KnowItAll Software Training

Chemometrics Analysis with KnowltAll Trendfinder

Spectrum Analysis

How to Use KnowItAll Trendfinder to Perform Chemometrics Analysis

Purpose

These exercises demonstrate how to use KnowltAll Trendfinder to perform Chemometics analysis on various spectra.

Objectives

These exercises will teach you to apply KnowltAll Trendfinder to

- ➤ IR
- > LC-MS
- GC-MS
- Raman
- UV-Vis

Background

The KnowltAll Trendfinder application allows one to perform Chemometrics analysis of spectral and chromatographic data.

Training Files Used in This Lesson

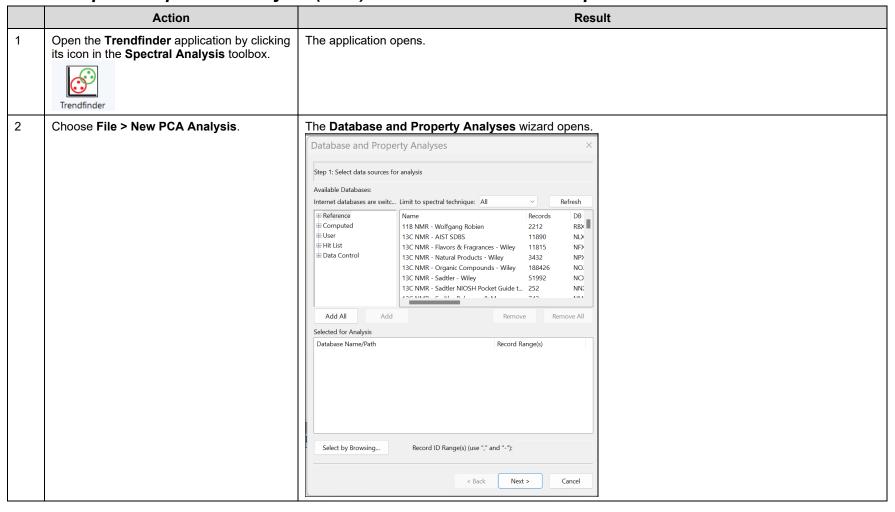
C:\Users\Public\Documents\Wiley\KnowItAll\Samples

KnowltAll Applications Used

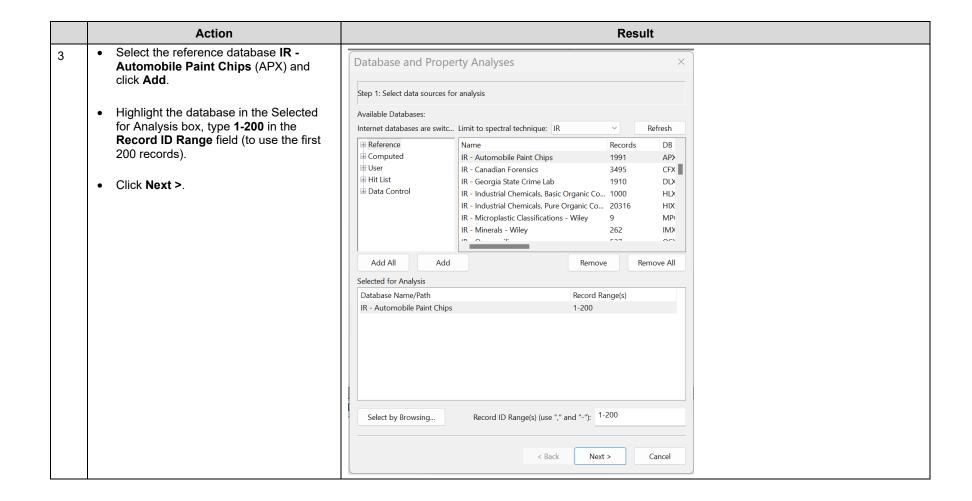
KnowItAll Trendfinder

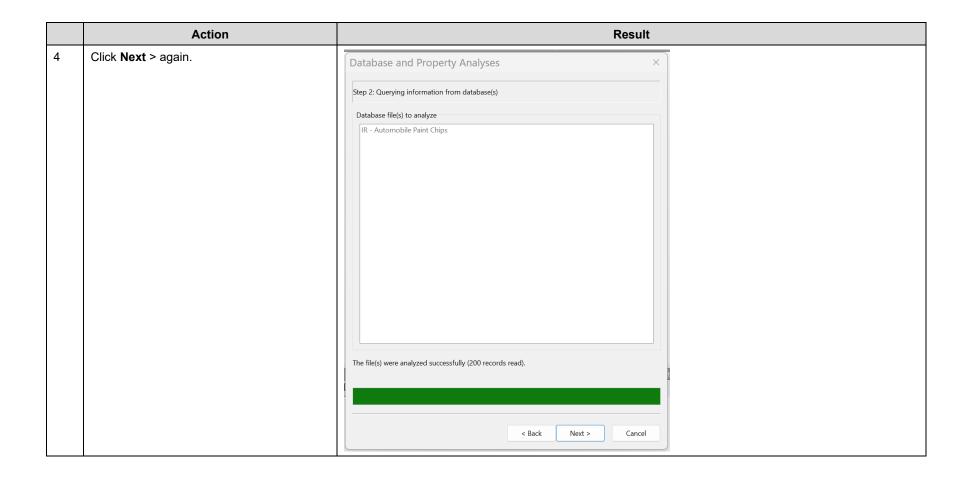
IR Example

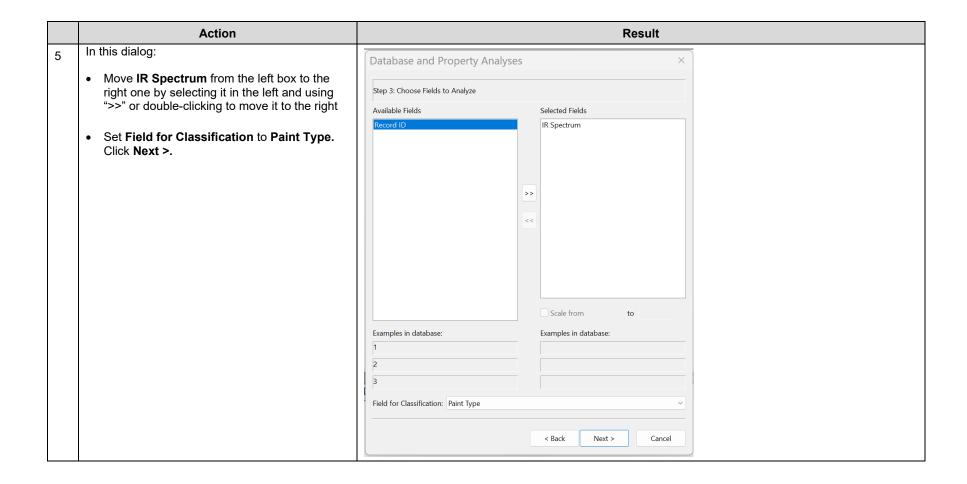
A. Principal Component Analysis (PCA) of Automobile Paint Chips

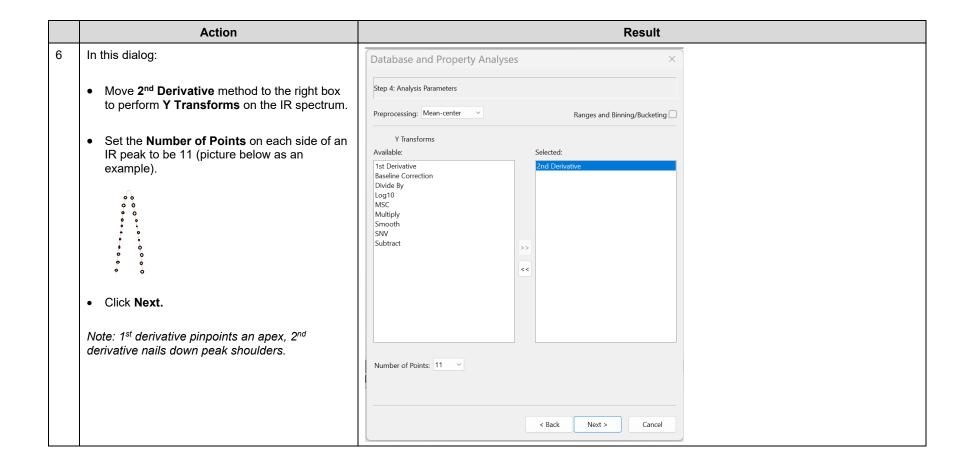


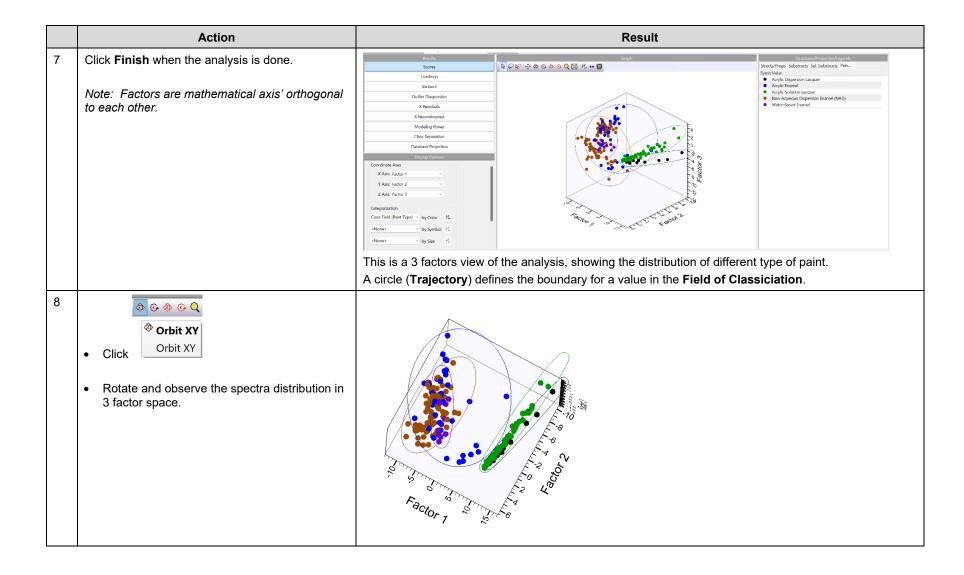


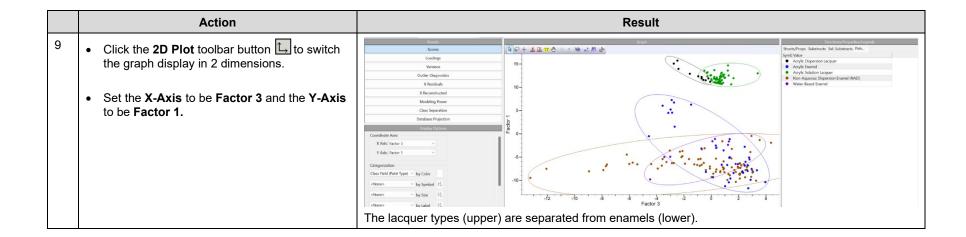


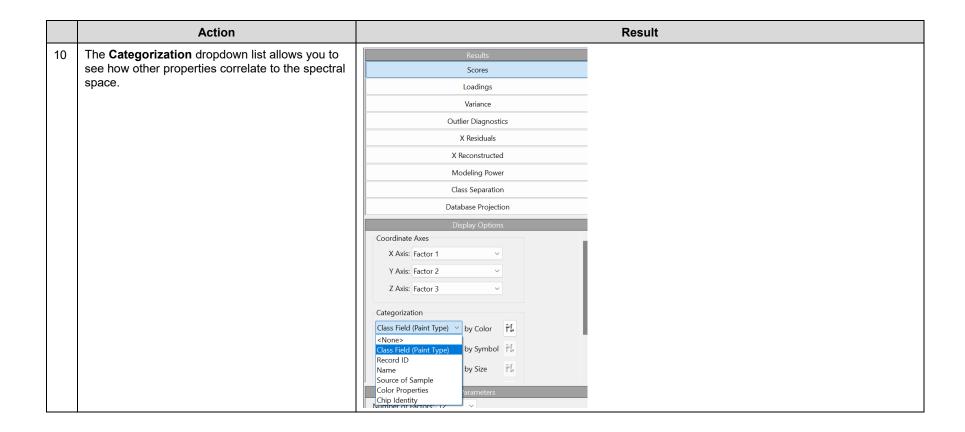


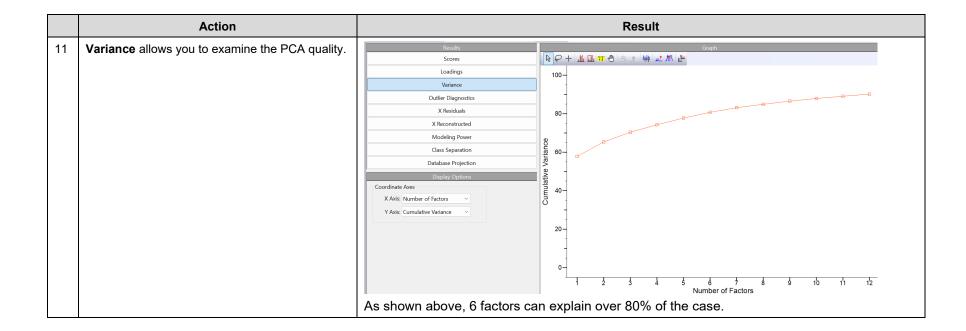


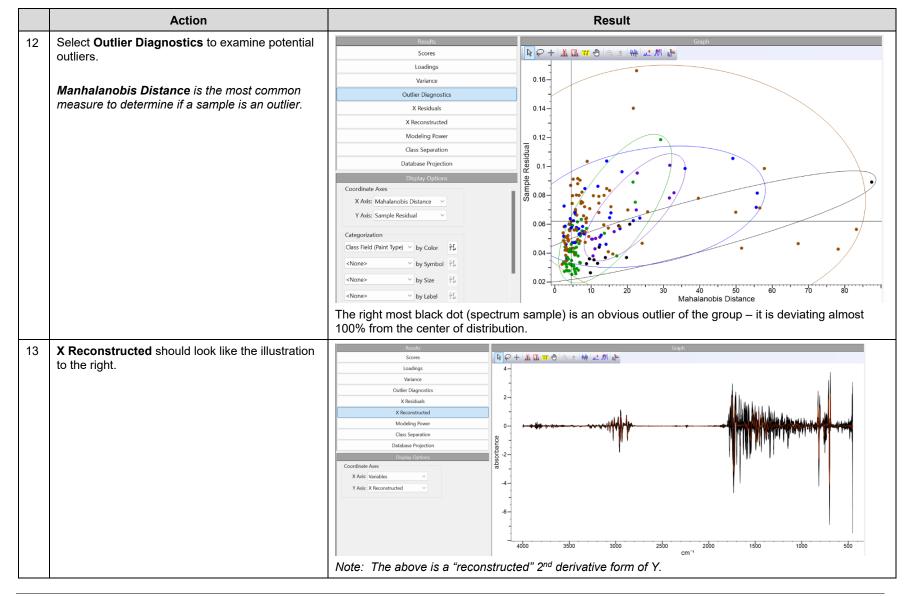




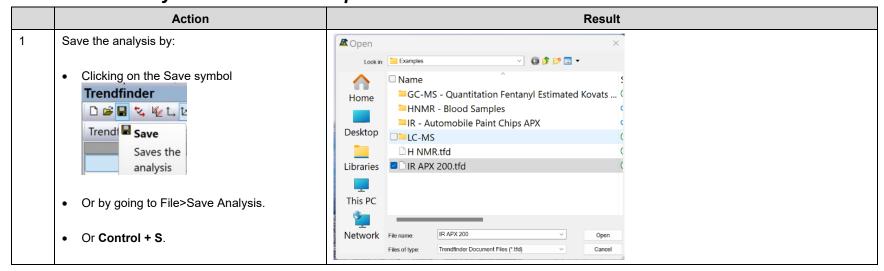


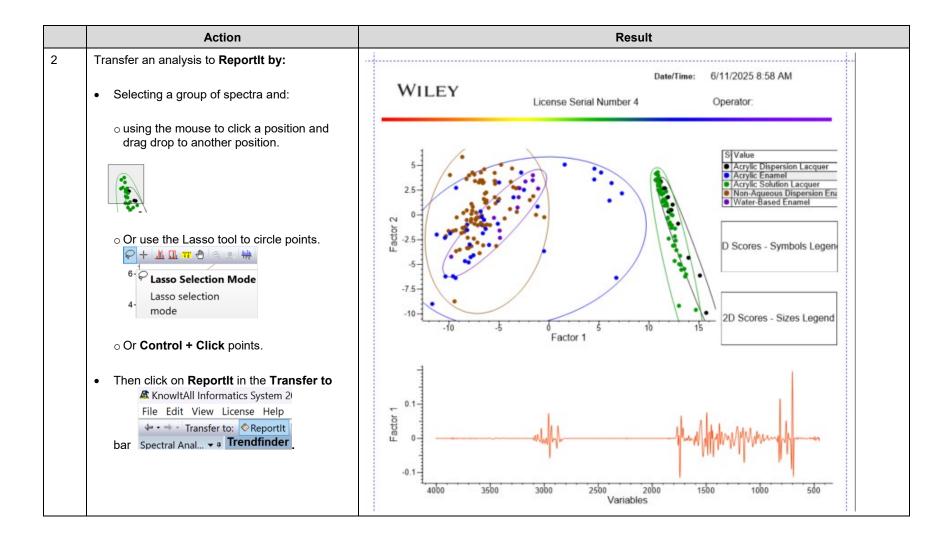


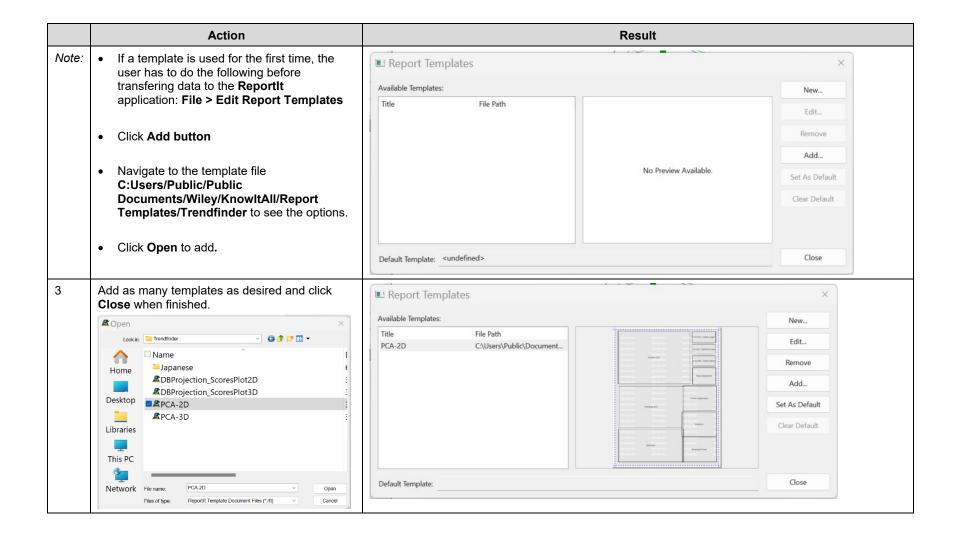




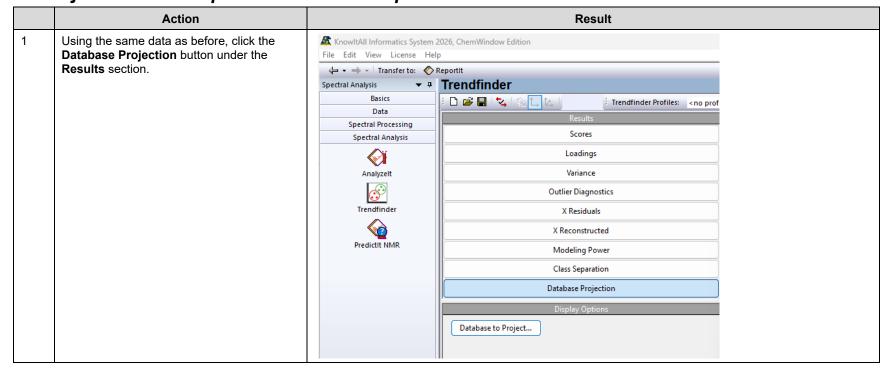
B. Save the Analysis and Create a Report

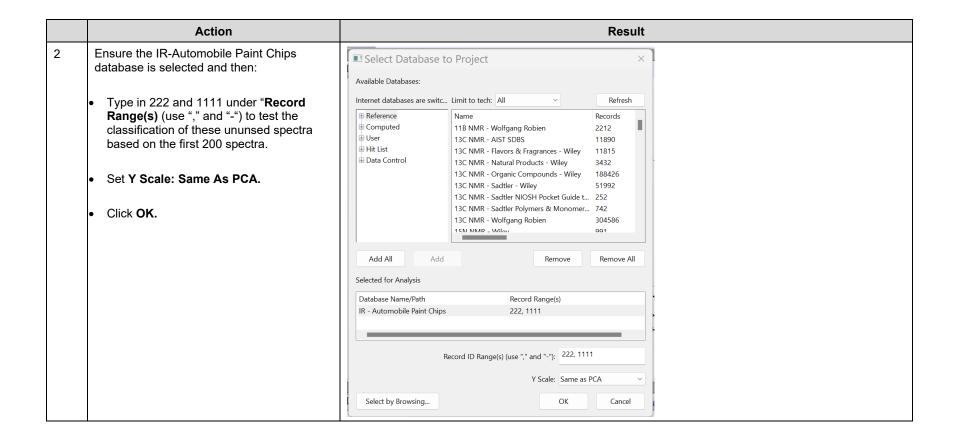


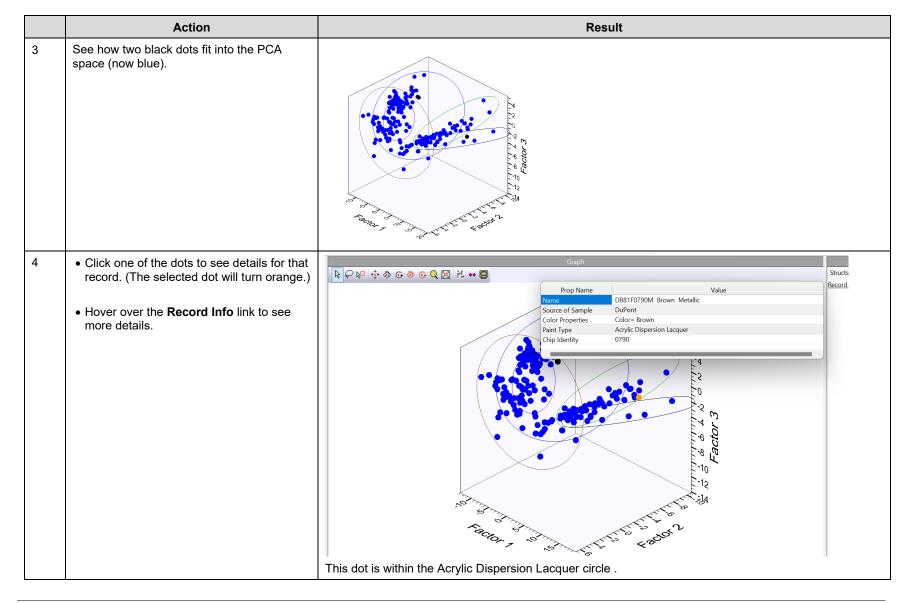


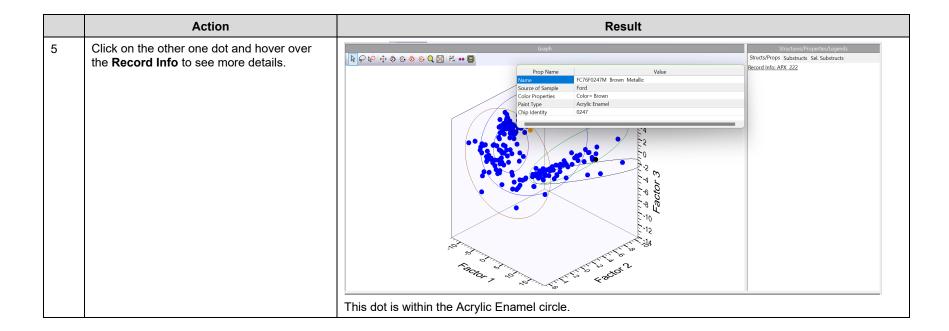


C. Project Unknown Spectra to the PCA "Space"



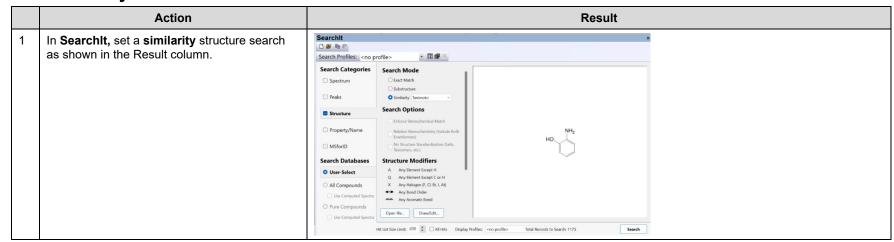


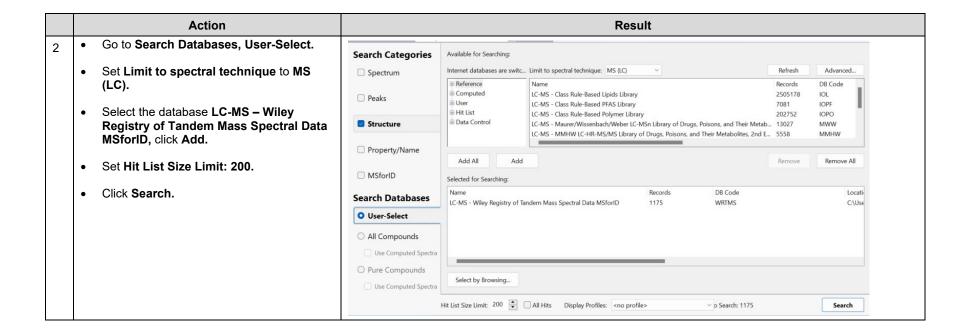


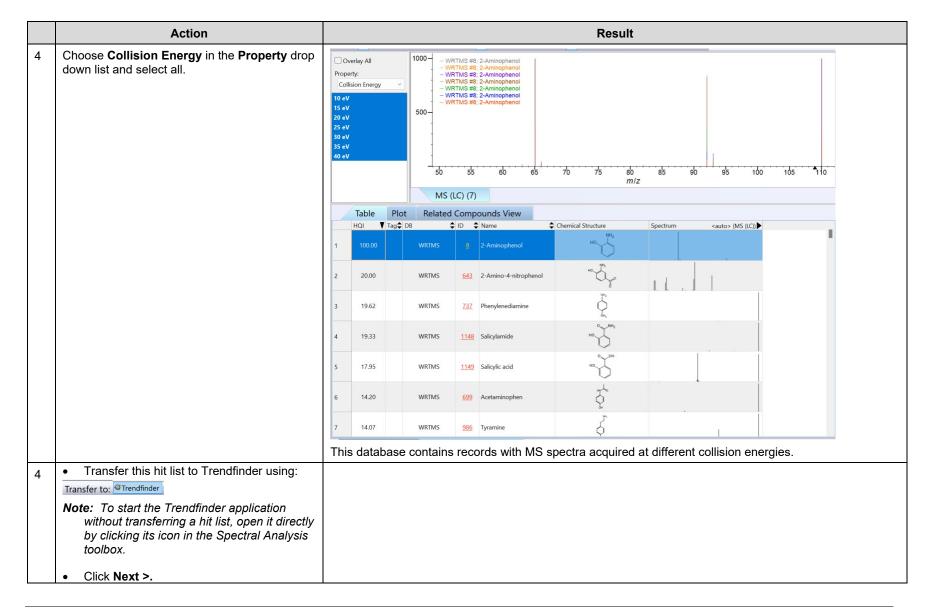


LC-MS

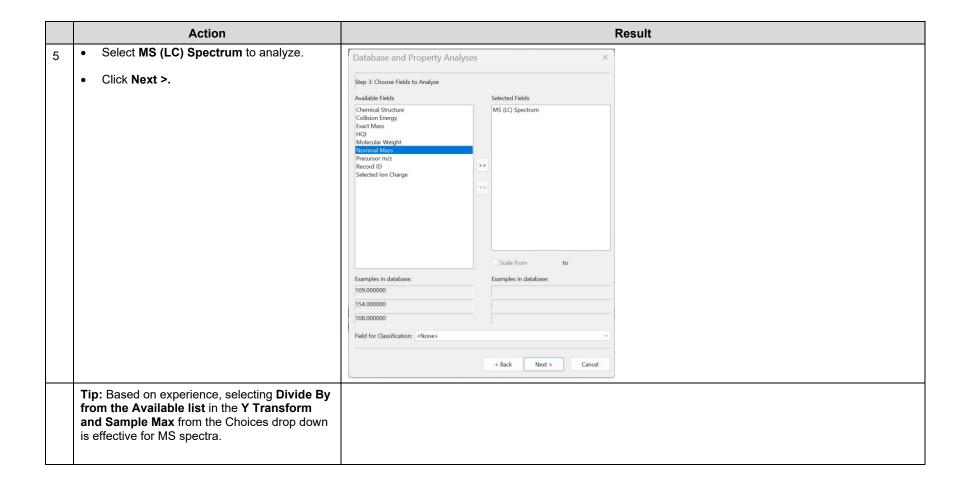
Hit List Analysis of Similar Structures

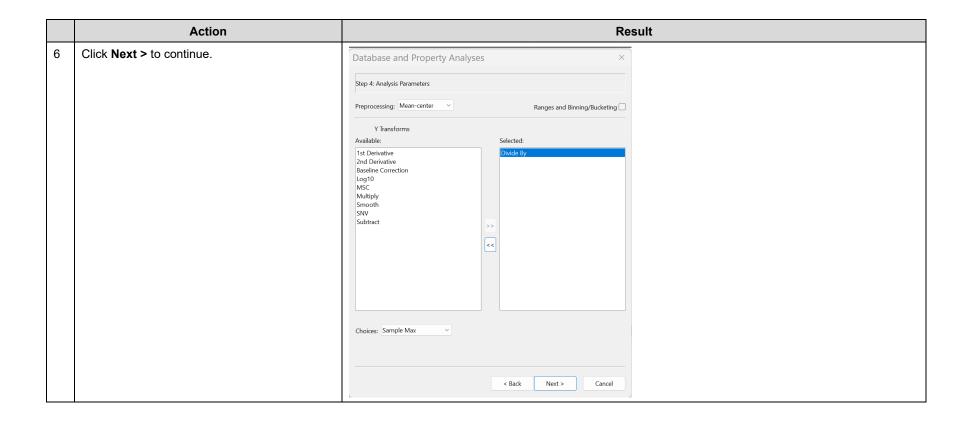


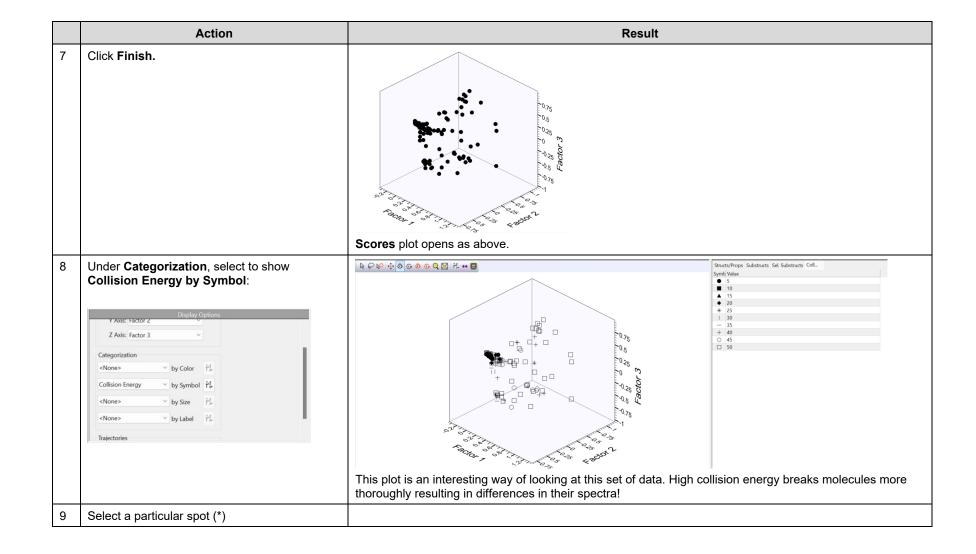




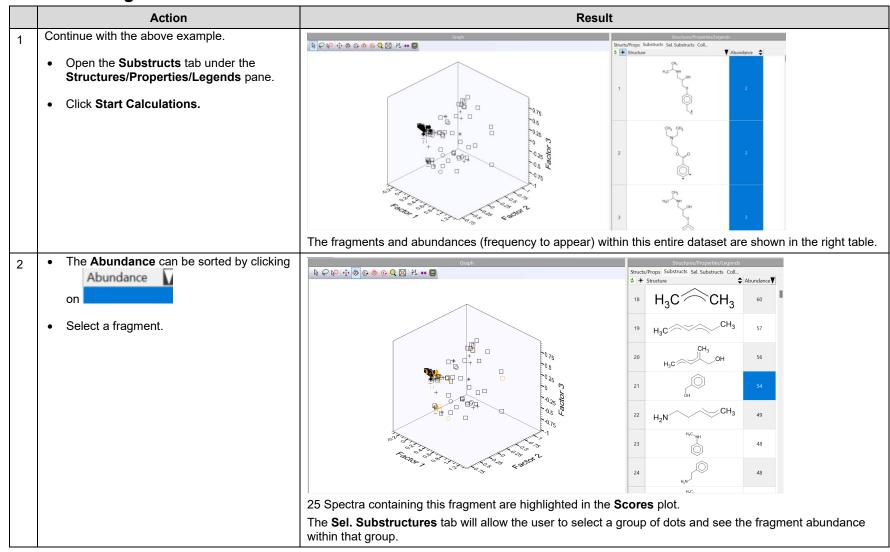




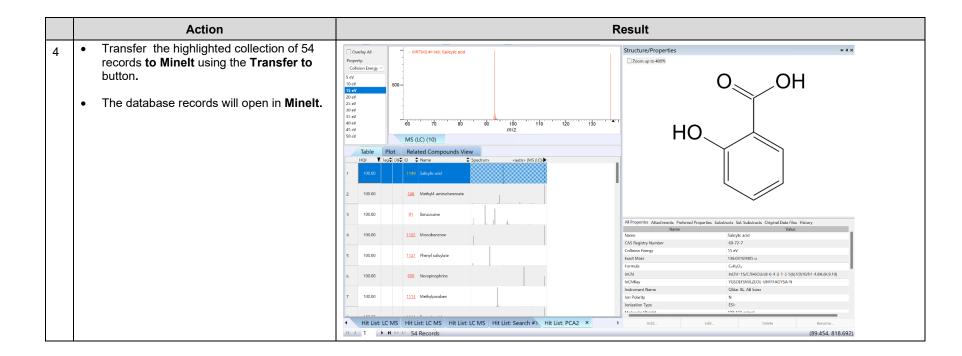




Common Fragments

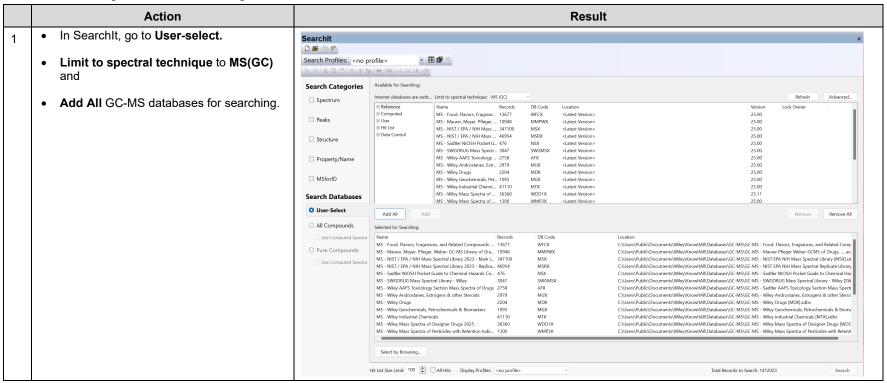


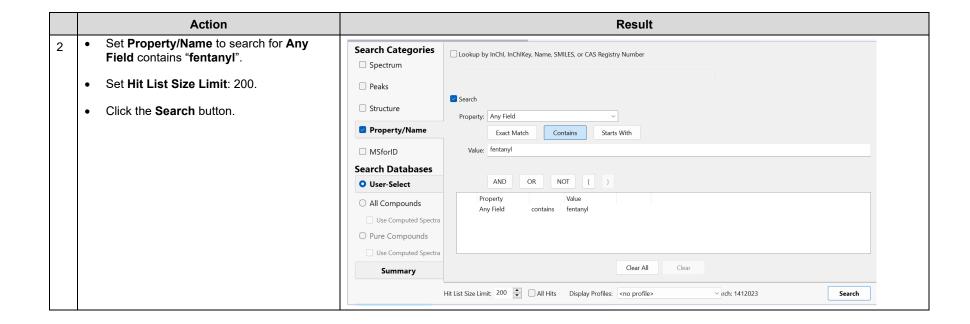


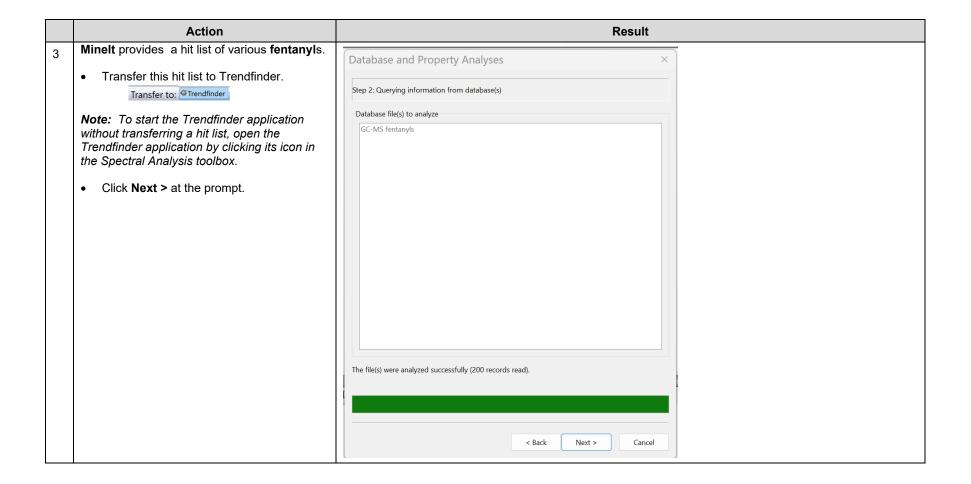


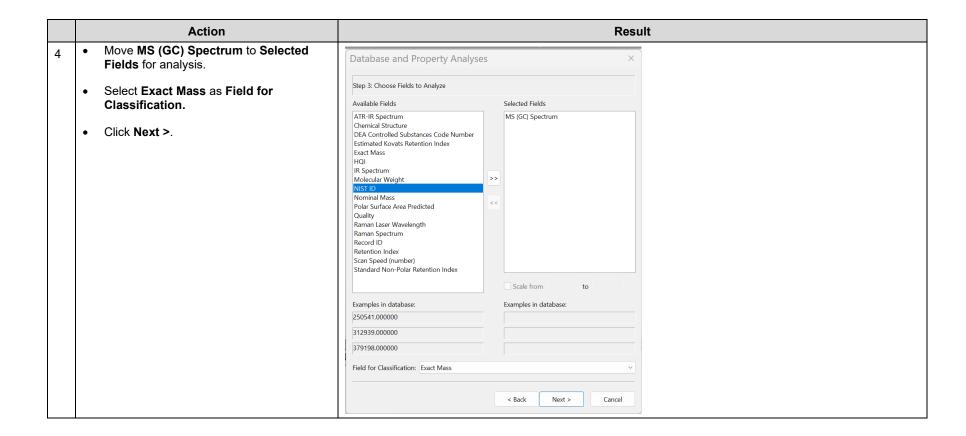
GC-MS

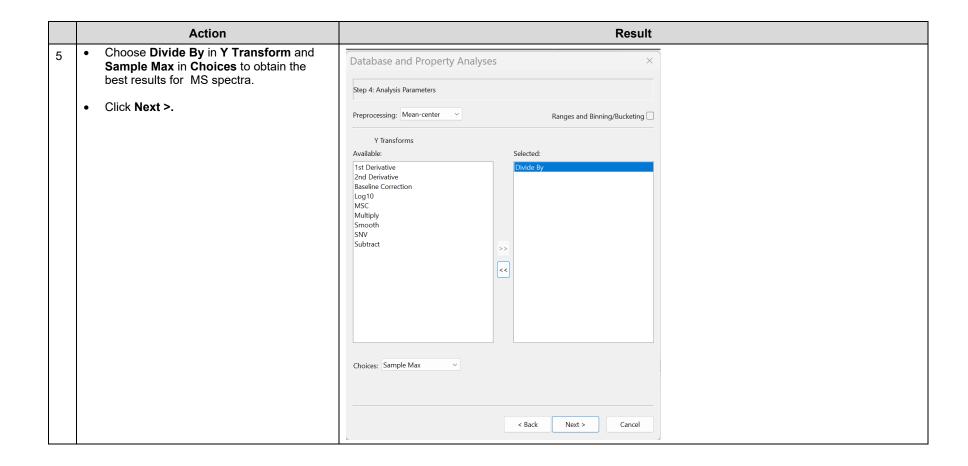
Hit List Analysis Of Fentanyls

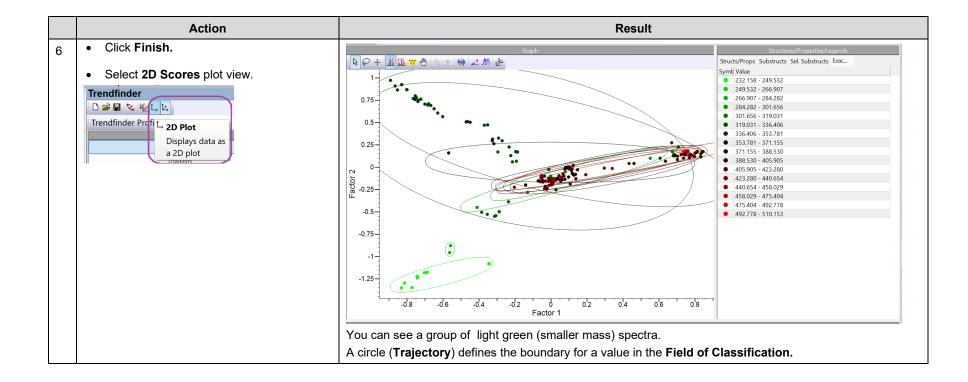


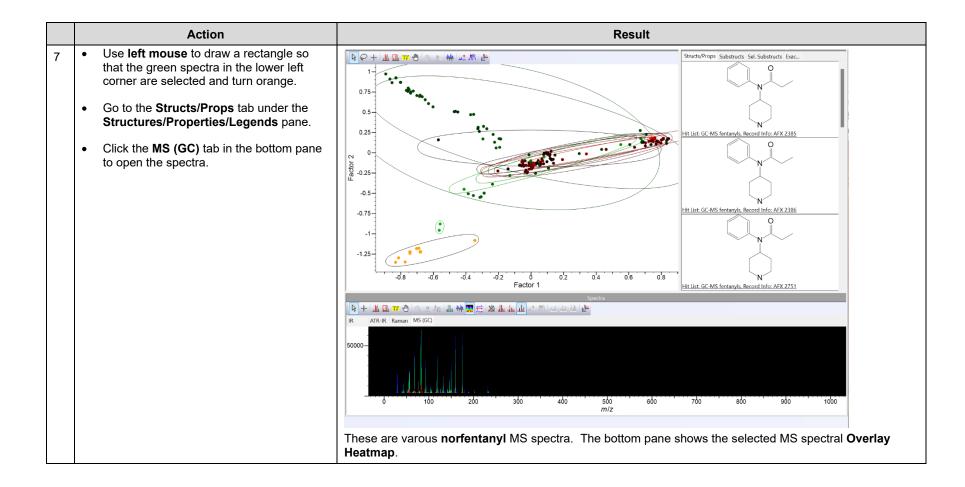


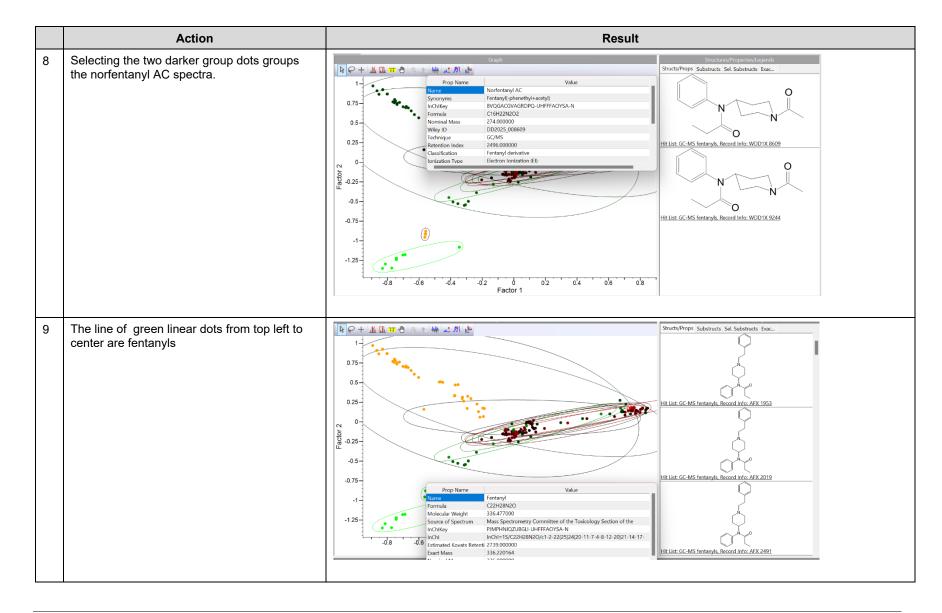






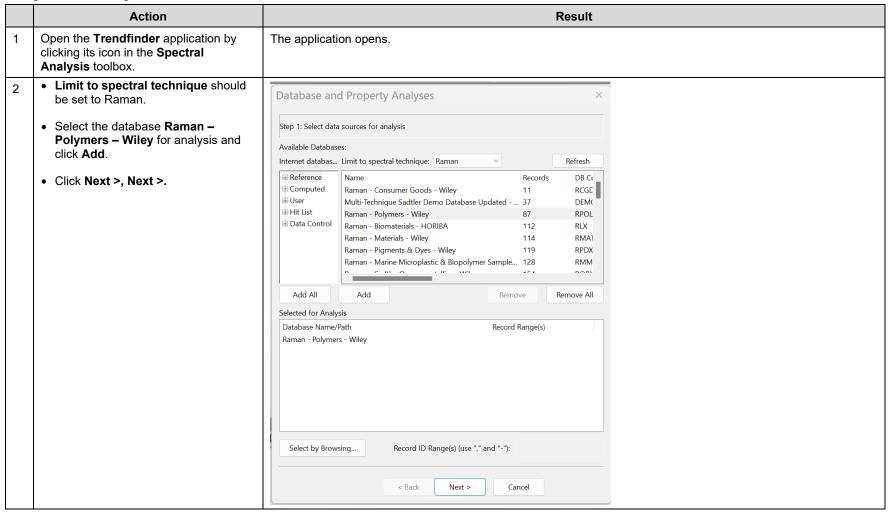




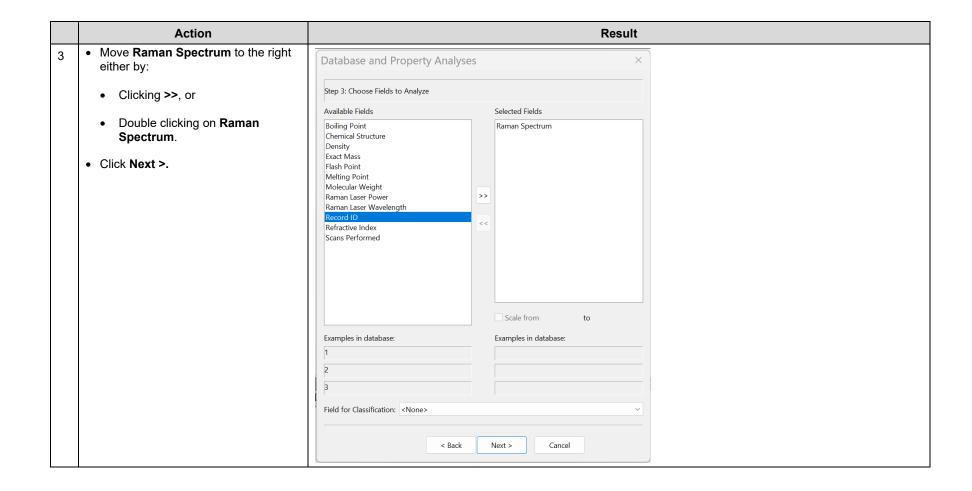


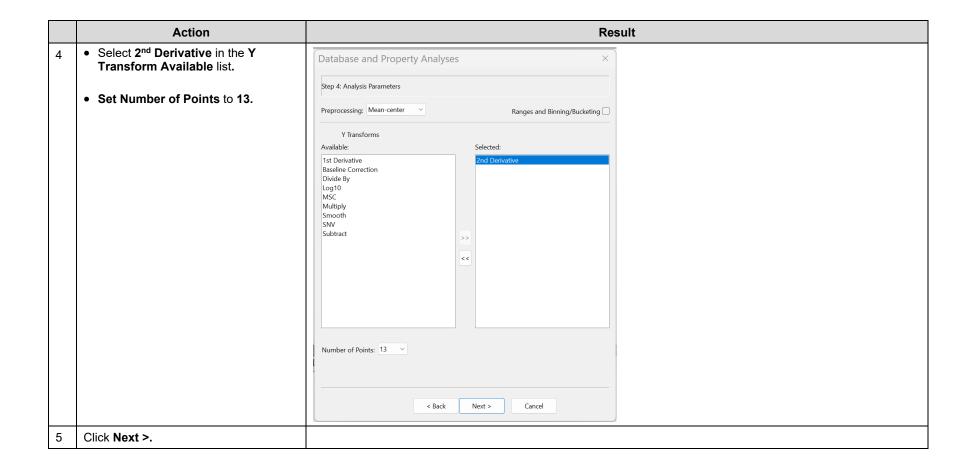
Raman

Polymer Analysis



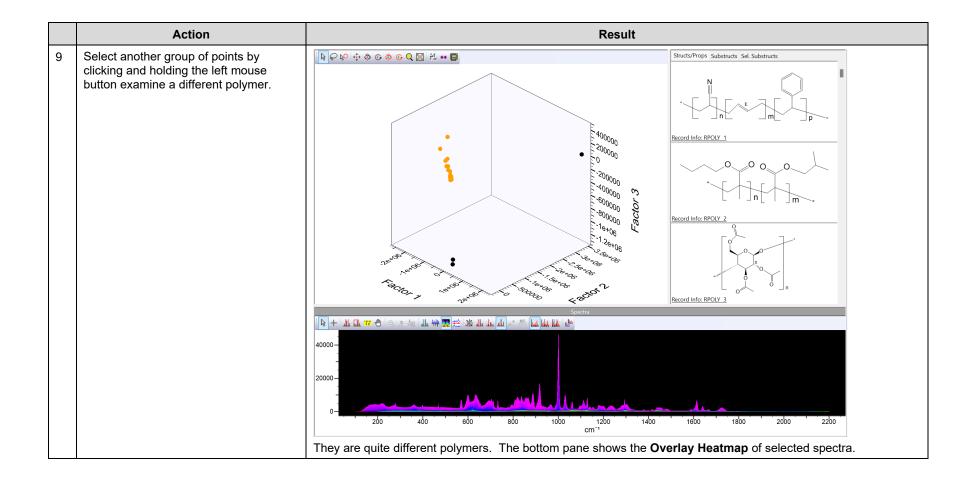






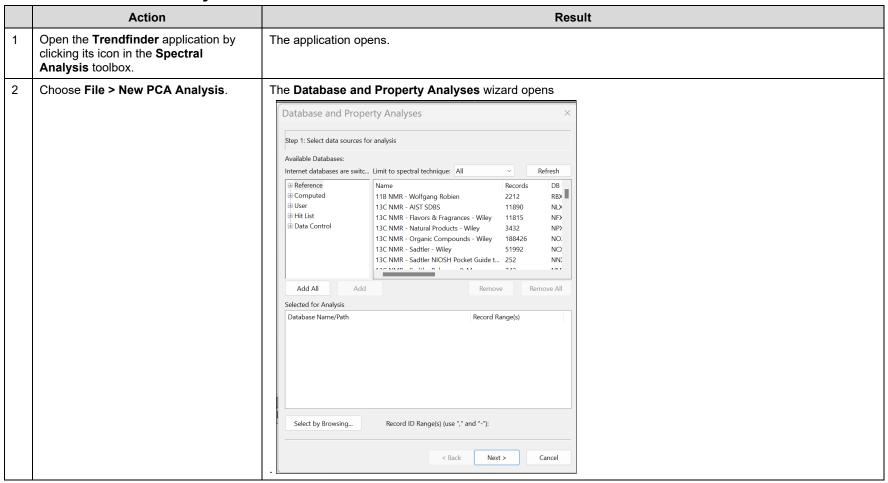
	Action	Result
6	Click Finish.	3 big groups are clearly identified.
7	Use the left mouse to select a group of points.	### ### ### ### #### #################

	Action	Result
8	Move to another point to examine a different polymer.	* Factor 3 Process of the second infer short

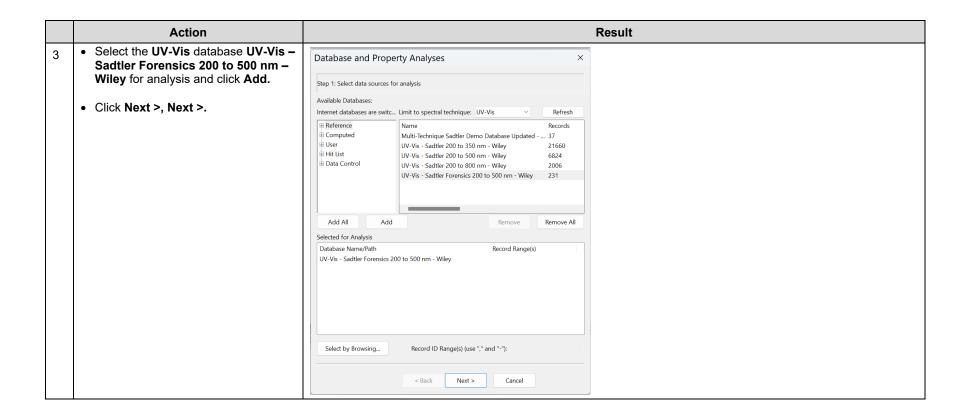


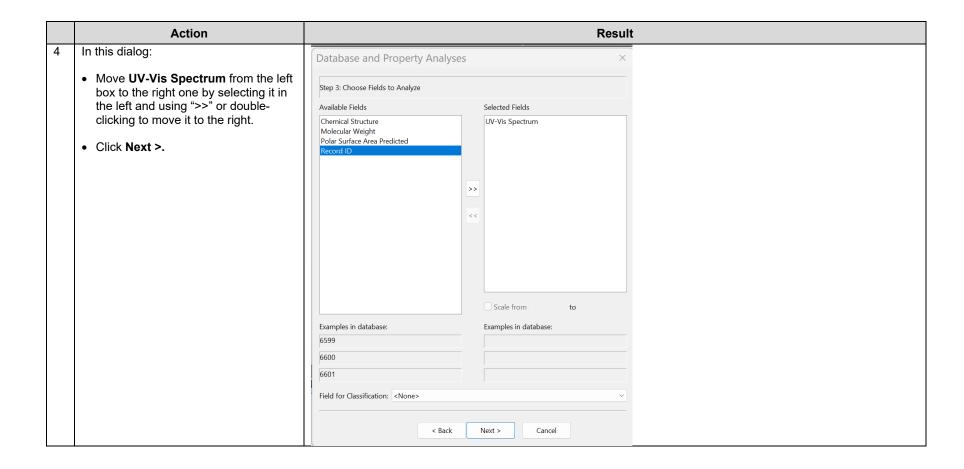
UV-Vis

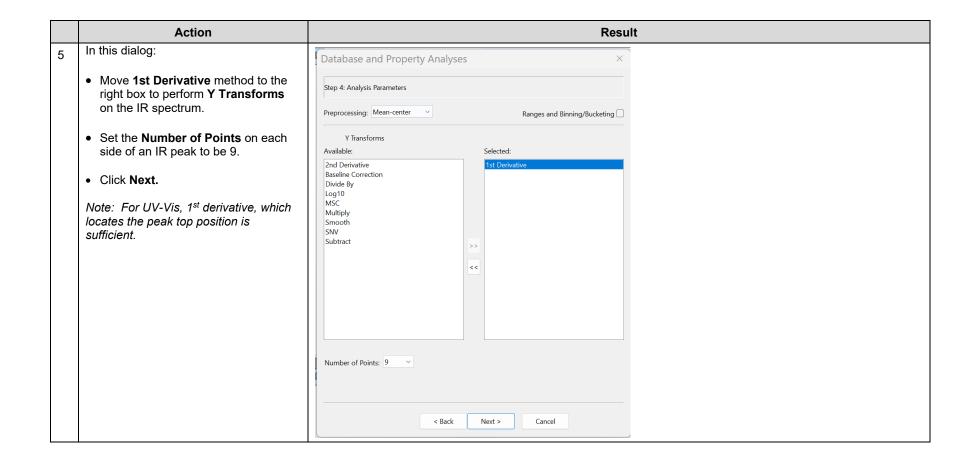
Forensic Material Analysis

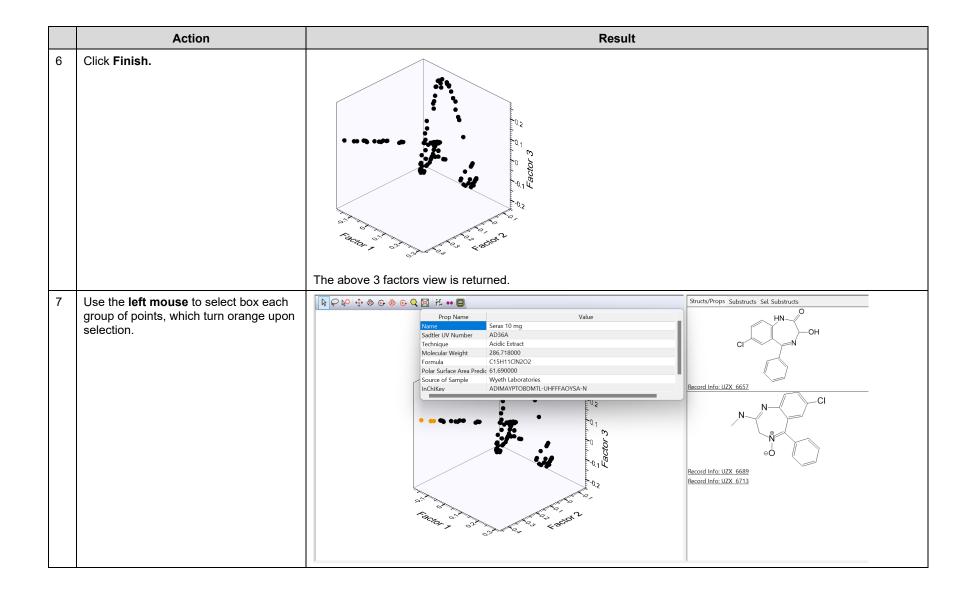


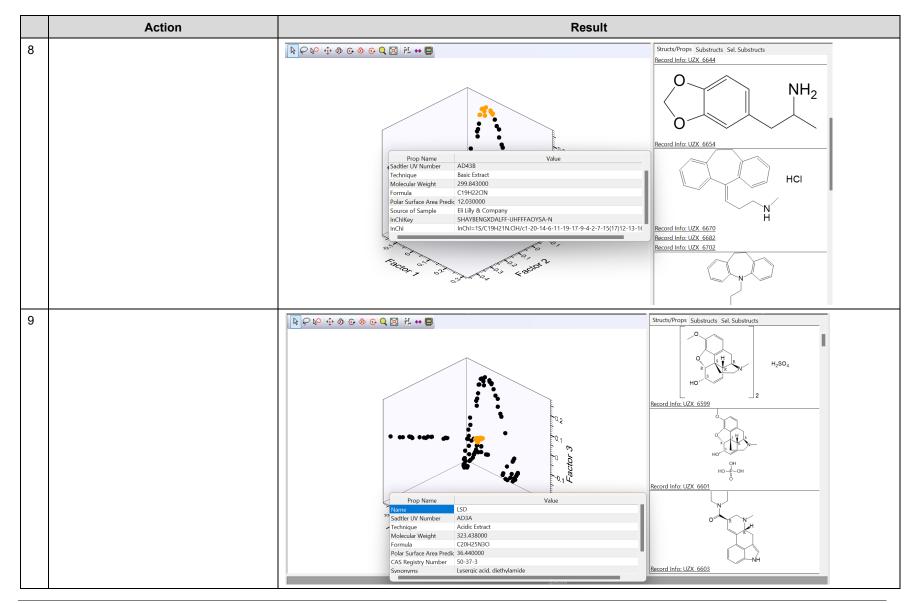










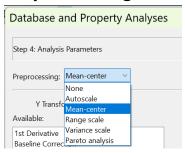


Principal Component Analysis (PCA) Theory

Principal Component Analysis (PCA) is a process which performs dimensionality reduction. Thus, it transforms a large set of variables into a smaller set of uncorrelated variables (principal components). At the same time, it retains most of the original data's variance. This portion of training will explain how it is applied to spectral data analysis by KnowltAll.

Parameters

Preprocessing



- None: No preprocessing occurs.
- Autoscale:

In Principal Component Analysis (PCA), "autoscale" refers to a preprocessing step where each variable in the dataset is standardized. This involves two main actions:

- 1. **Centering**: Subtracting the mean of each variable so that the mean of the transformed variable is zero.
- 2. Scaling: Dividing each variable by its standard deviation so that the variance of the transformed variable is one.

Autoscaling ensures that all variables contribute equally to the PCA, regardless of their original scales or units. This is crucial because PCA identifies directions of maximum variance, and without autoscaling, variables with larger scales could dominate the analysis.

- Mean-center: Centers the data relative to a reference point¹.
- Range scale: Min-max scaling which transforms the data to fit within a specific range².
- Variance scale: First, the variance for each valuable is calculated. Then, each variable is divided by the standard deviation.



• **Pareto analysis:** Pareto analysis is a decision-making tool based on the idea that 80% of a project's benefit can be achieved by doing 20% of the work, or conversely, 80% of problems can be traced to 20% of the causes. In other words, it posits that not all inputs have the same or even proportional impact on a given output³.

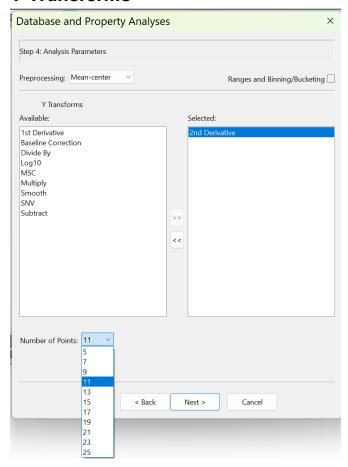


¹ Eigenvector Research Documentation Wiki (2012) *Advanced Preprocessing: Variable Centering*, https://www.wiki.eigenvector.com/index.php?title=Advanced Preprocessing: Variable Centering (accessed 2025-08-19).

² Geeks for Geeks (2025) *Normalization and Scaling*, Normalization and Scaling, Normalization and Normalization and Normalization and Normalization and Normalization and Normalization an

³ Kenton, W. (2025) Pareto Analysis: Definition, How to Create a Pareto Chart, and Example, https://www.investopedia.com/terms/p/pareto-analysis.asp (accessed 2025-08-19).

Y-Transforms



- 1st Derivative: parameter "Number of points" is the number of points on each side of a bell curve (peak).
- 2nd Derivative: parameter "Number of Points" definition like 1st derivative.
- Baseline Correction: to correct the baseline.
- **Divide By:** Various data matrix transformation and normalization methods.
 - Sample 1-norm: area normalization.

- Sample 2-norm: vector length normalization.
- Sample Max: sample max value (suitable for MS spectra).
- Sample Range: consider various instrument measurement differences.
- Value at Variable: normalize to the value at a particular variable n.
- Log10: Applies log10 to scale Y values.
- MSC: Multiple Scatter Variate⁴.
- **SNV:** Standard Normal Variate⁵.
- Multiply: Multiple Y by an editable numerical value.
- Smoothing: Uses our standard Savitzky-Golay algorithm to smooth noisy data.
- Subtract: The user can define the value to subtract.



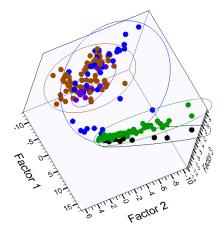
⁴ Fearn, T., Riccioli, C., Garrido-Varo, A., and Guerrero-Ginel, J.E. On the geometry of SNV and MSC, Chemometrics and Intelligent Laboratory Systems, **2009** 96(1), 22-26. Doi: https://doi.org/10.1016/j.chemolab.2008.11.006.

⁵ Standard Normal Variate (2025) Standard Normal Variate - an overview | ScienceDirect Topics, ScienceDirect (accessed 2025-08-19).

Result

Scores (plot)

A graphical representation that displays the scores of the first 2 or 3 principal components as Factors, mathematical axis' orthogonal to each other, allowing for the visualization of the relationships between observations in a dataset⁶. Selecting the first 200 records of the IR - Automobile Paint Chips (APX) database with the parameter **Mean-center**, results in the plot below:



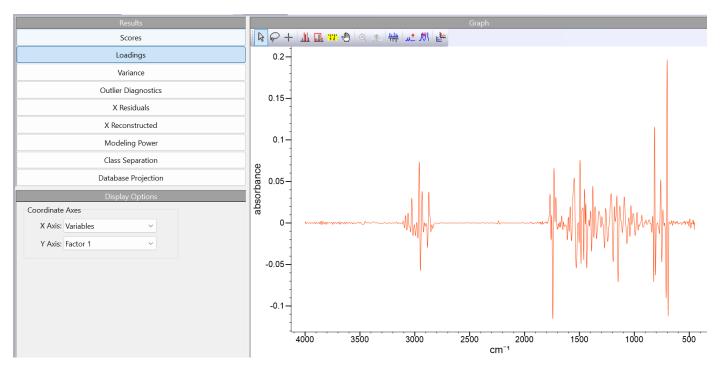
A circle (**Trajectory**) defines the boundary for a value in the **Field of Classification**).

⁶ Dunn, K.G. (2025) Latent Variable Modelling in *Process Improvement using Data*, (https://learnche.org/pid/latent-variable-modelling/principal-component-analysis/interpreting-score-plots-and-loading-plots) (accessed 2025-08-19).

Loadings

In order to show the relationship between the original variables and the principal components, it helps to understand how much each original variable contributes to the principal components and the nature of these contributions⁷. Using the above example, it would be:

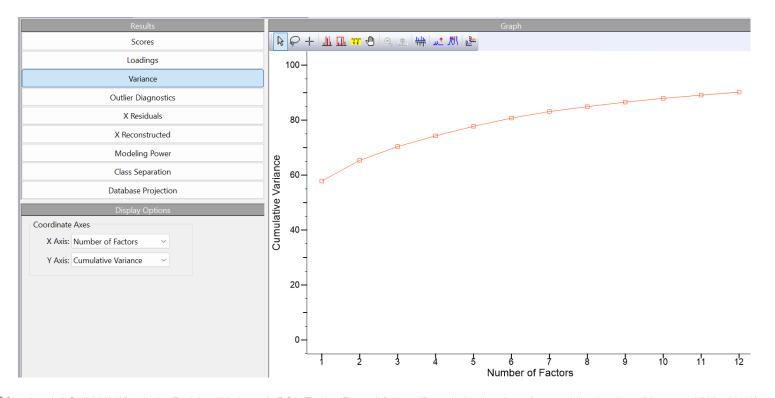




⁷ Schork, J. (2025) What are Loadings in PCA? Statistics Global (https://statisticsglobe.com/what-are-loadings-pca#loadings-in-pca) (accessed 2025-08-19).

Variance

Variance refers to the proportion of the total variance attributed to each principal component⁸. It helps us understand how much information is retained after dimensionality reduction. The fraction of variance explained by a principal component is the ratio between the variance of that principal component and the total variance⁹ When applied to the above example, the result is:



⁸ Chouinard, J.C. (2023) What is the Explained Variance in PCA (Python Example), https://www.jcchouinard.com/pca-explained-variance/(accessed 2025-08-19).

Outlier Diagnosis

It identify outliers by reducing dimensionality and visualizing data on scores plots. Here are the terms used in KnowltAll under the Outlier Diagnostics pane:

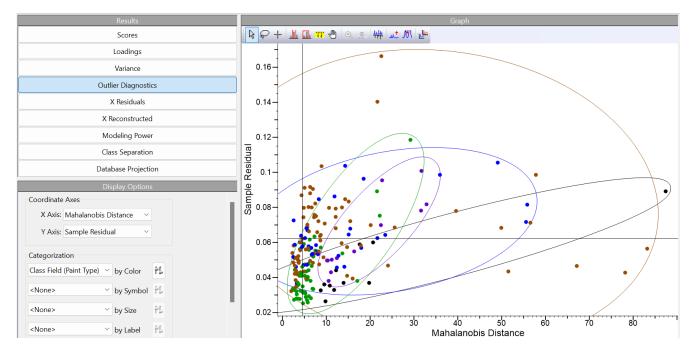
• Mahalanobis Distance¹¹: Measures a distance between 2 points. It is a multivariate generalization of the square of the standard score z=(x-µ)/o: how many standard deviations away P is from the mean of D. This distance is zero for P at the mean of D and grows as P moves away from the mean along each principal component axis. If each of these axes is re-scaled to have unit variance, then the Mahalanobis distance corresponds to standard Euclidean distance in the transformed space. The Mahalanobis distance is thus unitless, scale-invariant, and takes into account the correlations of the data set. In short, it measures how far a point is from the center of the data

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⁹ Cheplyaka, R. (2017) Explained variance in PCA, https://ro-che.info/articles/2017-12-11-pca-explained-variance (accessed 2025-08-19).

distribution, considering the covariance structure. PCA can be used to compute this distance in the reduced feature space. The following steps apply:

- Apply PCA to reduce dimensionality.
- Compute the Mahalanobis distance for each data point in the reduced space.
- Identify points with distances exceeding a threshold (e.g., based on a chi-squared distribution) as outliers. Using the above example, the result is:



- Samples: The ID of each sample (i.e., 1 to number of rows/spectra).
- Sample residual
- **F Ratio:** This is the statistic for evaluating whether two variances or standard deviations are significantly different. It is calculated by dividing one variance by another variance. If the null hypothesis is true, you expect F to have a value close to 1.0 most of the time. A large F ratio means that the variation among group means is more than you'd expect to see by chance. The F-distribution or F-ratio is a continuous probability distribution that arises frequently as the null distribution of a test statistic, most notably in the analysis of variance (ANOVA) and other F¹⁵.
- Probability



Record ID

X Residuals

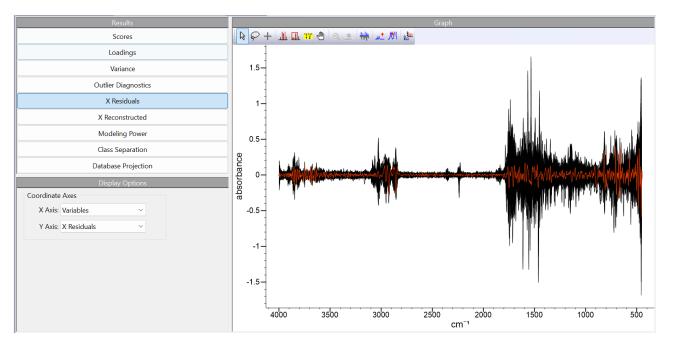
PCA residuals are calculated using the residual matrix $E = X - T P' = X - X^n$, where X is the original matrix and T P' is the PCA model. The residuals for each column in the original matrix can be calculated using the R 2 value, which gives an indication of how well the PCA model describes the data from that column. The function pcares(X,ndim) returns the residuals obtained by retaining ndim principal components of the n-by-p matrix X. PCA of a model residuals is based on how well the model translates the effect of variables in Z Z on the data we are analyzing. Using the **residual** matrix $E = X - T P' = X - X^n$, we can calculate the **residuals** for each column in the original matrix. This is summarized by the R 2 value for each column in X and gives an indication of how well the **PCA** model describes the data from that column¹³. Using the above example, we get:



¹⁰ Datathatmatters (2024) Outlier Detection Simplified: PCA Techniques for Improved Data Analysis https://datathatmatter.com/2024/11/03/outlier-detection-simplified-pca-techniques-for-improved-data-analysis/ (accessed 2025-08-19).

¹¹ Wikipedia (2025) Mahalanobis distance, https://en.wikipedia.org/wiki/Mahalanobis distance (accessed 2025-08-19).

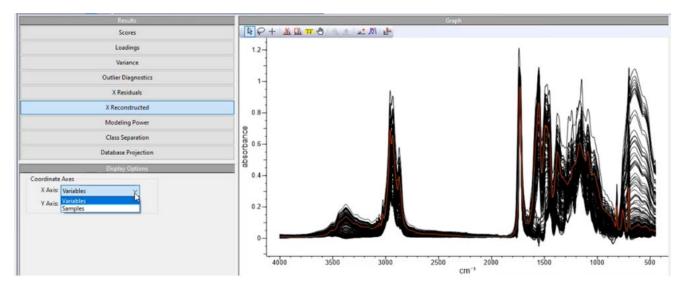
¹² GraphPad Software, LLC.(2025) Interpreting results: One-way ANOVA, https://www.graphpad.com/guides/prism/latest/statistics/f ratio and anova table (one-way anova).htm (accessed 2025-08-19).



¹³ Dunn, K.G. (2025) Latent Variable Modelling in *Process Improvement using Data*, https://learnche.org/pid/latent-variable-modelling/principal-component-analysis/interpreting-the-residuals (accessed 2025-08-19).

X-reconstructed

Reconstruct the original variables from a principal component¹⁴ It can be viewed as "reverse PCA". For the above dataset, we get:

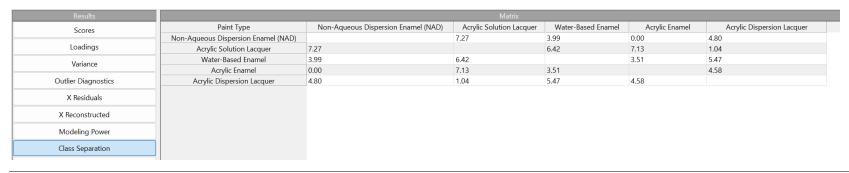


¹⁴ Stack Exchange (2025) How to reverse PCA and reconstruct original variables from several principal components? https://stats.stackexchange.com/questions/229092/how-to-reverse-pca-and-reconstruct-original-variables-from-several-principal-com">https://stats.stackexchange.com/questions/229092/how-to-reverse-pca-and-reconstruct-original-variables-from-several-principal-com">https://stats.stackexchange.com/questions/229092/how-to-reverse-pca-and-reconstruct-original-variables-from-several-principal-com (accessed 2025-08-19).

Modeling power

Class Separation

It measures how well different class are separated¹⁵. Our particular example for the 1st 1000 spectra:





KnowltAll Training Simple Sp	
	pectral Search - 59
¹⁵ Stack Exchange (2025) Measures of class separability in classification problems, https://stats.stackexchange.com/questions/46780/measures-of-class-separability-problems (accessed 2025-08-19).	ility-in-classification-