists of 285 chemicals (after removing salts, mixtures, and ambiguous compounds).

3.7. Ames mutagenicity data set

In the Ames test, frame-shift mutations or base-pair substitutions can be detected by exposure of histidine-dependent strains of Salmonella typhimurium to a test compound. When these strains are exposed to a mutagen, reverse mutations that restore the functional capability of the bacteria to synthesize histidine enable bacterial colony growth on a medium deficient in histidine (revertants). A compound is classified Ames positive if it significantly induces revertant colony growth in at least one of out of five strains. A dataset of 6512 chemicals was compiled by Hansen and coworkers from several different sources [77, 78]. The final dataset consists of 5743 chemicals (after removing salts, mixtures, ambiguous compounds, and compounds without CAS numbers).

3.8. Normal boiling point

The normal boiling point is defined as the temperature at which a chemical boils at atmospheric pressure. The data set for this endpoint was obtained from the boiling point data contained in EPI Suite [79]. Forty-one chemicals were removed from the data set because they were previously shown to be badly predicted and had experimental values which were significantly different (>50K) from other sources such as NIST[80] and LookChem [81]. The final data set contained 5759 chemicals. The modeled property was the boiling point in °C.

3.9. Density

The density is defined as mass per unit volume. The data set for this endpoint was obtained from the density data contained in LookChem [81]. The data set was restricted to chemicals with boiling points greater than 25°C (or the boiling point was unavailable). The data set was further restricted to chemical with densities > 0.5 and < 5 g/cm^3. The final dataset consisted of 8909 chemicals. Data from LookChem are not peer reviewed but the set is very large and thus provides a large degree of structural diversity. The modeled property was density in g/cm^3.

3.10. Flash point

The flash point is defined as the lowest temperature at which a chemical can vaporize to form an ignitable mixture in air. A dataset of 8362 chemicals was compiled from lookchem.com [81]. Chemicals with flash points greater than 1000°C were omitted from the data set. The modeled property was the flash point in °C.

3.11. Thermal conductivity

Thermal conductivity is defined as a materials ability to conduct heat. The thermal

conductivity at 25°C for 442 chemicals was obtained from Jamieson and Vargaftik [82, 83]. Thermal conductivity values were obtained from Jamieson and Vargaftik as follows:

- If a value is available at 25°C this value is used
- If an experimental value is not available, a value is extrapolated to 25°C (as long as the closest data point is within 10°C of 25°C)
- If the temperature coefficient is not available (or only a single data point is available), the thermal conductivity of the nearest data point is used (as long as the closest data point is within 10°C of 25°C)
- Only data with a quality grade of A or B (preferably grade A) in Jamieson were used. The thermal conductivities for the chemicals in common between Jamieson and Vargaftik agreed rather well (R2 = 0.95 for 381 compounds). The modeled property was the thermal conductivity in mW/mK.

3.12. Viscosity

Viscosity is a measure of the resistance of a fluid to flow in cP defined as the proportionality constant between shear rate and shear stress). The viscosity at 25°C for 557 chemicals was obtained from Viswanath and Riddick [84, 85]. The viscosity values were obtained from Viswanath and Riddick were obtained as follows:

1. If a value is available at 25°C this value is used
2. If an experimental value is not available, a value is extrapolated to 25°C (as long as the closest data point is within 10°C of 25°C) using the following empirical correlation:

$$\log_{10} viscosity = A + B/T$$

Extrapolation was used in order to expand size of the overall dataset. The modeled property was $\log_{10}$(viscosity cP).

3.13. Surface tension

Surface tension is a property of the surface of a liquid that allows it to resist an external force. The surface tension at 25°C for 1416 chemicals was obtained from the data compilation of Jaspar [86]. The experimental values (at 25°C) are estimated using an empirical correlation, which is fit to experimental data from Jaspar:

$$\text{surface tension} = A - BT$$

The estimated experimental surface tension value is only used if the closest experimental data point is within 10°C of 25°C. The modeled property was the surface tension in dyn/cm.

3.14. Water solubility

Water solubility is defined as the amount of chemical that will dissolve in liquid water to form a homogeneous solution. A dataset of 5020 chemicals was compiled from the database in EPI Suite [79]. Chemicals with water solubilities exceeding 1,000,000 mg/L were omitted from the overall dataset. In addition, data were limited to data points that are within 10°C of 25°C. The water solubility is an important property because

sometimes the predicted LC50 values for aquatic species can exceed the water solubility. The modeled property was −Log10(water solubility mol/L).

3.15. Vapor pressure

Vapor pressure is defined as the pressure of a vapor in mmHg in thermodynamic equilibrium with its condensed phases in a closed system. The vapor pressure at 25°C for 2511 chemicals was obtained from the database in EPI Suite [79]. The modeled property was Log10(vapor pressure mmHg).

3.16. Melting point

Melting point is the temperature, in °C, at which a chemical in the solid state changes to a liquid state. The melting point for 9385 chemicals was obtained from the database in EPI Suite [79]. The modeled property was Log10(vapor pressure mmHg).

4. VALIDATION RESULTS

4.1. 96 hour fathead minnow LC$_{50}$

4.1.1. Statistical External Validation

The consensus approach achieved the best results in terms of all the prediction statistics (see Table 4.1.1). The hierarchical method achieved the best results of any of the individual QSAR methods. Statistics highlighted in pink represent predictions where a condition in equation 18 or 19 was not met. Models, which do not meet these conditions, are not invalid, per se, but should be used with caution. The predicted values for the test set for the fathead minnow LC50 endpoint for the consensus method are given in Figure 4.1.1.

Table 4.1.1. Prediction results for the fathead minnow LC$_{50}$ test set

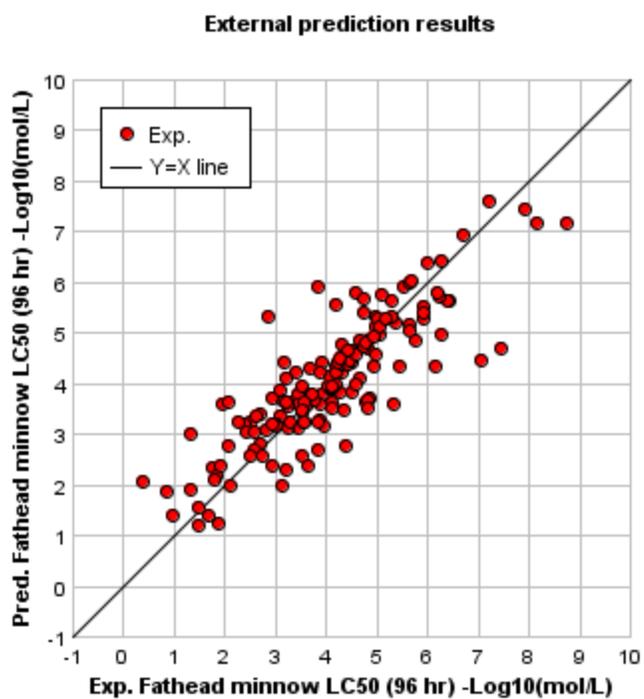| Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.710	0.075	0.966	0.801	0.574	0.951
Single Model	0.704	0.134	0.960	0.803	0.605	0.945
Group contribution	0.686	0.123	0.949	0.811	0.579	0.872
Nearest neighbor	0.667	0.080	1.000	0.877	0.649	0.939
Consensus	0.729	0.115	0.966	0.767	0.551	0.951

Figure 4.1.1. Experimental vs predicted values for the fathead minnow LC$_{50}$ test set

4.2. 48 hour *Daphnia magna* LC$_{50}$

4.2.1. Statistical External Validation

The consensus method achieved the best results in terms of both prediction accuracy and coverage (see Table 4.2.1). The prediction results for the consensus method are given in Figure 4.2.1.

Table 4.2.1. Prediction results for the *D. magna* LC$_{50}$ test set

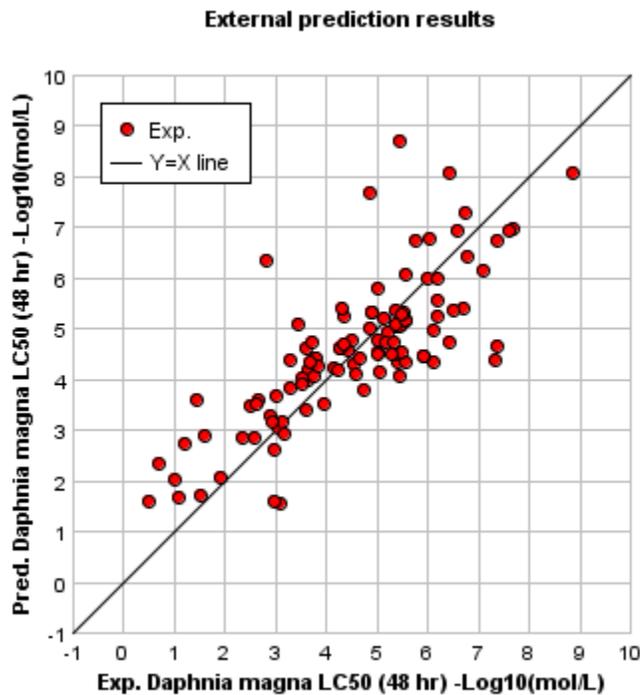| Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.630	0.232	0.954	1.018	0.759	0.982
Single Model	0.530	0.250	0.979	1.191	0.913	0.982
Group contribution	0.476	0.413	0.963	1.152	0.879	0.853
Nearest neighbor	0.642	0.122	0.966	1.010	0.724	0.899
Consensus	0.616	0.233	0.969	1.042	0.786	0.982

Figure 4.2.1. Experimental vs predicted values for the *Daphnia magna* LC$_{50}$ test set

4.3. *Tetrahymena pyriformis* 50% growth inhibitory concentration (IGC$_{50}$)

4.3.1. Statistical External Validation

Again, the consensus method achieved the best results (see Table 4.3.1). The R^2 value for the consensus method in version 4.1 of TEST was slightly lower than the value for version 4.0. This is because the data set has been expanded to include a wider variety of chemical classes. The prediction results for the consensus method are given in Figure 4.3.1.

Table 4.3.1. Prediction results for the *T. pyriformis* IGC$_{50}$ test set

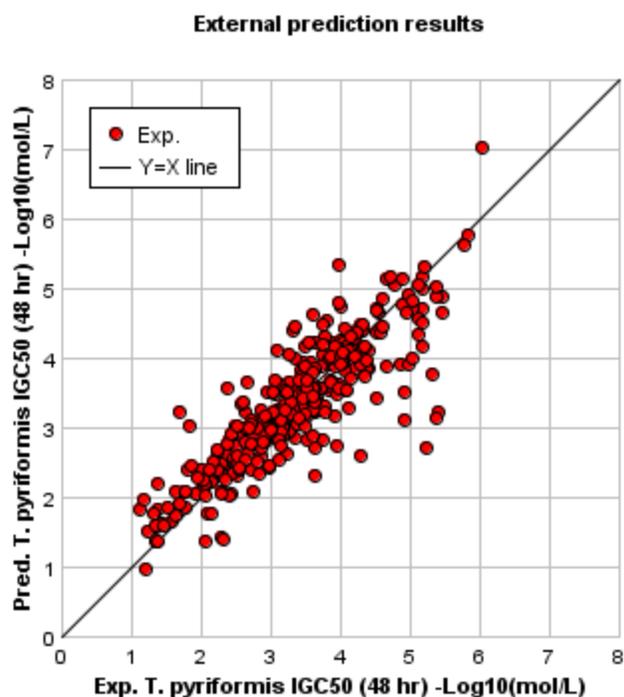| Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.718	0.023	0.978	0.540	0.358	0.933
Group contribution	0.682	0.066	0.994	0.576	0.411	0.955
Nearest neighbor	0.600	0.170	0.976	0.638	0.451	0.986
Consensus	0.739	0.070	0.983	0.505	0.355	0.966

Figure 4.3.1. Experimental vs predicted values for the *T. pyriformis* IGC$_{50}$ test set

4.4. Oral rat LD$_{50}$ dataset

4.4.1. Statistical External Validation

It was not possible to develop a single model or a group contribution model that fit the entire training set (see Table 4.4.1). The consensus method achieved the best results in terms of both prediction accuracy and prediction coverage. The prediction statistics for this endpoint were not as good as those for the other endpoints. This is not surprising because this endpoint has a higher degree of experimental uncertainty and has been shown to be more difficult to model than other endpoints [87]. The prediction results for the consensus method are given by in Figure 4.4.1.

Table 4.4.1. Prediction results for the oral rat LD$_{50}$ test set

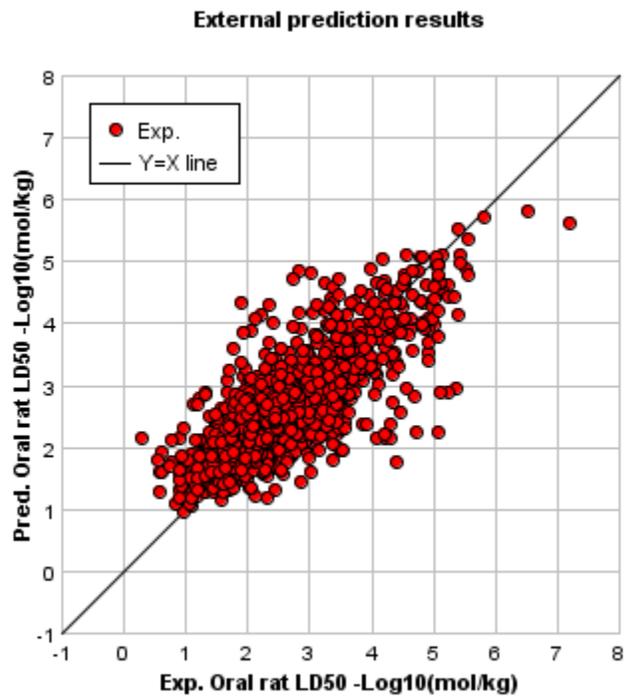| Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.578	0.184	0.969	0.650	0.460	0.875
Nearest neighbor	0.557	0.243	0.961	0.656	0.477	0.993
Consensus	0.633	0.188	0.968	0.595	0.436	0.875

Figure 4.4.1. Experimental vs predicted values for the oral rat LD$_{50}$ test set

4.5. Bioaccumulation factor (BCF)

4.5.1. Statistical External Validation

Again, the consensus method yielded the best statistics if one considers both prediction accuracy and coverage (see Table 4.5.1.). The prediction results for the consensus method are given in Figure 4.5.1.

Table 4.5.1. Prediction results for the BCF test set

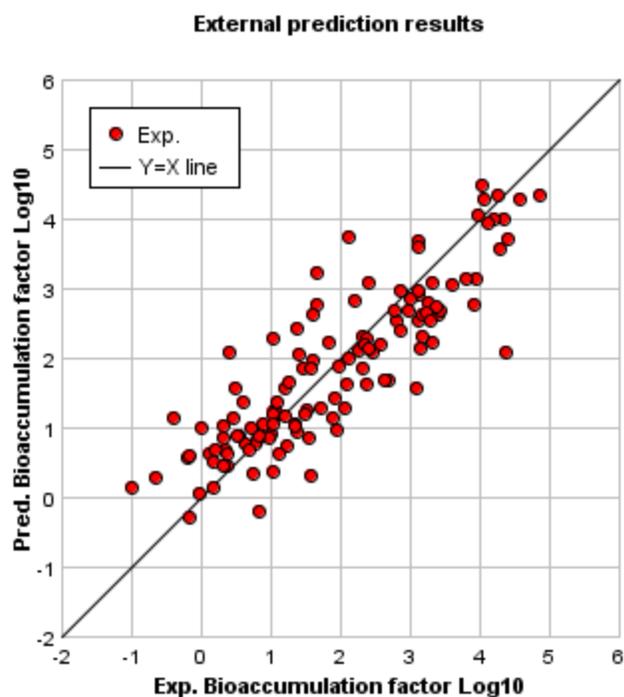| Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.735	0.019	0.888	0.712	0.541	0.926
Single Model	0.742	0.082	0.901	0.684	0.542	0.926
Group contribution	0.675	0.187	0.888	0.761	0.623	0.874
Nearest neighbor	0.609	0.099	0.931	0.884	0.604	0.948
Consensus	0.754	0.076	0.898	0.670	0.523	0.926

External prediction results

Figure 4.5.1. Experimental vs predicted values for the BCF test set

The BCFBAF (bioconcentration factor bioaccumulation factor) module (v. 3.00) of US EPA's EPI Suite software package [79] yielded an R^2 value of 0.766 and MAE of 0.50 (for the same chemicals that were able to be predicted by the consensus method). Thus, the predictions for the consensus method are comparable to those from EPI Suite. However, this may not be a fair comparison because some of the chemicals in the prediction set may have appeared in the training set for the BCF model in EPI Suite.

4.6. Developmental toxicity

4.6.1. Statistical External Validation

The consensus method achieved the best results for the EPA developed QSAR methods (in terms of prediction accuracy and coverage) (see Table 4.6.1). All of the methods achieved appreciably higher prediction sensitivities than specificities. This is acceptable for regulatory applications because it is desired to minimize the number of false negatives.

Table 4.6.1. Prediction results for the reproductive toxicity test set

Method	Concordance	Sensitivity	Specificity	Coverage
Hierarchical clustering	0.724	0.829	0.471	1.000
Single Model	0.732	0.850	0.438	0.966
Nearest neighbor	0.795	0.844	0.667	0.759
Consensus	0.772	0.900	0.471	0.983

4.7. Ames mutagenicity

4.7.1. Statistical External Validation

Again, the consensus method achieved the best prediction accuracy (concordance) and prediction coverage (see Table 4.7.1). The single model and group contribution methods could not be applied to this endpoint. All of the methods achieved a nice balance of prediction sensitivity and specificity.

Table 4.7.1. Prediction results for the Ames mutagenicity test set

Method	Concordance	Sensitivity	Specificity	Coverage
Hierarchical clustering	0.763	0.776	0.746	0.956
Nearest neighbor	0.770	0.783	0.753	0.990
Consensus	0.777	0.794	0.755	0.948

4.8. Normal boiling point

4.8.1. Statistical External Validation

The consensus method achieved the best statistics in terms of both prediction accuracy and coverage (see Table 4.8.1). In general, the prediction statistics for the physical properties were excellent. The prediction results for the consensus method are given in Figure 4.8.1.

Table 4.8.1. Prediction results for the normal boiling point test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.950	0.001	0.991	18.690	10.592	0.935
Group contribution	0.897	0.002	0.997	27.554	17.001	0.977
Nearest neighbor	0.877	0.005	0.968	29.967	19.754	0.988
Consensus	0.940	0.003	0.986	20.547	12.488	0.977
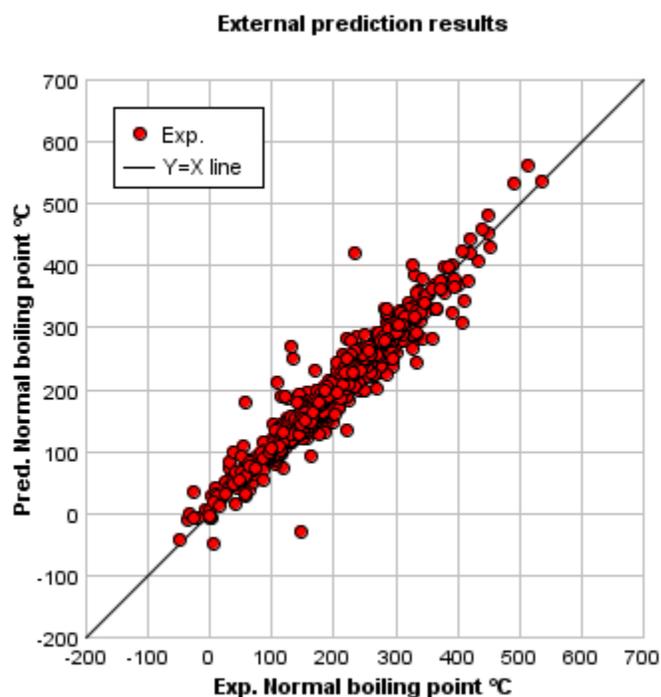
Figure 4.8.1. Experimental vs predicted values for the normal boiling point test set

4.9. Density

4.9.1. Statistical External Validation

For this property, the hierarchical and FDA methods gave a slightly higher R^2 value than the consensus method (see Table 4.9.1.). However, the consensus method yielded a near 100% prediction coverage. The prediction results for the consensus method are given in Figure 4.9.1.

Table 4.9.1. Prediction results for the density test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.972	0.001	0.997	0.053	0.026	0.942
Group contribution	0.872	0.005	0.997	0.116	0.071	0.992
Nearest neighbor	0.858	0.021	0.979	0.121	0.073	0.997
Consensus	0.938	0.006	0.990	0.080	0.046	0.992
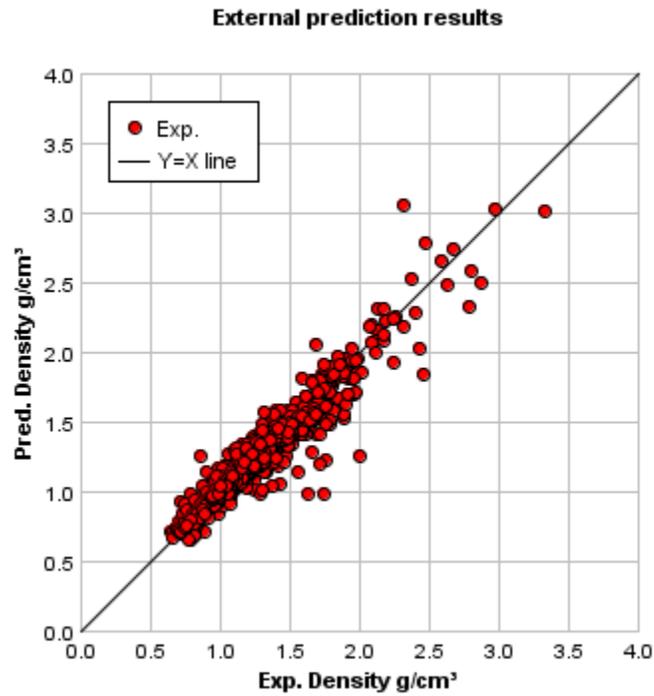
Figure 4.9.1. Experimental vs predicted values for the density test set

4.10. Flash point

4.10.1. Statistical External Validation

For this property, the consensus method gives the best results in terms of prediction accuracy and coverage (see Table 4.10.1). The prediction results for the consensus method are given in Figure 4.10.1.

Table 4.10.1. Prediction results for the flash point test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.870	0.008	0.961	28.911	16.753	0.924
Group contribution	0.834	0.009	0.968	33.630	20.426	0.987
Nearest neighbor	0.801	0.018	0.925	36.833	23.832	0.993
Consensus	0.873	0.010	0.953	29.064	17.571	0.987
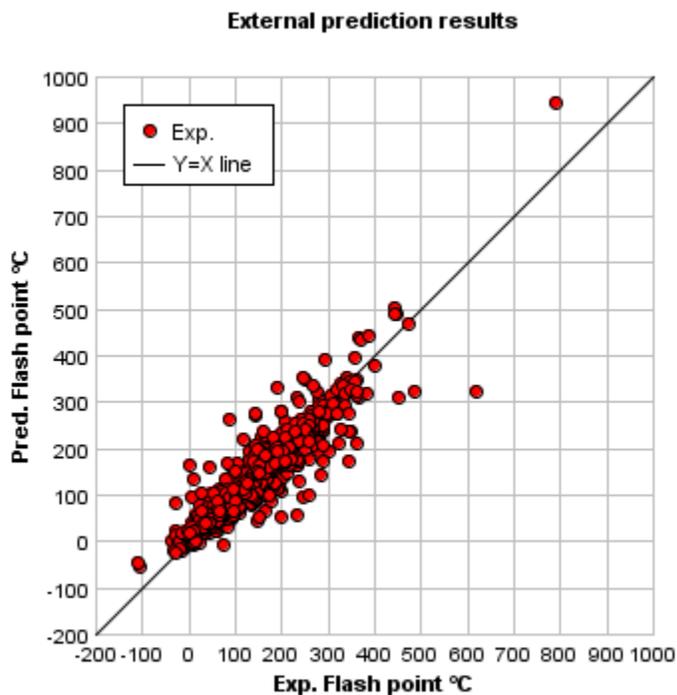
4.10.1. Experimental vs predicted values for the flash point test set

4.11. Thermal conductivity

4.11.1. Statistical External Validation

For this property, the hierarchical method gives similar results to the consensus method (see Table 4.11.1). The prediction results for the consensus method are given in Table 4.11.1.

Table 4.11.1. Prediction results for the thermal conductivity test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.905	0.025	0.996	11.062	6.771	0.956
Single Model	0.890	0.031	0.992	11.864	8.524	0.956
Group contribution	0.803	0.088	0.979	15.898	9.825	0.911
Nearest neighbor	0.884	0.021	1.004	12.832	8.449	0.978
Consensus	0.913	0.042	0.993	10.936	6.802	0.956
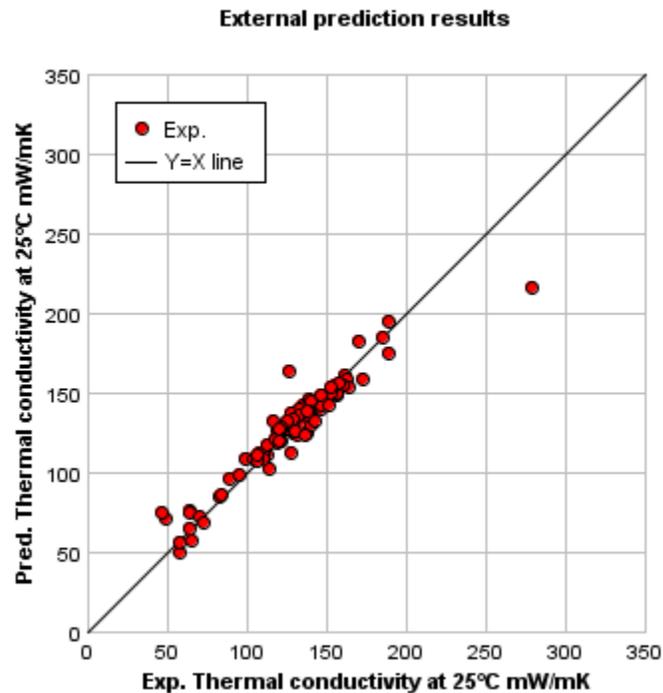
Figure 4.11.1. Experimental vs predicted values for the thermal conductivity test set

4.12. Viscosity

4.12.1. Statistical External Validation

For this property, the consensus method gives the best results if you consider both prediction accuracy and coverage (see Table 4.12.1). The low k values for this endpoint can be attributed to the two possible outliers in the test set that fall below the Y=X line. The prediction results for the consensus method are given Figure 4.12.1.

Table 4.12.1. Prediction results for the viscosity test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.867	0.001	0.808	0.215	0.131	0.929
Single Model	0.642	0.011	0.624	0.347	0.218	0.929
Group contribution	0.888	0.002	0.830	0.200	0.113	0.814
Nearest neighbor	0.757	0.009	0.725	0.289	0.194	0.920
Consensus	0.864	0.005	0.751	0.228	0.133	0.929
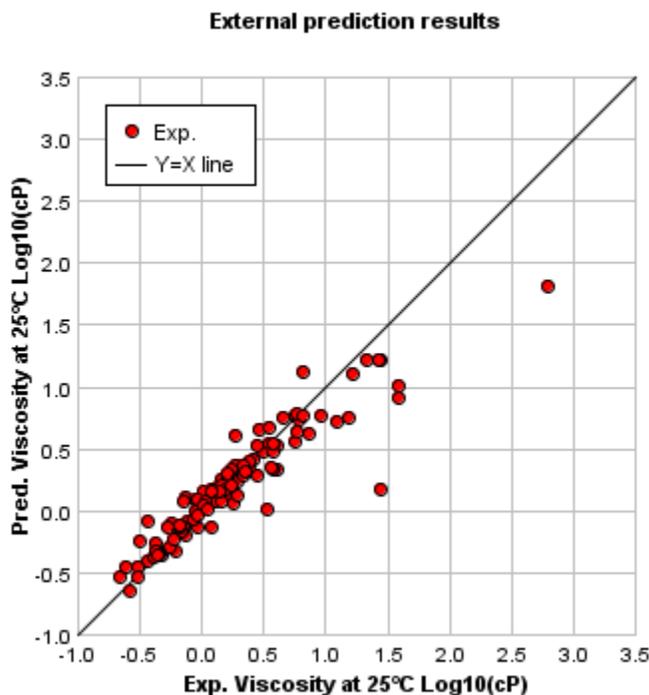
Figure 4.12.1. Experimental vs predicted values for the viscosity test set

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4.13. Surface tension

4.13.1. Statistical External Validation

For this property, the consensus method gives the best results in terms of prediction accuracy and coverage (see Table 4.13.1(. The prediction results for the consensus method are given Figure 4.13.1.

Table 4.13.1. Prediction results for the surface tension test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.929	0.016	0.989	1.792	1.038	0.919
Group contribution	0.794	0.044	0.986	2.933	2.114	0.926
Nearest neighbor	0.759	0.068	0.973	3.317	1.923	0.936
Consensus	0.889	0.033	0.985	2.245	1.414	0.926

Figure 4.13.1. Experimental vs predicted values for the surface tension test set

4.14. Water solubility

4.14.1. Statistical External Validation

For this property, the consensus method gives the best statistics in terms of prediction accuracy and coverage (see Table 4.14.1). The prediction results for the consensus method are given in Figure 4.14.1.

Table 4.14.1. Prediction results for the water solubility test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.835	0.015	0.943	0.900	0.600	0.934
Group contribution	0.766	0.039	0.933	1.074	0.798	0.982
Nearest neighbor	0.791	0.022	0.950	1.024	0.735	0.985
Consensus	0.844	0.025	0.941	0.872	0.617	0.980

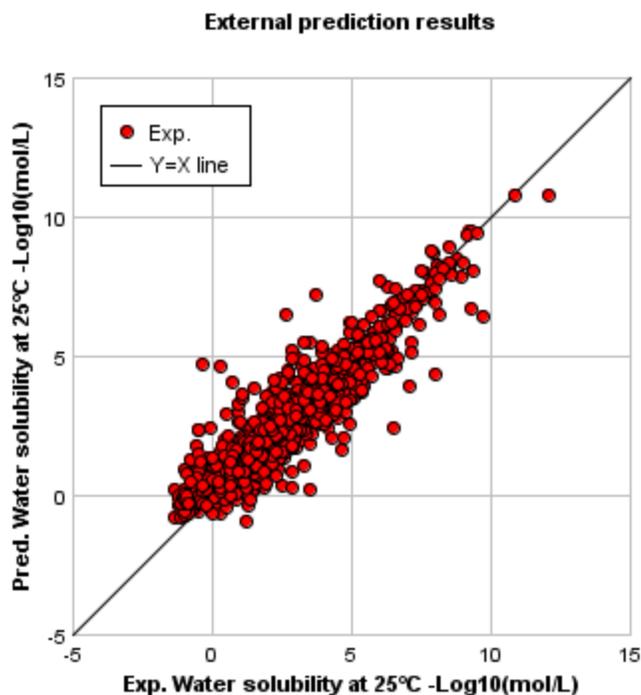**External prediction results**

Figure 4.14.1. Experimental vs predicted values for the water solubility test set

4.15. Vapor pressure

4.15.1. Statistical External Validation

The prediction statistics were excellent and again the consensus method achieved the best results (see Table 4.15.1). The prediction results for the consensus method are given in Table 4.15.1.

Table 4.15.1. Prediction results for the vapor pressure test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.955	0.001	0.976	0.754	0.460	0.940
Group contribution	0.929	0.001	1.020	0.999	0.608	0.968
Nearest neighbor	0.878	0.001	0.937	1.251	0.824	0.980
Consensus	0.948	0.001	0.978	0.818	0.500	0.970
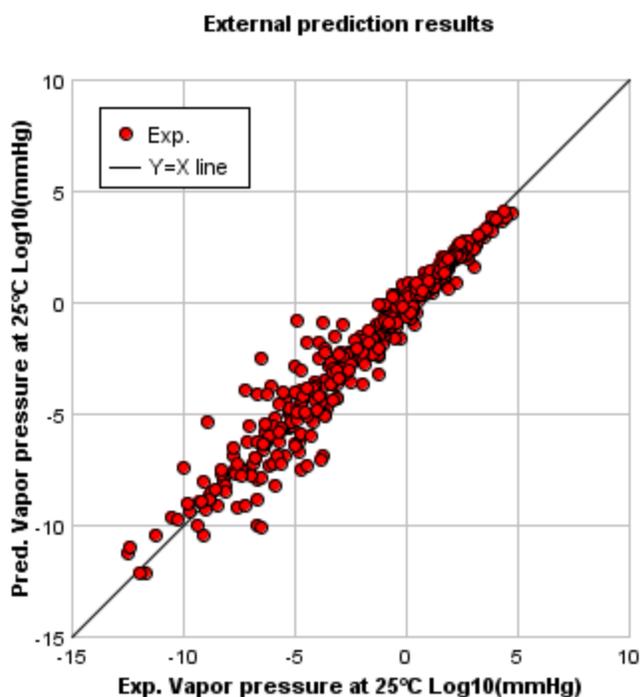
Figure 4.15.1. Experimental vs predicted values for the vapor pressure test set

4.16. Melting point

4.16.1. Statistical External Validation

The prediction statistics were very good and the again the consensus method achieved the best results (see Table 4.16.1.). The prediction results for the consensus method are given in Figure 4.16.1.

Table 4.16.1. Prediction results for the water solubility test set

Method	R^2	$\dfrac{R^2 - R_0^2}{R^2}$	k	RMSE	MAE	Coverage
Hierarchical clustering	0.809	0.011	0.891	44.509	31.480	0.932
Group contribution	0.704	0.065	0.837	54.947	41.274	0.997
Nearest neighbor	0.738	0.017	0.850	52.092	37.832	0.998
Consensus	0.813	0.026	0.858	43.771	31.888	0.998

41
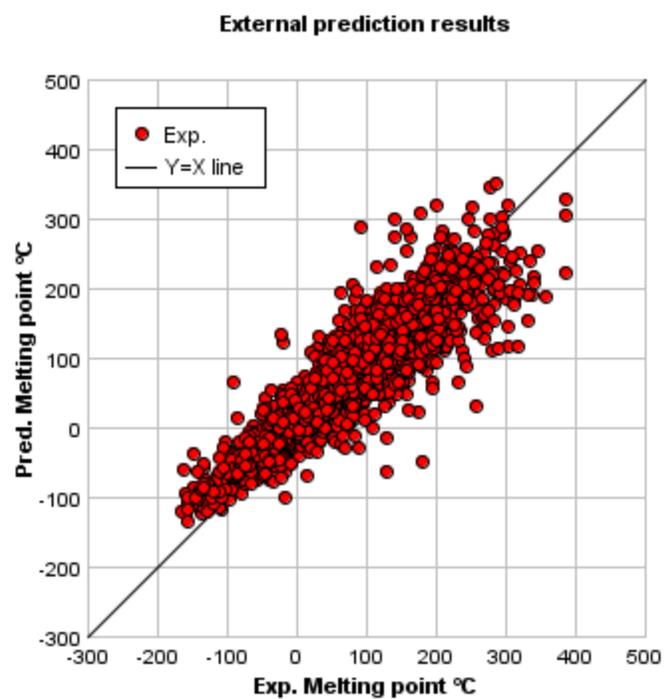
Figure 4.16.1. Experimental vs predicted values for the melting point test set

5. USING THE WEB SERVICE

5.1. Downloading the Web-TEST project

To download the Web-TEST source code, utilize TortoiseGit (https://tortoisegit.org/) to download the repository located at https://martitm@bitbucket.org/scidataexperts/web-test.git

5.2. Importing the project into Eclipse

To import the WebTEST package into the Eclipse IDE (Eclipse for Java Developers, https://www.eclipse.org):
1. Select File…Import…Existing Maven projects.
2. Navigate to the project folder which contains "pom.xml".
3. Click Finish.

5.3. Building WebTEST in Maven

To build the WebTEST jar file using Maven, run the following from the command prompt:

➢ mvn clean package

To skip the unit tests run the following command:

➢ mvn clean package -DskipTests

5.4. Starting a local server for WebTEST

To run start a server to run WebTEST enter the following from a command prompt (or use a Windows .bat file):

➢ java -jar target/WebTEST.jar server config.yml

where target is the folder where the WebTEST.jar file is located (see previous section) and config.yml specifies the settings for the server:

```
server:

  applicationConnectors:

    - type: http

      port: 8100

  adminConnectors:

    - type: http

      port: 8101
```

5.5. Running a client to perform batch calculations

To start a client to run batch calculations enter the following at a command prompt:

➤ java -jar target/WebTEST.jar poke -i inputFilePath -o outputFilePath -u URL -e endpointAbbreviation -m methodAbbreviation

Parameter	Description
inputFilePath	path for the input text file with molecular structures (.smi or .sdf)
outputFilePath	Path for the output text file (.json)
URL	URL for the server running WebTEST • http://localhost:8100/ (server running on local machine) • http://webtest.sciencedataexperts.com/ (code development server) • https://comptox.epa.gov/dashboard/web-test/) (NCCT server)
endpoint Abbreviation	

Endpoint	Abbreviation
Fathead minnow LC50 (96 hr)	LC50
Daphnia magna LC50 (48 hr)	LC50DM
T. pyriformis IGC50 (48 hr)	IGC50
Oral rat LD50	LD50
Bioaccumulation factor	BCF
Developmental Toxicity	DevTox
Mutagenicity	Mutagenicity
Normal boiling point	BP
Vapor pressure at 25°C	VP
Melting point	MP
Flash point	Density

	Density	FP
	Surface tension at 25°C	ST
	Thermal conductivity at 25°C	TC
	Viscosity at 25°C	Viscosity
	Water solubility at 25°C	WS

method Abbreviation		
	Method	**Abbreviation**
	Hierarchical clustering	hc
	Single model	sm
	Nearest neighbor	nn
	Group contribution	gc
	Consensus	consensus (default)

For example, the following command will calculate vapor pressure for a batch of chemicals using a server ran on the user's machine:

> java -jar target/WebTEST.jar poke -i data/VP_prediction_small.sdf -o test-results/VP_prediction_small.json -u http://localhost:8100/ -e VP

Output from this command appears as follows:

```
    uuid:              "917e3c38-f406-479d-aac3-42e0c180b780"
    predictionTime:    1501883553675
    software:          "T.E.S.T (Toxicity Estimation Software Tool)"
    softwareVersion:   "4.2"
    condition:         "25°C"
    endpoint:          "Vapor pressure at 25°C"
    method:            "Consensus"
  ▼ predictions:
    ▼ 0:
        id:            "56-55-3"
        smiles:        "C=1C=CC=2C=C3C(C=CC=4C=CC=CC43)=CC2C1"
        expVal:        "-6.678"
        expValMass:    "0.000"
        predVal:       "-7.954"
        predValMass:   "0.000"
    ▼ 1:
        id:            "57-10-3"
        smiles:        "O=C(O)CCCCCCCCCCCCCCC"
        expVal:        "-6.420"
        expValMass:    "0.000"
        predVal:       "-6.617"
        predValMass:   "0.000"
```

SMILES text files (.smi) should contain the SMILES string and a unique identifier on each line. A comma, tab, or a space can separate the SMILES string and the identifier. The text file should not container a header line.

For example to import benzene and formaldehyde, the contents of the text file should be as follows:

```
c1ccccc1  71-43-2
C=O  50-00-0
```

For best results, one should use .sdf files with either a "CAS" or a "Name" field included to uniquely identify each chemical in the file. The program first looks for a "CAS" field and then looks for "Name" field when assigning identifiers. For example, a sample from .sdf file including formaldehyde would be as follows:

```
Formaldehyde
csChFnd80/07260508122D

  2  1  0  0  0  0  0  0  0  0999 V2000
   0.0000  0.0000  0.0000 C  0  0  0  0  0  0  0  0  0  0  0  0
   1.4000  0.0000  0.0000 O  0  0  0  0  0  0  0  0  0  0  0  0
  1  2  2  0  0  0  0
M  END

> <CAS>
50-00-0

> <Name>
Formaldehyde

$$$$
```

5.6. Run batch calculations without using a server

To perform calculations using the WebTEST jar file without a server run the following command:

> ➢ java -jar target/WebTEST.jar predict -i inputFilePath -o outputFilePath -e endpointAbbreviation -m methodAbbreviation

To run all endpoints with all methods, run the following:

> ➢ java -jar target/WebTEST.jar predict -i inputFilePath -o outputFilePath

5.7. "GET" API call

One can run a single chemical on the server by entering the following URL in a web browser:

➤ URL/endpointAbbreviation?smiles=desiredSmiles&method=methodAbbreviation

where

Parameter	Description
URL	URL for the server running WebTEST • http://localhost:8100/ (server running on local machine) • http://webtest.sciencedataexperts.com/ (code development server) • https://comptox.epa.gov/dashboard/web-test/) (NCCT server)
endpoint Abbreviation	<table><tr><td>**Endpoint**</td><td>**Abbreviation**</td></tr><tr><td>**Fathead minnow LC50 (96 hr)**</td><td>LC50</td></tr><tr><td>**Daphnia magna LC50 (48 hr)**</td><td>LC50DM</td></tr><tr><td>**T. pyriformis IGC50 (48 hr)**</td><td>IGC50</td></tr><tr><td>**Oral rat LD50**</td><td>LD50</td></tr><tr><td>**Bioaccumulation factor**</td><td>BCF</td></tr><tr><td>**Developmental Toxicity**</td><td>DevTox</td></tr><tr><td>**Mutagenicity**</td><td>Mutagenicity</td></tr><tr><td>**Normal boiling point**</td><td>BP</td></tr><tr><td>**Vapor pressure at 25°C**</td><td>VP</td></tr><tr><td>**Melting point**</td><td>MP</td></tr><tr><td>**Flash point**</td><td>Density</td></tr><tr><td>**Density**</td><td>FP</td></tr><tr><td>**Surface tension at 25°C**</td><td>ST</td></tr><tr><td>**Thermal conductivity at 25°C**</td><td>TC</td></tr><tr><td>**Viscosity at 25°C**</td><td>Viscosity</td></tr><tr><td>**Water solubility at 25°C**</td><td>WS</td></tr></table>
desiredSmiles	SMILES string to run
method Abbreviation	<table><tr><td>**Method**</td><td>**Abbreviation**</td></tr><tr><td>**Hierarchical clustering**</td><td>hc</td></tr><tr><td>**Single model**</td><td>sm</td></tr><tr><td>**Nearest neighbor**</td><td>nn</td></tr><tr><td>**Group contribution**</td><td>gc</td></tr><tr><td>**Consensus**</td><td>consensus (default if method omitted)</td></tr></table>

For example, to calculate water solubility for ethanol using the consensus method:

➢ http://webtest.sciencedataexperts.com/WS?smiles=CCO

The output is as follows:

```
uuid:               "2c6d7152-6e49-47f0-a8c2-8f0385e54fee"
predictionTime:     1501884653670
software:           "T.E.S.T (Toxicity Estimation Software Tool)"
softwareVersion:    "4.2"
condition:          "25°C"
endpoint:           "Water solubility at 25°C"
method:             "Hierarchical clustering"
predictions:
  0:
      id:           "C_1501884653670"
      smiles:       "OCC"
      expVal:       "-1.337"
      expValMass:   "1001180.703"
      predVal:      "-1.338"
      predValMass:  "1002625.241"
```

The GET API call can be used as a quick health check on the server.

5.8. "POST" API call

The URL for a post call is as follows:

➢ URL/endpointAbbreviation

where the URL and endpointAbbreviation options are as given in previous sections.

The Request Body for a post API call is as follows:

Request Body

{
  "query": "smiles1\nsmiles2\nsmiles3\n",
  "format": "inputFormat",
   "method": "methodAbbreviation"
}

Where \n is the new line character, and the other parameters are given by:

Parameter	Description		
inputFormat			
	Format	**Abbreviation**	
	MDL MOL file	MOL	
	MDL SDF file	SDF	
	SMILES file	SMI or SMILES	
method Abbreviation			
	Method	**Abbreviation**	
	Hierarchical clustering	hc	
	Single model	sm	
	Nearest neighbor	nn	
	Group contribution	gc	
	Consensus	consensus (default if method omitted)	

5.9. Docker

The file is as follows:

```
FROM java:8-jre

COPY config.yml /opt/WebTEST/
COPY target/WebTEST.jar /opt/WebTEST/

EXPOSE 8100 8101

VOLUME /opt/WebTEST

WORKDIR /opt/WebTEST
CMD ["java", "-jar", "WebTEST.jar", "server", "config.yml"]
```

Commands for building and running Docker containers

To build the WebTEST Docker container, run the following at the command line:
➢ docker build -t epa/webtest .

To build a specific version of WebTEST Docker container, run the following:
➢ docker build -t epa/webtest:0.1 .

To run WebTEST Docker container interactively, run the following:
➢ docker run -it --name webtest -p 8100:8100 epa/webtest

To run WebTEST Docker container in a daemon mode, run the following:

- docker run -d --name webtest -p 8100:8100 epa/webtest

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