

CIUSuite 2 User Guide

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A Note on Terminology

- The terms “drift time” for the y-axis and “collision voltage” for the x-axis of a CIU fingerprint are used throughout this manual. However, analyses are generally independent of the nature of the axes, with a few caveats:
 - The ion mobility data should always be on the y-axis (but this can be arrival time, drift time, CCS, elution voltage, etc.)
 - The x-axis should be the independent variable. However, it can be just about anything that causes a change in observed IM (collision voltage, source/cone voltage, source temperature, solution temperature, laser energy, etc.)

1. Installation, Requirements and Source Code

- Installation:
 - Download **CIUSuite2_Setup.exe** from <https://sites.lsa.umich.edu/ruotolo/software/ciusuite-2/>
 - Double-click on the downloaded setup icon to run the installer and follow the prompts on screen
- Requirements (installer/executable version)
 - Windows
 - Tested on Win 7, should work on newer Windows in theory, but may not
 - No other requirements
 - Setup will install a local Python interpreter and all required packages and resources

1. Installation, Requirements and Source Code

- Source Code

- Source can be found at <https://github.com/ruotololab/CIUSuite2>
- To run:
 - Download source and resource files (all included in the above repository)
 - All source and resource files must be placed in the same folder for the program to operate
 - Run CIU2_Main.py with Python

- Requirements (Building from source)

- Python 3
 - Built on Python 3.5.3, should work on any 3.5+ but hasn't been tested
- Packages:
 - Numpy, scipy, matplotlib, sklearn, LMfit, pygubu, PyQt5

2. Importing Raw Data

- CIUSuite 2 reads data from ‘_raw.csv’ format
 - Comma-separated values file (text)
 - First row is activation energy values (green)
 - First column is ion mobility values (blue)
 - Intensity data fills the matrix (white). Each column represents the summed arrival time distribution at a given activation energy.
- Activation and IM values can be anything (as long as they are numbers)
 - E.g. activation axis can be collision voltage, laser power, solution temperature, etc.

Ion Mobility Axis (e.g. 'drift time (ms)')	Activation Energy Axis (e.g. 'collision voltage (V)')				
		10	15	20	...
	0	0	2	0	...
	0.182	5	7	2	...
	0.364	0	0	1	...

2. Importing Raw Data

- Generating _raw.csv files
 - ****** Automated converters are available to generate _raw.csv files directly from vendor raw data formats. Making _raw.csv files by hand is not necessary for most instruments/applications. ******
 - Waters .raw data: TWIMExtract
 - See <https://sites.lsa.umich.edu/ruotolo/software/twim-extract/> for details and links to download software and get instruction manual
 - Agilent .d data: converter being built
 - See [TBD – will update once out of beta]

2. Loading Data: the .ciu file

- After raw data has been processed with CIUSuite 2, a “.ciu” file is created to save the data and any processing results for future reference.
 - A .ciu file contains:
 - Raw data
 - Processed data (after normalization and any smoothing, cropping, interpolation, etc.)
 - Analysis results (e.g. detected features, fitted Gaussians, CIU50 values, etc.)
 - Parameters used to generate the processed data and analysis results
 - .ciu files are saved automatically after all processing steps and can be loaded using the load ‘.ciu’ button in CIUSuite 2.

3. Parameters

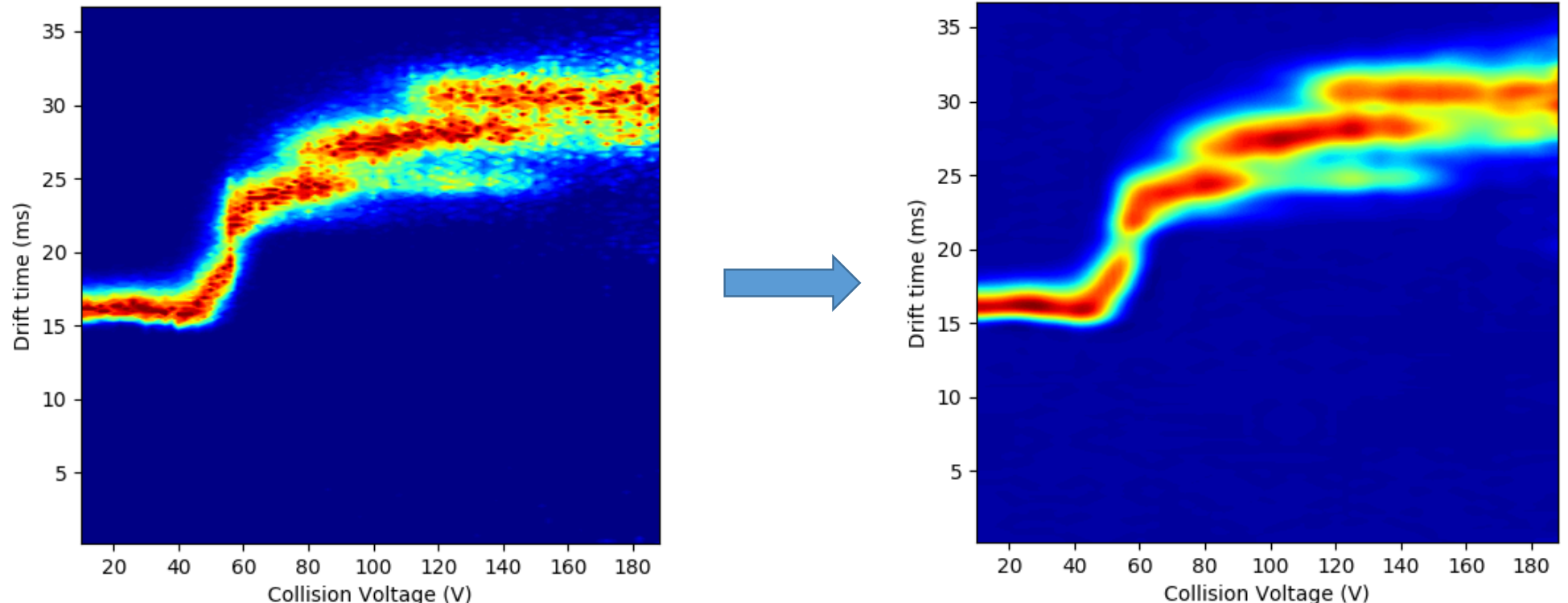
- The parameters used in analysis are saved into the .ciu file – so to see how any particular data was analyzed, use the ‘print parameters from file’ button.
 - NOTE: these are updated every time the .ciu file is saved (which is after most analyses), so it is possible in some cases to overwrite them after the fact
- If you want to save parameters so that you don’t have to keep entering them, use the ‘update default parameters’ button, which will save all current parameter values to be the defaults.

3. Output Plot Options

- The output plots that are generated by most analyses are highly customizable
- *** The 'Change Output Plot Options' button is where to find options for ALL output plots ***
 - Color scheme, filetype (.png, .pdf, .svg, etc), plot size and resolution, font size, and whether to display colorbars, legends, title, axes titles
- NOTE: title hierarchy
 - If a "Custom Plot Title" is provided, it will be displayed even if "Use Filename as Title" is set to False. The custom plot title takes precedence over the filename title.
 - If 'Use Filename as Title' is set to True and no custom title is provided, the filename will be displayed above the output plot
- NOTE: not all plots have all features available
 - e.g. the basic CIU_plot doesn't have a legend, so changing the whether a legend is displayed won't have any effect on that particular plot

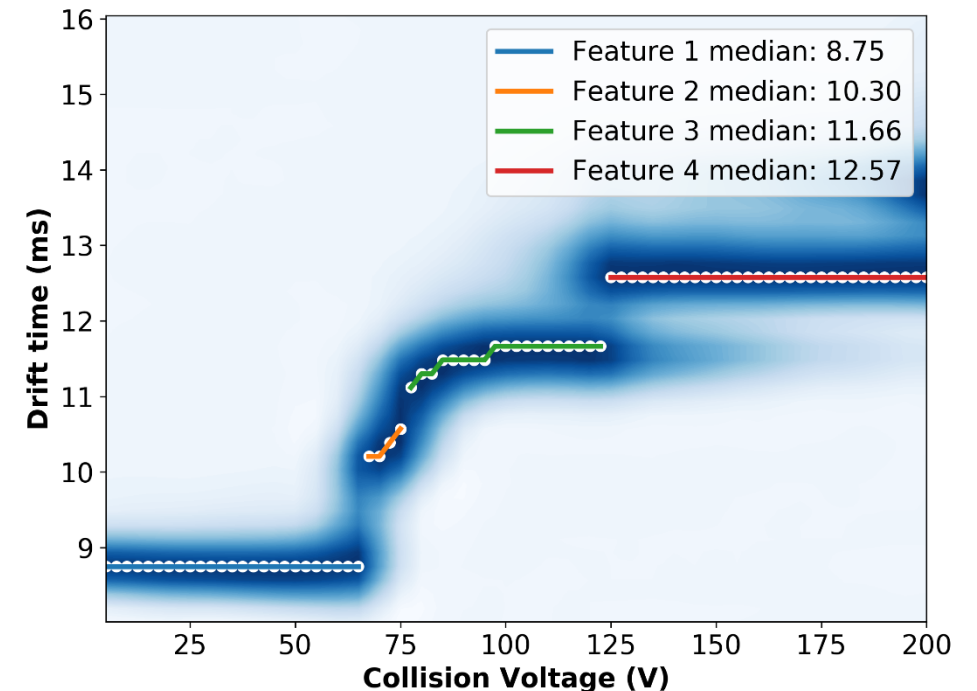
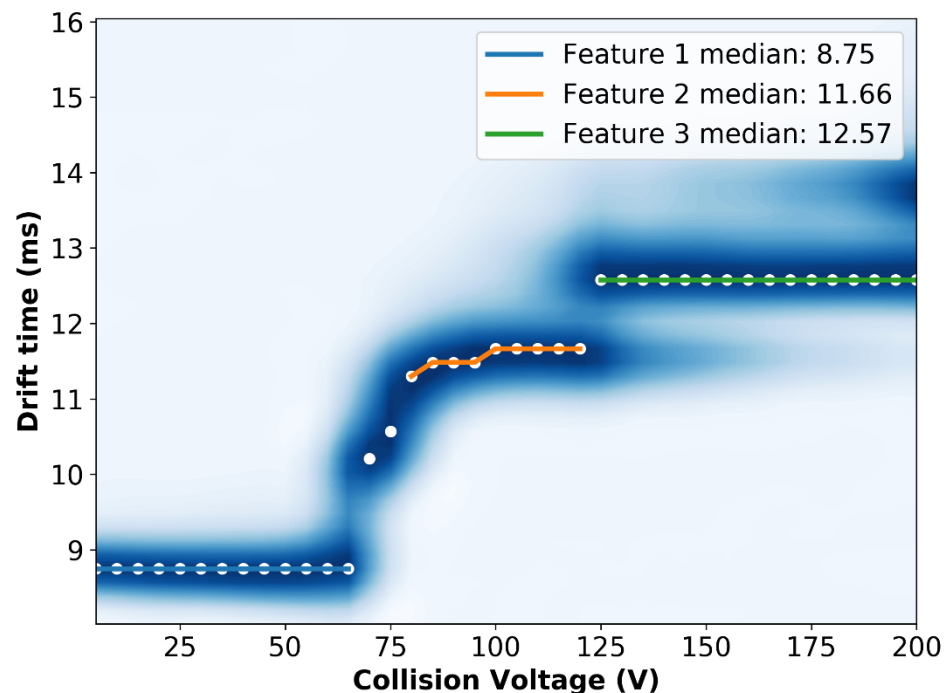
4. Data Processing: Smoothing

- A 2D Savitzky-Golay filter is used to smooth by default. 1D S-G filter (in drift time only) or no smoothing can be used instead if desired
- Window Size: The size (in steps/bins) of the filter to use (in both dimensions) for smoothing. Larger windows will include more data in the smooth, increasing smoothing but potentially blurring features
- Iterations: The number of times to smooth in succession



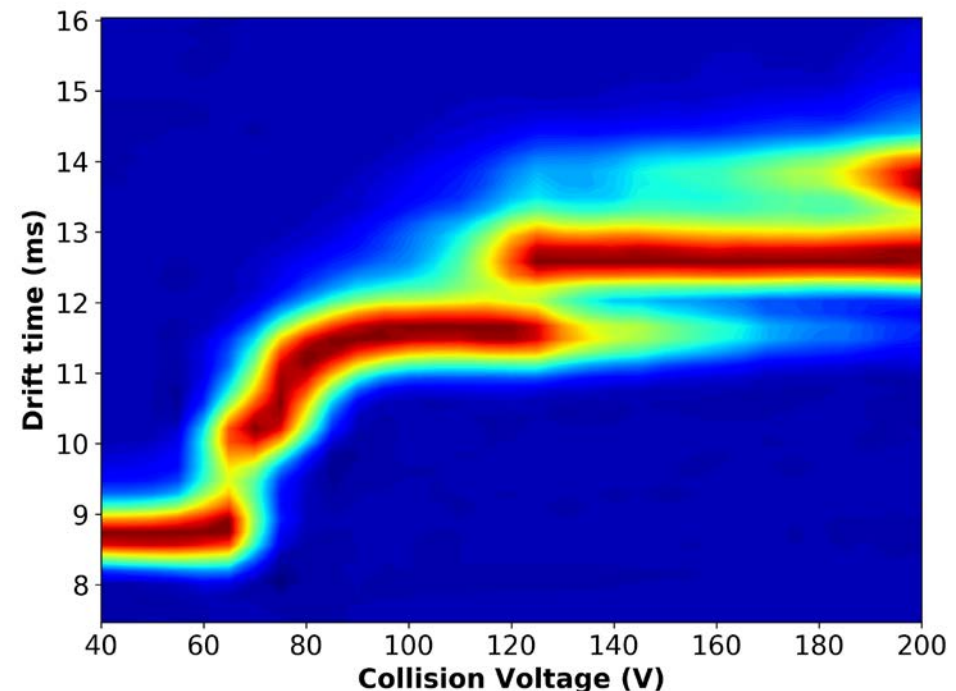
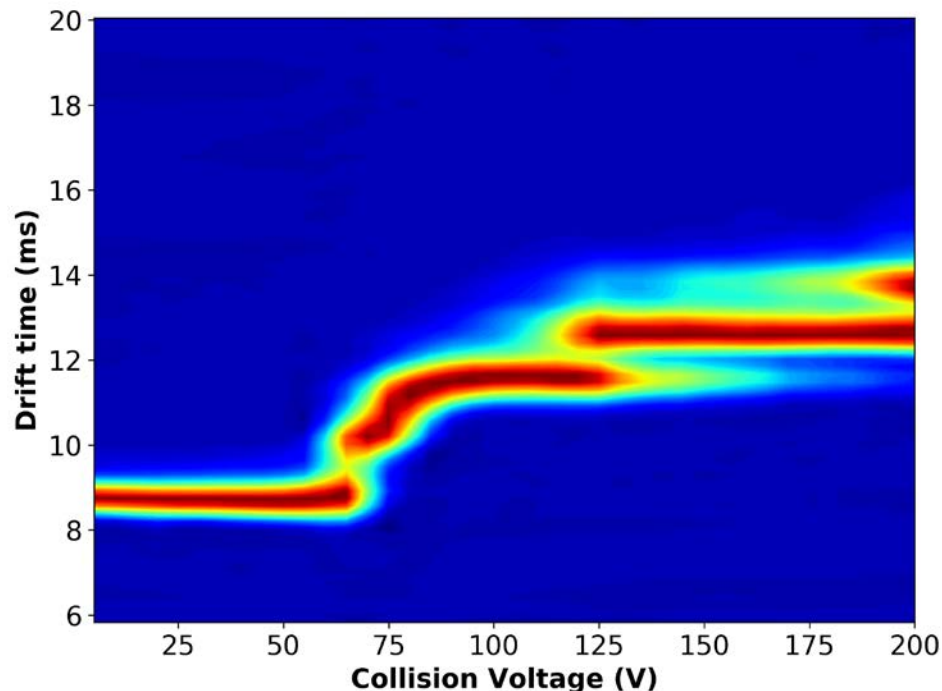
4. Data Processing: Interpolation

- Interpolation increases the number of bins/steps along an axis (or both axes).
 - Interpolating the activation axis can be very helpful for feature detection (shown below) to find features that are only present for a few steps in the original data
 - Interpolating the drift time/mobility axis can be helpful for Gaussian fitting
- Interpolation is done by a “factor,” or fold change in the number of bins. For example, interpolating by a factor of 2 means the number of bins along the axis will double (factor of 3 will triple, etc.).



4. Data Processing: Cropping

- Cropping cuts the fingerprint down to the specified dimensions in one or both axes.
 - This can be useful to focus on particular areas of interest, or simply to generate higher quality visuals.
 - The cropping menu will automatically detect the starting boundaries of the first fingerprint loaded in the processing table
- NOTE: cropping will REMOVE any feature detection/Gaussian fitting/etc. from a .ciu file because the boundaries used for those analyses are no longer valid



4. Data Processing: Restore Original Data

- Any smoothing, interpolation, or cropping can be undone by using the ‘restore original data’ button.
 - This loads the original raw data (saved from the original _raw.csv file used to generate a given .ciu file)
 - You will be prompted to do smoothing on the restored data. If you do not want to smooth, select “none” as the smoothing method.
- NOTE: Restoring original data will clear ALL processing and analysis from the file

4. Data Processing: Averaging

- Multiple replicate datasets can be merged into a single average fingerprint using the average button.
 - Averaging generates a new .ciu file containing the averaged data that can be used for further analysis/comparisons/etc
- NOTE: the averaging button will combine all files loaded in the table by default, so make sure only replicates of the same thing are loaded. Or use the 'analyze files from/to' entries to select only the files to be averaged.

4. Data Processing: Gaussian Fitting

- Gaussian fitting models the arrival time distribution as a sum of Gaussian functions (peaks) corresponding to one or more conformations of the analyte ions
- Fitting can be done in two modes:
 - 1) Protein only mode
 - All peaks are assumed to be from the analyte, and are expected to fall within a relatively narrow distribution of peak widths
 - 2) Denoising mode (signal and noise present)
 - Both analyte and other (noise) components are fit. Noise components are assumed to have larger width than analyte components, and can thus be separated and filtered out.
- Terminology:
 - In many places, the term “protein” is used to refer to the signal/analyte peak and “non-protein” to noise peak(s). This does not mean that fitting only works for proteins – so long as the width of signal and noise peaks are different, this method should be able to differentiate any signal peaks from any noise peaks.

4. Data Processing: Gaussian Fitting Parameters

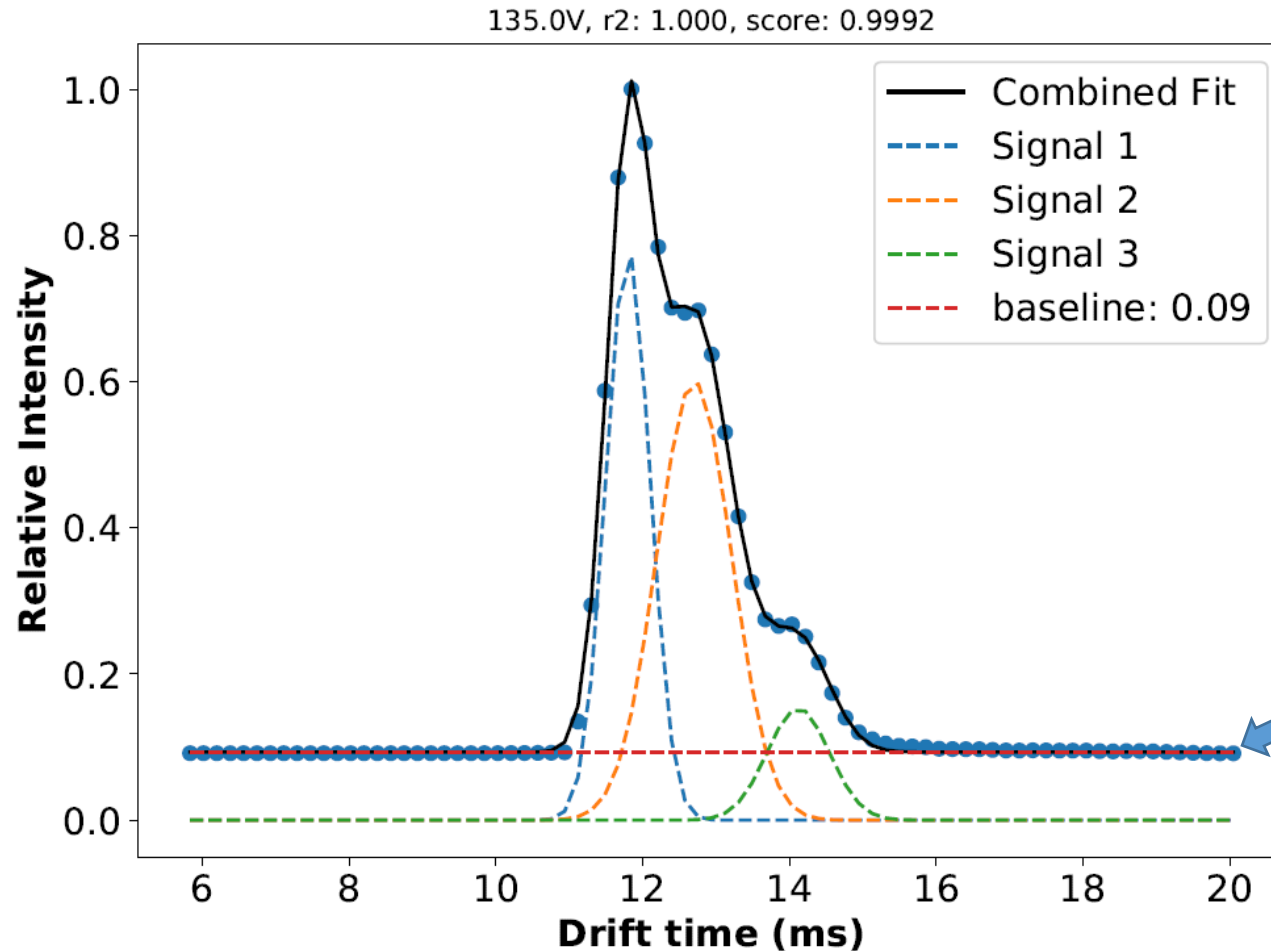
- Protein/Signal Only Mode:
 - True/False – True for protein only, False for protein and noise
- Minimum Peak Amplitude:
 - Minimum normalized (0 to 1) intensity for a peak to be fit
- Save Diagnostics:
 - If True, generates plots of all fits considered during the optimization, not just the highest scoring ones chosen. Generally not necessary unless debugging.
- Number of Cores for Multithreading:
 - Uses Python's multiprocessing module to increase the speed of calculations (otherwise, it can take several minutes per file).
 - NOTE: this can cause problems on some systems because of how it interacts with the operating system. If you experience problems, set this value to 1, which will perform serial processing instead and not use multiprocessing at all.

4. Data Processing: Gaussian Fitting Parameters

- Max Protein Components:
 - The maximum number of protein (signal) peaks to consider fitting at a single collision voltage. Higher numbers can improve results, but will increase processing time significantly.
- Expected Protein Peak Width:
 - ****This value is VERY important****
 - This is the expected width (full width at half max, FWHM, in the units of your ion mobility axis) of the protein peak(s). It depends on your instrument resolution and the protein/analyte in question, which is why you have to put the value in manually.
 - If you aren't sure what value to use, try fitting with the defaults and see what the resulting peak widths are; use that as a guide for refining the input width.
- Protein Peak Width Tolerance:
 - Protein peak widths are constrained to be within (Expected width +/- Tolerance), meaning that any peaks with widths outside this range will NOT be considered by the fitting algorithm.
 - Same units as expected peak width
- Peak Overlap Mode: (see manuscript SI for details)
 - “strict” penalizes peaks that overlap > 50% and is good for preventing overlapped fits
 - “relaxed” is the recommended setting – it penalizes overlaps of > ~85% but not so harshly as to prevent overlapping peaks from being considered when comparing to other solutions.
 - “none” means no peak overlap penalties will be applied. Use this if you think you have closely-overlapped peaks, but be aware that overfitting is very possible.

4. Data Processing: Gaussian Fitting Parameters

- Baseline mode: If True, includes a “baseline” function in the fit that provides a flat, vertical offset for all Gaussian functions. Useful in cases where data has a significant non-zero baseline (e.g. below)

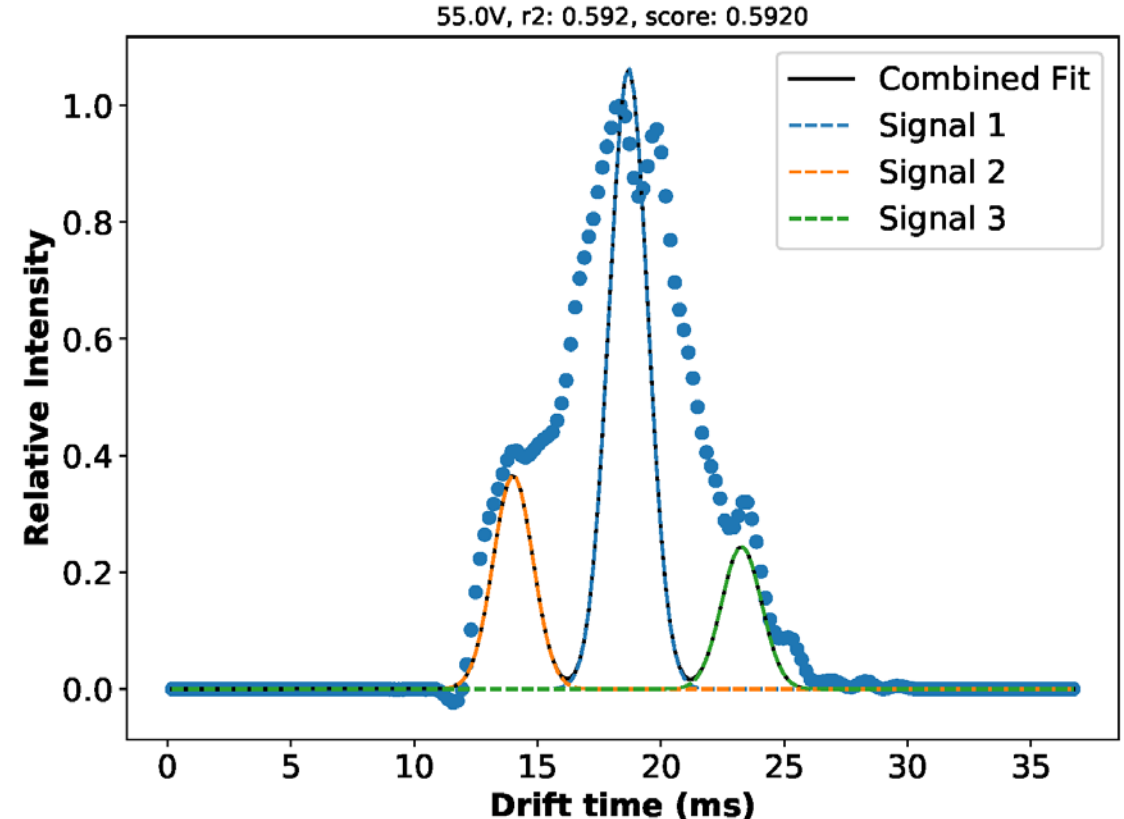


Input data does not drop to 0 away from peaks – it has a baseline. In this case, the baseline is about 9% relative intensity

4. Gaussian Fitting - Troubleshooting

It can be challenging to get accurate and consistent Gaussian fit results because the parameters used are critical and can vary significantly for different proteins and/or instruments. Some guidelines for improving fit quality are on the following slides

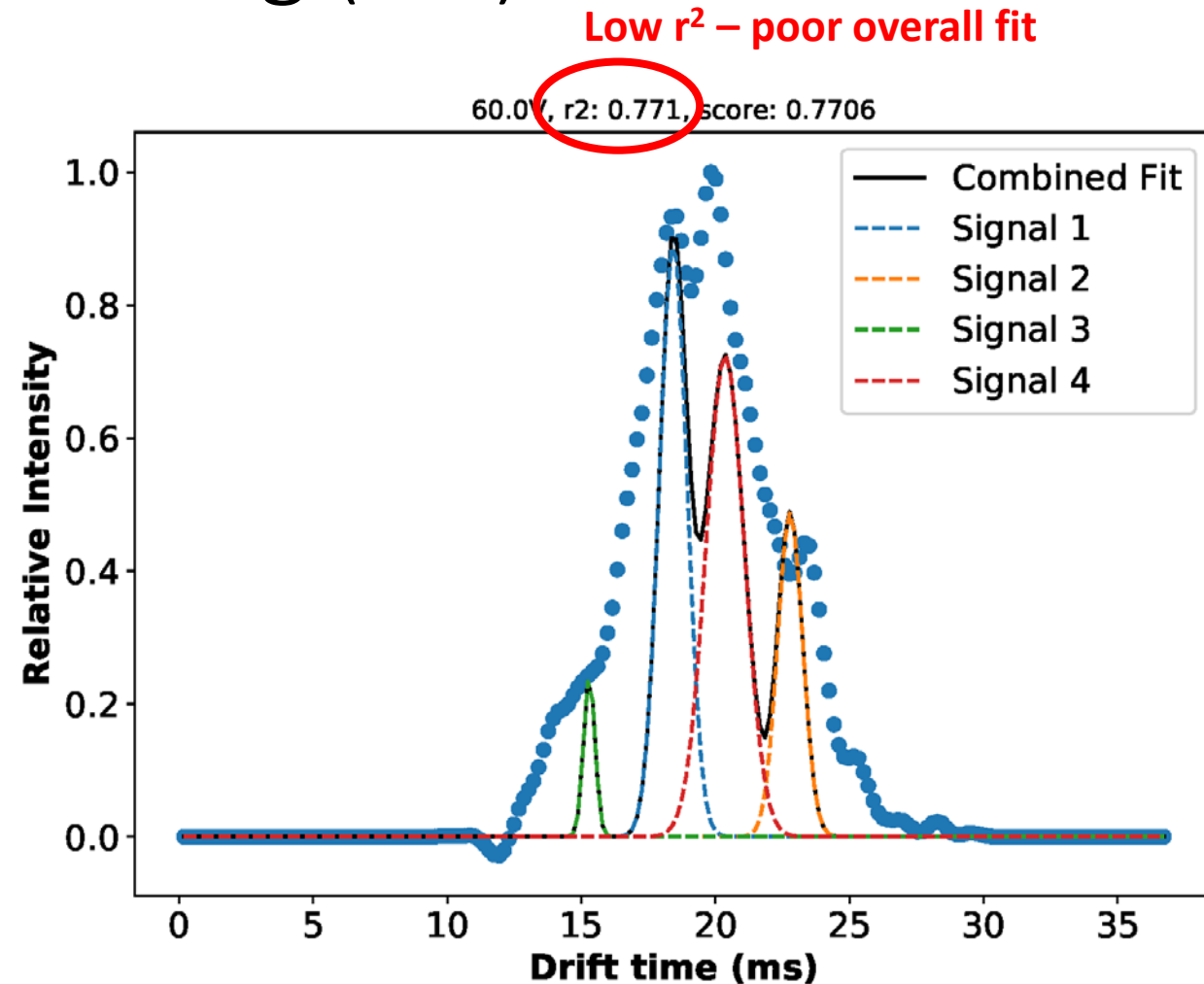
- **The more components allowed, the better the fits will be**
 - Allowing more components gives the fitting algorithm more chances to get the 'right' answer with different initial conditions. Overfitting will be filtered out by the scoring system (adjust between 'strict' and 'relaxed' as needed if overfitting is a problem), so the only downside to allowing extra components is that the fit will take longer.



Too few components are allowed in this example – there are at least 4 peaks present, but only 3 are fit due to limitations on number of components. Try allowing more components than needed to get a better chance of good results (e.g. for this data, 6-8 components would be good)

4. Gaussian Fitting – Troubleshooting (ctd)

- If your combined fits aren't matching the data ($r^2 < 0.98$ or so), the parameters need to be adjusted
 - The peak widths and number of components are constrained by the parameters set by the user, and it is entirely possible that the parameters provided do not allow a good fit.
 - E.g. if the actual width of the peaks is not in the range of allowed widths, *the correct fits will never be found because they are disallowed by the parameters used!*
 - A good strategy when you don't know what your width values are is to allow a wide range of widths (by setting the 'peak width tolerance' to be a large value), letting the fitting algorithm find good widths, and then using those output values as a guide in future rounds of fitting. The widths can be found in the output `_gaussians.csv` file.

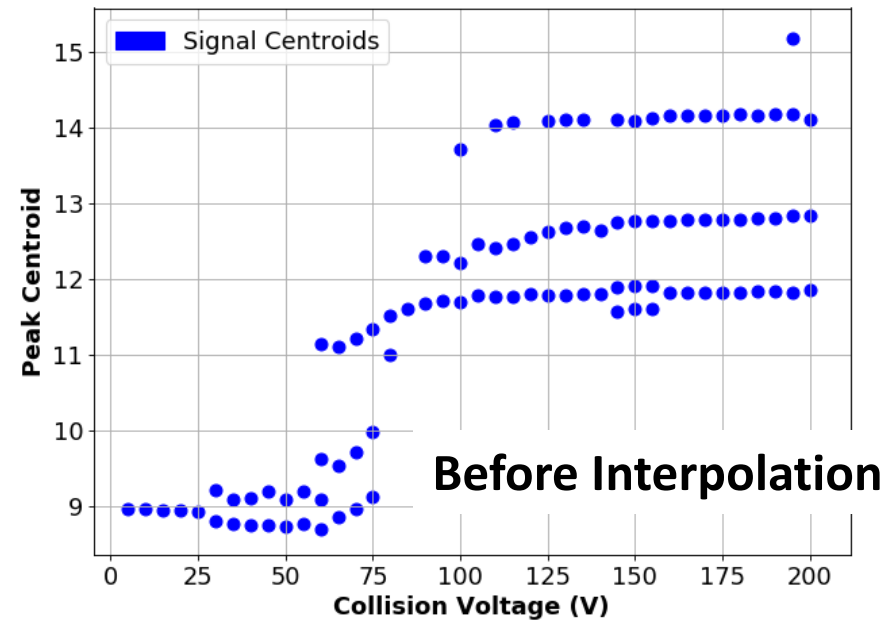


The peaks in this example are constrained to be too narrow – they don't match the actual width of the observed peaks, resulting in a poor fit. (There are also too few components allowed)

4. Gaussian Fitting – Troubleshooting (ctd)

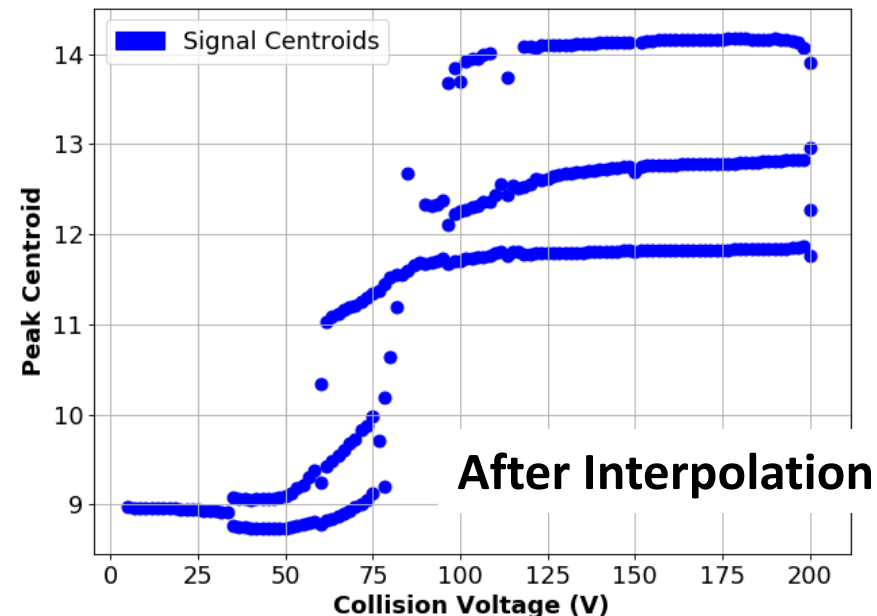
- If adjusting width/number of components isn't helping, try interpolating the data

- Interpolating across the drift time axis helps Gaussian fitting by increasing the number of points being fit for a given peak
- Interpolating across the collision voltage axis is also helpful, because it gives the fitting more opportunities to find the right answer
 - For example, if the fitting is 90% accurate, with 20 collision voltages, 2 would be incorrect. With 60 interpolated voltages, 6 would be incorrect, but because they are generally not next to each other, they are easier to ignore in feature detection/etc.



Interpolating across the drift time axis improved the quality of individual fits (slightly)

Interpolating across the collision voltage axis made it easier to distinguish good fits from bad (and improved feature detection accuracy)



In this example, changing peak overlap method to 'strict' could also be helpful to reduce the congestion in the first transition region

4. Noise Removal Mode: Gaussian Fitting

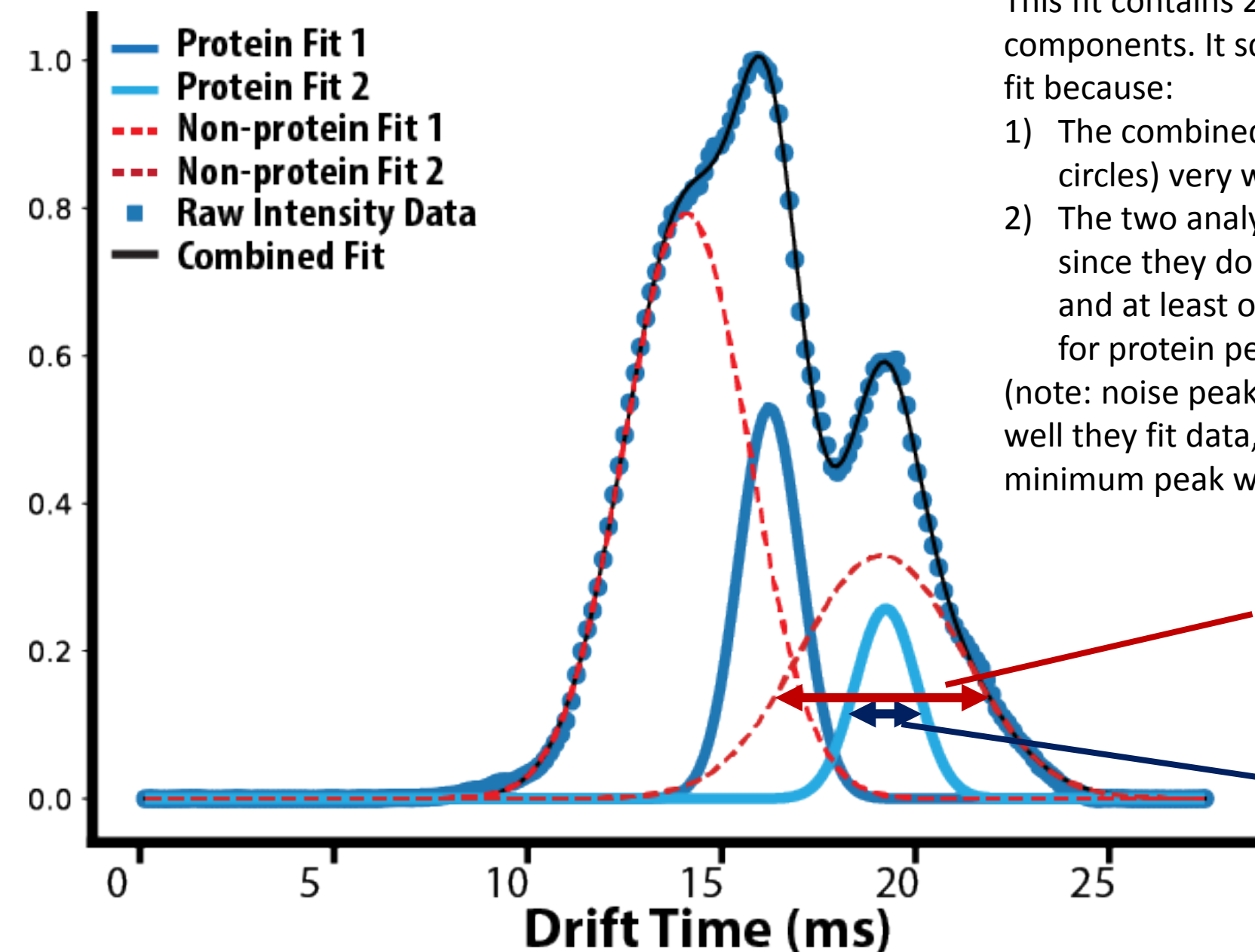
****THESE PARAMETERS ARE FOR NON-PROTEIN MODE ONLY – THEY ARE NOT USED IN PROTEIN ONLY MODE****

- Min/Max NonProtein Components:
 - The minimum and maximum number of non-protein peaks to consider in fits. Increasing the Max number generally improves fit quality but will significantly increase fitting time. The Min number is useful if you know your data always has a certain number of nonprotein peaks, but generally shouldn't be adjusted.
- Minimum Width NonProtein:
 - ****THIS VALUE IS VERY IMPORTANT****
 - The minimum width for non-protein components. This must be greater than the maximum protein width (which is equal to [Expected protein width + protein width tolerance]) for accurate results, and generally should be at least $(1-2 * \text{tolerance})$ greater than max protein width for best results.
 - Because the algorithm uses only peak width to differentiate protein from non-protein components, the more different their widths are, the more accurate the results will be.
- Minimum amplitude for highest protein peak:
 - If a fit has no protein peaks above this amplitude, it is heavily penalized. This prevents fitting only non-protein components, and should be adjusted to reflect the relative intensity of protein/noise in your data.

4. Data Processing: Gaussian Noise Removal

- Gaussian fitting in Non-Protein mode generates a list of Protein and Non-Protein peaks. The non-protein peaks can be removed to allow for cleanup of noisy data.
- There are two ways to do this:
 - 1) Run Gaussian fitting, then do feature detection in Gaussian mode. The feature detection will only consider protein peaks, effectively removing the noise from Gaussian feature data but leaving the original raw CIU data intact.
 - Gaussian feature data is used for classification, so this is all that is necessary to run classification in Gaussian mode.
 - NOTE: CIU50 relies on the original raw data to some extent, even in Gaussian mode, so this will NOT completely remove the effects of noise on CIU50 analyses. For that, mode #2 is recommended.
 - 2) After feature detection, use the “reconstruct from Gaussians” button to generate a new .ciu file using the data from only the fitted protein Gaussians.
 - It’s recommended to smooth this data afterwards, as amplitude values will vary after noise is removed
 - This reconstructed data can then undergo feature detection/CIU50 analysis in standard mode because the noise has been removed already
 - NOTE: if all the noise isn’t removed, Gaussian fitting can be performed again on the reconstructed data, followed by a second reconstruction (and this process can be repeated as many times as necessary)

4. Data Processing: Gaussian Noise Removal Example



This fit contains 2 analyte and 2 noise peaks, for a total of 4 components. It scored highly and was chosen as the correct fit because:

- 1) The combined fit (black) matches the observed data (blue circles) very well ($r^2 > 0.99$)
- 2) The two analyte components do not incur any penalties since they do not overlap significantly with each other and at least one of them is above the minimum amplitude for protein peaks (both of them are in this case).

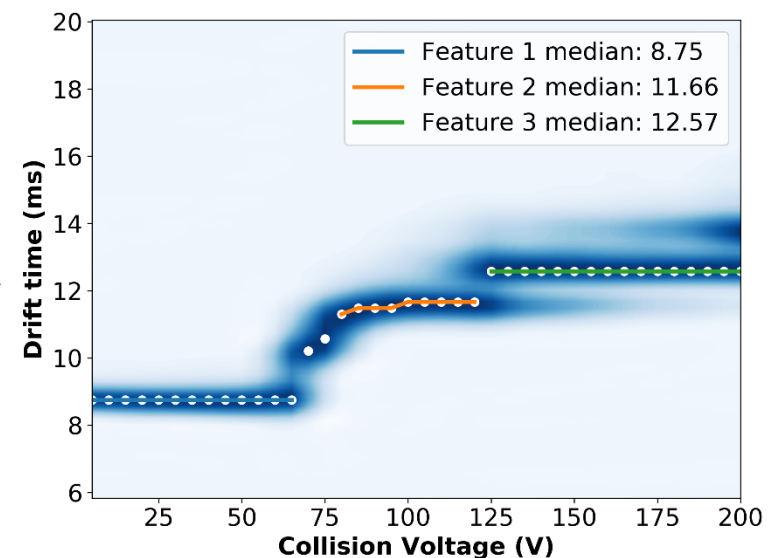
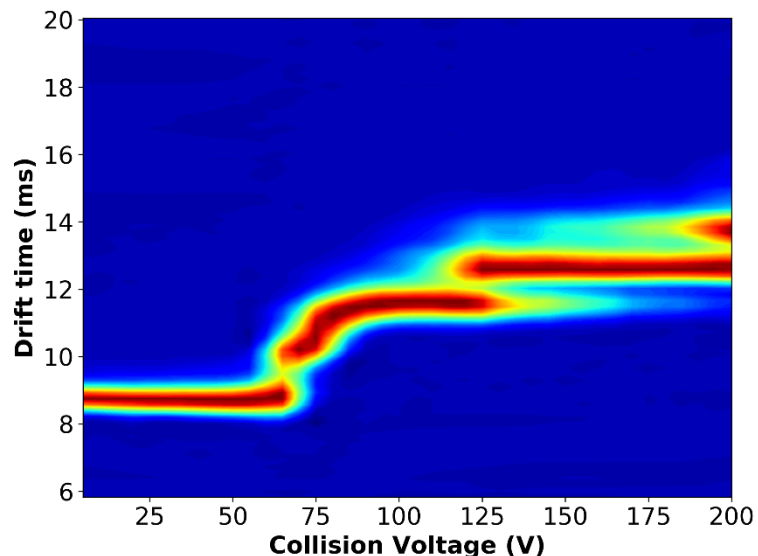
(note: noise peaks are not scored by anything other than how well they fit data, but are constrained to be above the minimum peak width specified).

Noise ("non-protein") peak width (FWHM).
Because the noise peaks are much wider than the protein peaks, they can be distinguished by the fitting algorithm.

Analyte ("protein") peak width (FWHM).

5. Data Analysis: Feature Detection

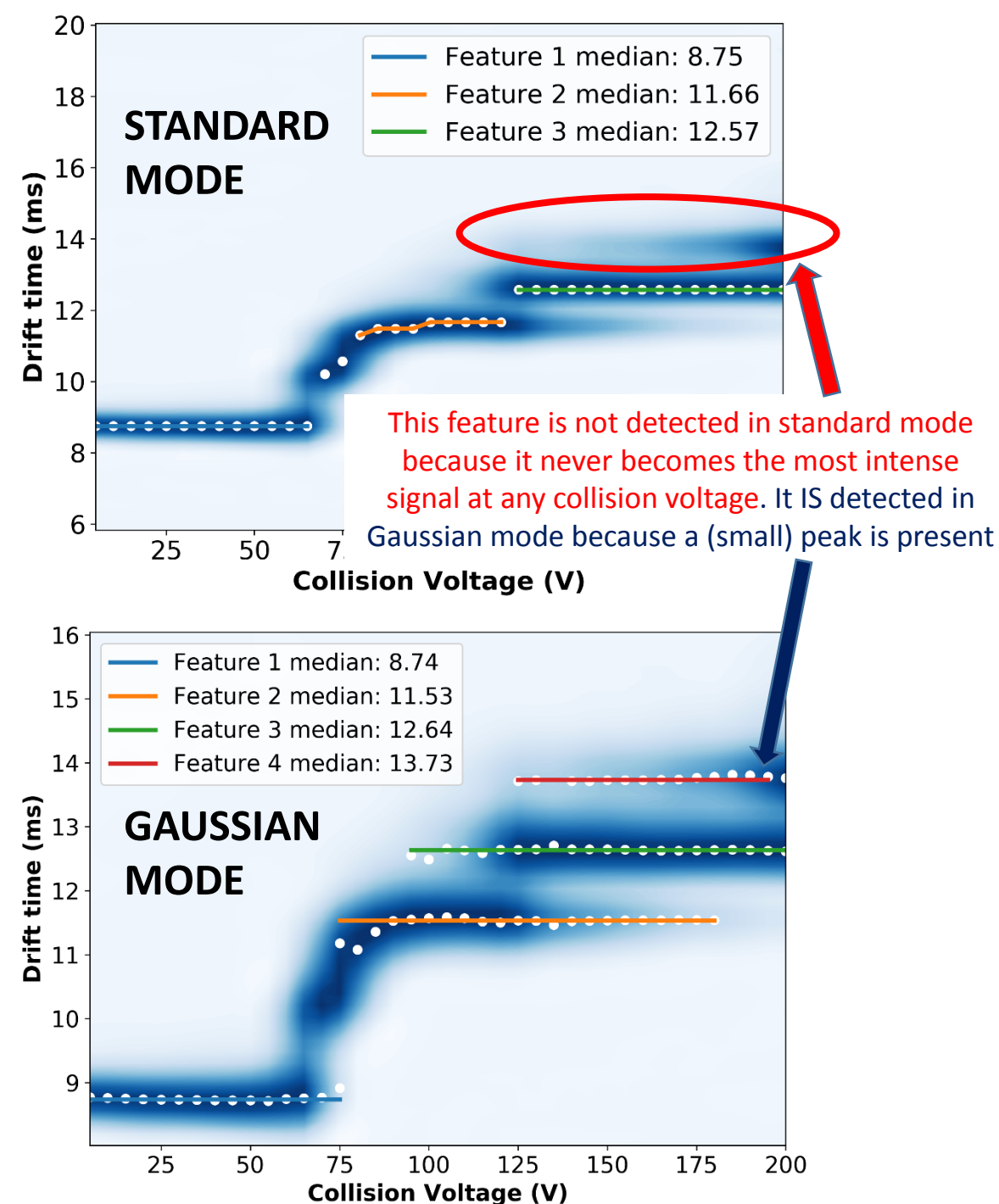
- Features are detected by looking for “flat” regions of a fingerprint
 - “Flat” meaning that the drift time observed is constant across a range of activation energies
- Only the apex of the arrival time distribution at each collision voltage is considered in “standard” mode
 - The apex values are shown as the white circles on the features plot



5. Data Analysis: Feature Detection

Gaussian vs Standard mode

- “Standard” mode uses apex drift time at each collision voltage used to determine features
- “Gaussian” mode uses fitted Gaussian centroids instead of raw apex drift times
 - This means that features can overlap (more than 1 feature can be present at a given collision voltage). This is a key difference between Gaussian and standard modes: **Gaussian mode detects all voltages where features are present, whereas standard mode only detects voltages where a feature is dominant** (more intense than all other features).
 - Gaussian mode will also show features that never become the most intense signal, like the 4th feature (red) in the example at right. It is not detected in standard mode because it never reaches 100% relative intensity.
- Gaussian mode requires that Gaussian fitting has previously been performed on the data



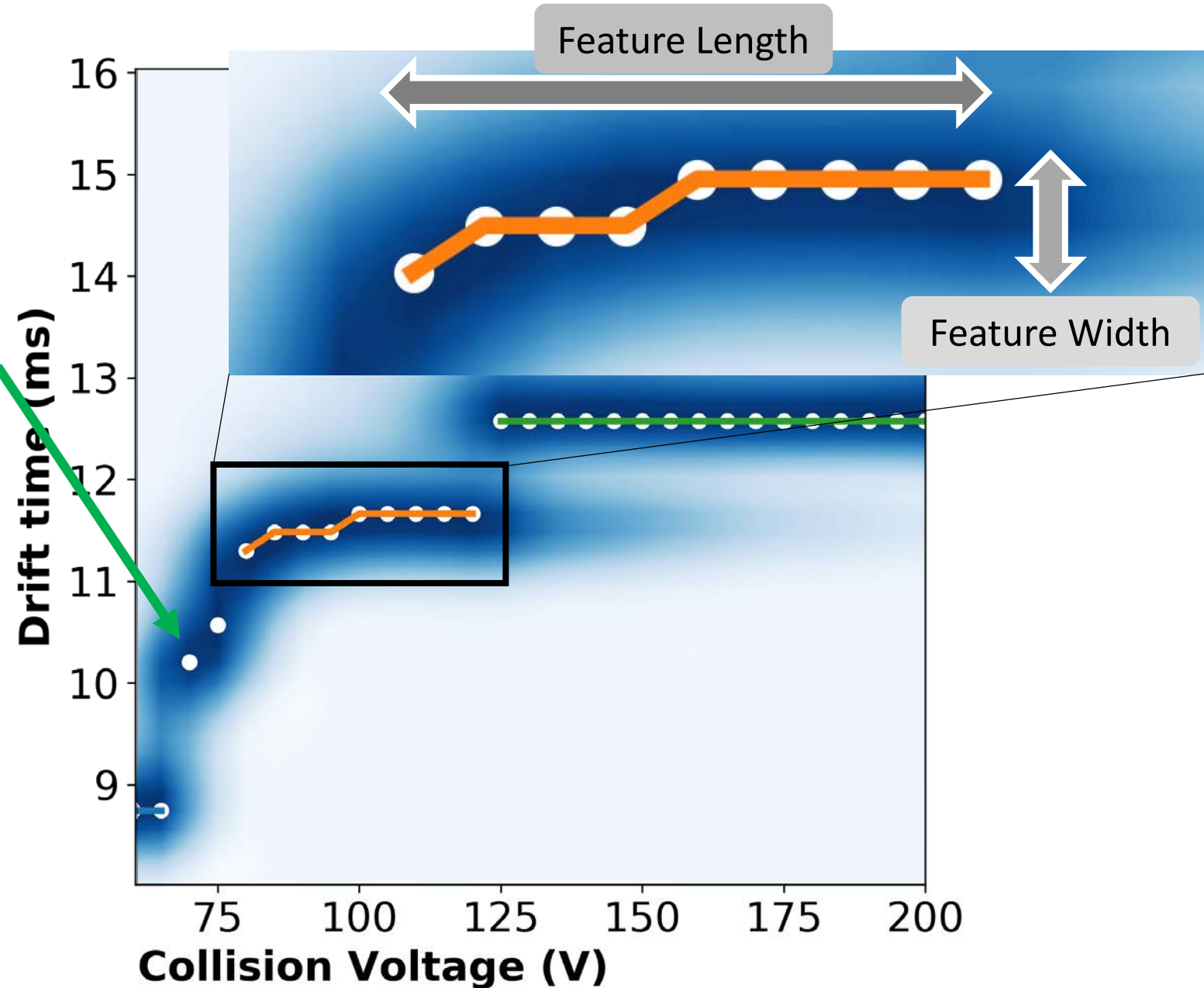
5. Data Analysis: Feature Detection - Parameters

Minimum Feature Length (steps):

- The minimum number of collision voltages across which a feature is stable to be counted as a feature
- The yellow feature has length 9, because it includes 9 voltages (from 85 to 125 V in 5V steps)
- The two dots to the left of the example feature are NOT considered a feature by themselves in this example because the minimum length was set to 4
- *NOTE: if you want to detect a feature that has a length of only 1-2 steps, interpolate along the activation axis to increase the number of steps*

Feature Allowed Width:

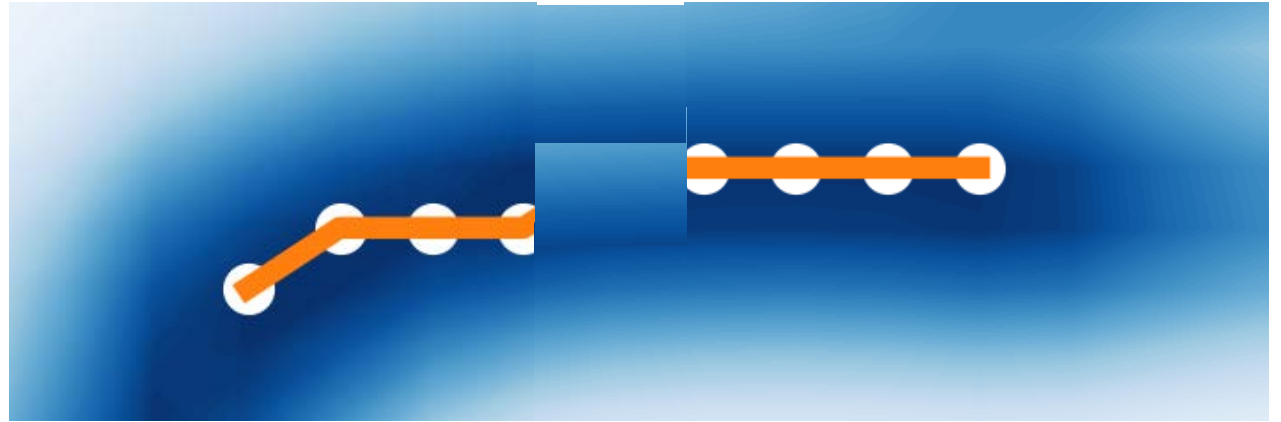
- The distance from the feature median (in mobility axis units) a point can be and still be considered part of the feature.
- For example, if the width was reduced, the left-most point of the example feature (at lower drift time) could be excluded for being too different from the other points. Or if the width was increased, the two points not included in any features could be included in the yellow feature



5. Data Analysis: Feature Detection - Parameters

Maximum CV Gap Length (steps)

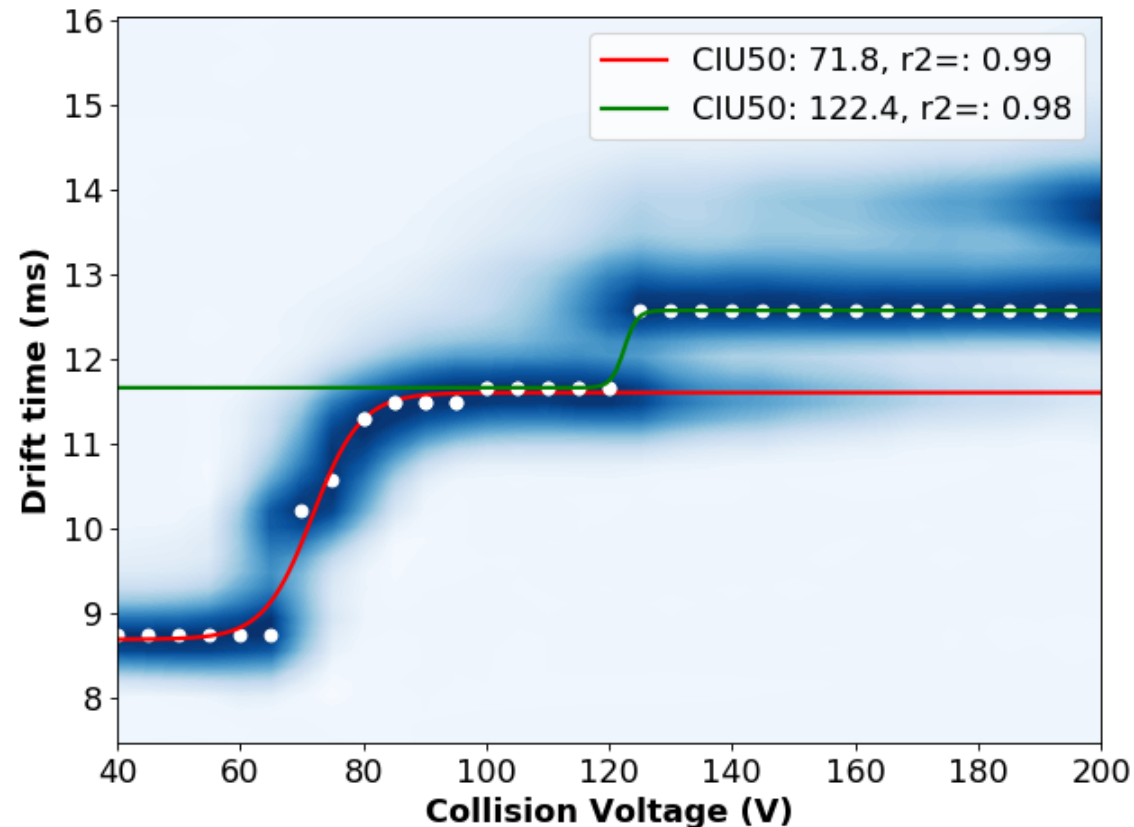
- The maximum number of steps (along the activation axis) between points of a feature before it is considered a break between features
- The points on either side of a gap must still fall within the allowed width to be considered part of a feature
- Gap length is generally more important in Gaussian mode than standard mode



A 'gap' of 1 step is present in between parts of this feature. If the Maximum Gap Length is 2 (or more), this will be detected as 1 feature
If the Maximum Gap Length is 1, this will be detected as 2 different features because of the interruption from the gap

5. Data Analysis: CIU50

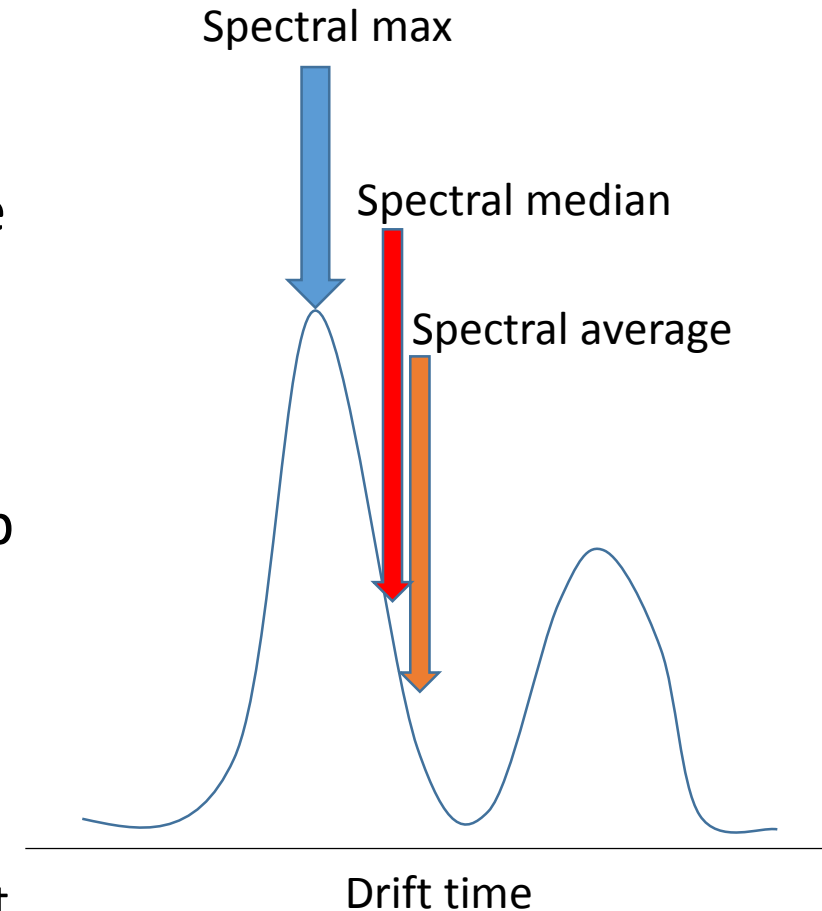
- CIU50 analysis fits a sigmoid (logistic) function to the features detected by Feature Detection
- “CIU50” refers to the midpoint of the transition between two features



5. Data Analysis: CIU50 Parameters

Spectral Centroiding Mode:

- Max: (Default) In max mode, each collision voltage is reduced to just the location (drift time) of the most intense peak. This is equivalent to centroiding the drift time peak by taking the max value.
 - Max mode is the most robust because it is generally insensitive to noise
- Average and Median: In some cases (e.g. if features overlap at similar intensity across many voltages), different centroiding can be helpful. In average/median mode, the arrival time distribution is centroided to the average or median, respectively, of the distribution at each collision voltage.
 - This generally produces much less steep transitions, and can result in poor fits (as transitions may no longer resemble sigmoids)
 - NOTE: average and median include ALL data in the arrival time distribution, and should NOT be used if more than two features overlap at any point (or if significant noise is present), as the presence of other features/noise will affect the transition data



5. Data Analysis: CIU50 Parameters

Transition Region Padding:

- CIU50 fitting determines transition regions using the boundaries of detected features. Additional data is included in the actual logistic function fitting to ensure fidelity to the raw data, which is called the 'padding'.
 - Generally, this parameter should be equivalent to 2-4 collision voltage steps and does not need to be adjusted. In some cases, where fitting is poor (or if using average/median centroiding), adjusting the size of the padding region can improve fit quality.

Standard vs Gaussian Mode:

- Just like Feature Detection, CIU50 analysis can use Gaussian data.
 - Unlike feature detection, Gaussian mode CIU50 analysis is not significantly different from standard mode (peak max values of the raw data are used rather than Gaussian centroids), but uses the Gaussian feature data correctly to set up the fitting.
 - ****NOTE:** transition fitting ONLY considers features that reach 100% relative intensity, so some features detected by Gaussian fitting may not have a transition fit to them. This is because they have not yet reached the CIU50 point in the transition from the previous feature.
 - **NOTE:** performing standard mode CIU50 analysis on Gaussian feature detection results will likely cause a crash

5. Data Analysis: Classification

- Classification works in two steps:
 - 1) Build a classification scheme using known data (i.e. data that you know can be grouped into certain classes)
 - 2) Use the scheme to classify unknown data into the groups you set up
- For example, to classify IgG subtypes 1, 2, 3, and 4:
 - Building the scheme requires at least 3 replicates of each class. Class 1 = IgG1, class 2 = IgG2, etc.)
 - Once the scheme is constructed, unknown data can be analyzed against it. The output is a probability list for each unknown and each class, like:
 - Unknown 1 = 80% class 3 (IgG3), unknown 2 = 95% class 4 (IgG4), etc.

5. Data Analysis: Classification

- To build a classification scheme, click the 'Build Classification' button
 - A pop will ask for the number of classes you want to classify
 - Then, a series of popups will ask for:
 - The name of Class 1
 - The data files corresponding to Class 1
 - The name of Class 2
 - The data files corresponding to Class 2
 - (etc. if more classes were specified)
 - NOTE: The data files chosen for each class are crucial to the success of the classification. Generally, having more replicates for each class is better – because more of the possible variation within each class will be accounted for in the resulting classification scheme.
 - ****The differences between classes generally need to be larger than the differences within classes for a classification scheme to be successful!****
 - Thus, if the replicates (within a class) have substantial differences between them, it may be challenging to generate a robust classifying scheme

5. Data Analysis: Classification Parameters

Cross Validation Score Tolerance:

- This is a minor heuristic added to reduce overfitting. Generally, the highest score (most accurate scheme) is used for classification. In some cases, there may be a scheme with similar accuracy but many fewer features. If the score of the scheme with fewer features is within this tolerance of the score of the scheme with more features, the scheme with fewer features will be chosen.

Data Mode: “All data” vs “Gaussian”

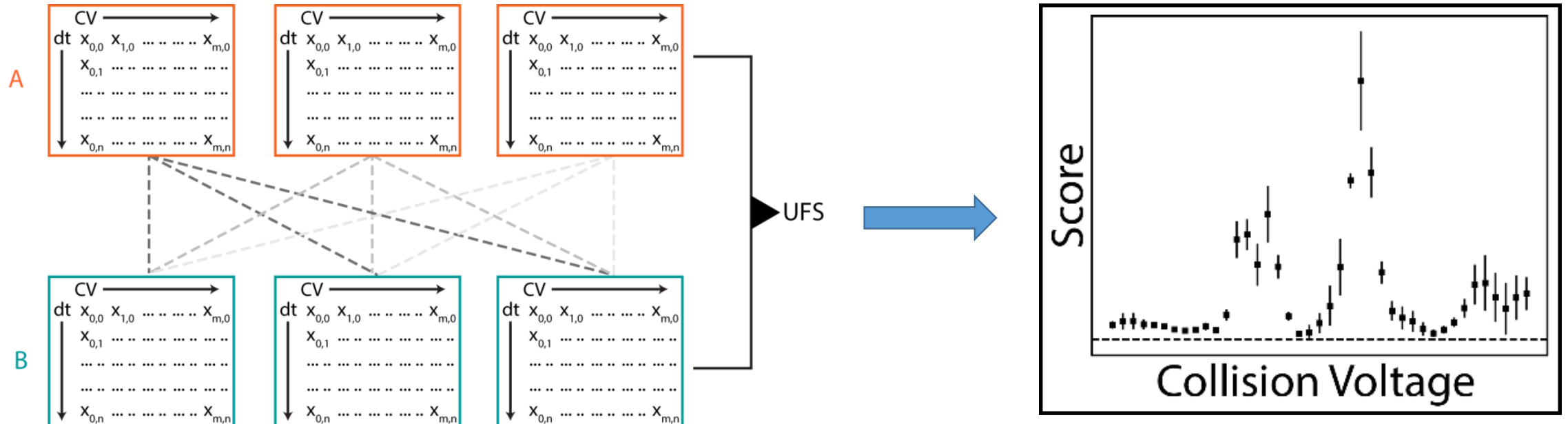
- All data mode uses the entire CIU dataset for classification. Gaussian mode uses only the centroid, width, and amplitude of the fitted Gaussians, greatly reducing the amount of input data. This is particularly helpful when attempting to classify noisy datasets where Gaussian de-noising can reduce variability within classes.

Voltage Selection Mode:

- Manual selection of the voltage(s) to use in the classifying scheme is possible by switching this from automatic to manual.

5. Data Analysis: Classification Diagnostics

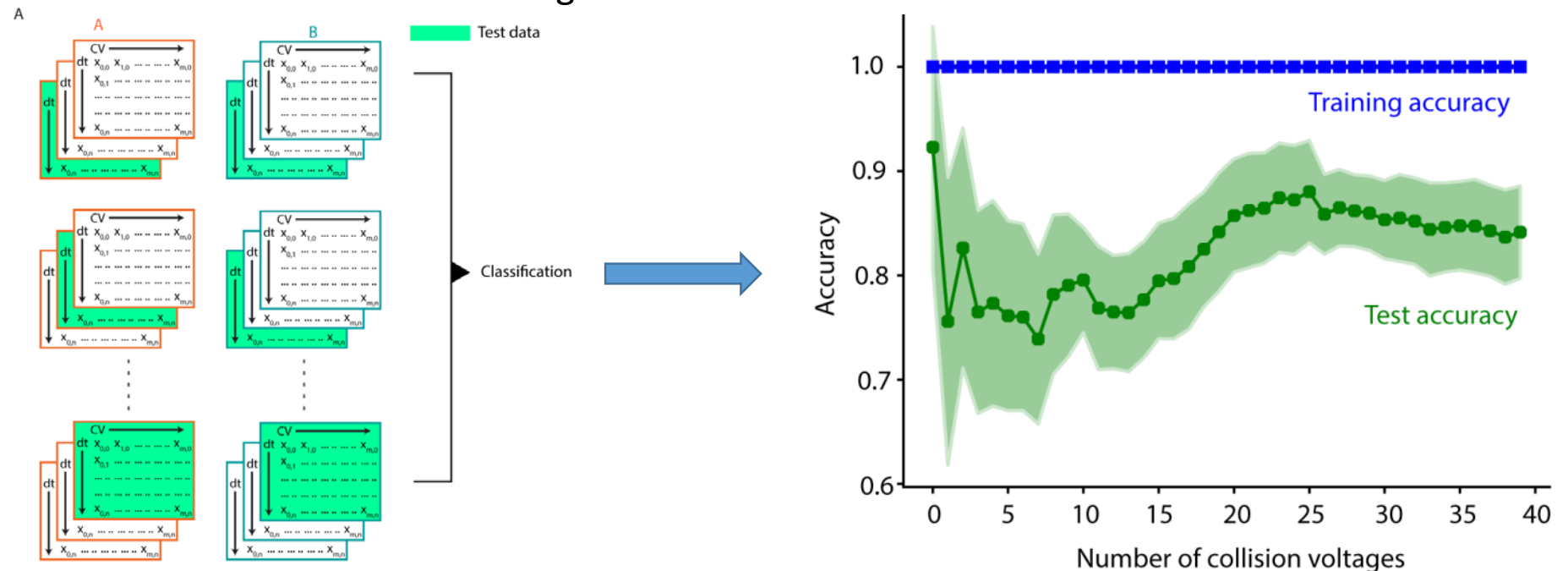
- After a scheme is constructed, several diagnostic outputs are generated
 - UFS output: Voltage Selection plot
 - UFS (univariate feature selection) compares inter- and intra-class variation at each collision voltage using F-tests. ($F = \text{inter-class variation} / \text{intra-class variation}$)
 - An output plot of UFS score is generated as in the lower right. The score ($-\log_{10}(\text{p-value})$) for each collision voltage is displayed with error bars. The higher the score, the more difference between classes at that voltage relative to the differences within classes at that voltage.



5. Data Analysis: Classification Diagnostics

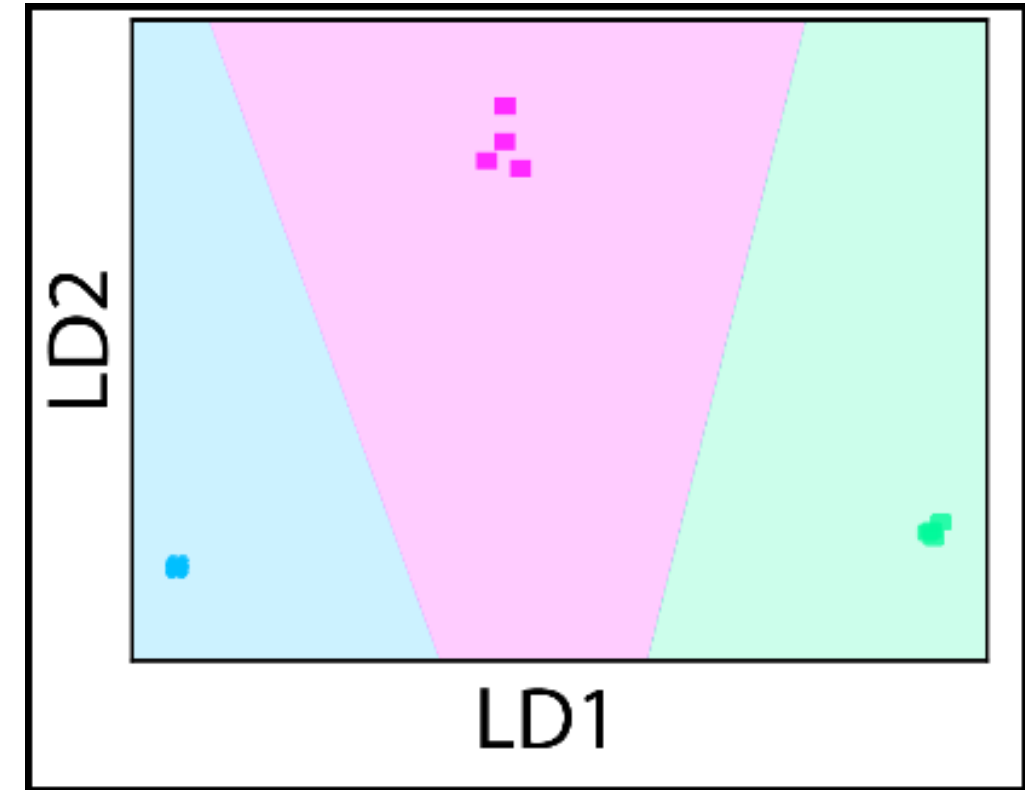
- Cross Validation plot

- “Leave one out” cross validation (illustrated below left, each input takes a turn being the test data) is used to evaluate the accuracy of the classification at each possible number of voltages included.
 - Voltages are added to the classification in decreasing order of score from the UFS output (see previous page)
- A cross validation plot showing the training (blue) and test (green) accuracy with error bars (shaded) as a function of the number of voltages used is produced, as in the lower right. The highest test accuracy is chosen as the final number of voltages for the scheme.
 - Except if the highest accuracy is within tolerance (default 0.05) of the accuracy of a lower number of voltages, the scheme with the lower number of voltages will be used instead. Reduce tolerance to 0 to avoid this behavior.



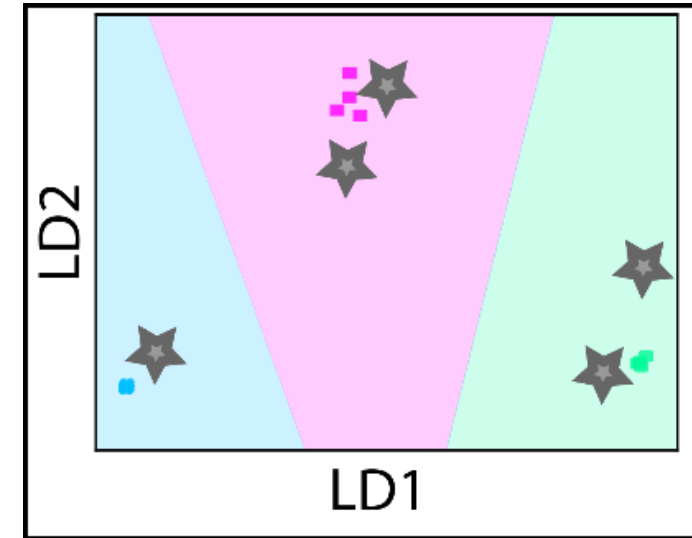
5. Data Analysis: Classification Diagnostics

- Decision Region (classification) plot
 - The linear discriminant space used for classification is divided into regions corresponding to each class, and the locations of the training data within the space are shown (for up to 4 classes. Above 4 classes, the plot would be more than 3D and thus challenging to generate..).
 - In the example at right, 3 classes are used (generating a 2D linear discriminant space). Cross validation test data results are shown in the colored squares.
 - Generally, a good classification scheme is one that:
 - 1) Clearly groups the input data into separate regions of the LD space, and does not put any data in the wrong region
 - 2) Correctly classifies true test data, i.e. data that was withheld from building the scheme and used as 'unknown' data (but which has a known class).
 - **If the initial decision regions plot looks good, but withheld test data is not classified correctly, it means the scheme is overfitting the training data and/or there is additional variation within classes not being captured in the training data. Look carefully at the data and make sure it seems reasonable to classify (i.e. there are true differences between classes and they are larger than the differences within classes)**



5. Data Analysis: Classifying Unknowns

- Once a classification scheme is constructed, a .clf file is saved (the names of each of the classes .clf).
- To classify unknowns, simply load .ciu file(s), then press the 'classify unknown' button.
 - A popup will ask you to select the classifying scheme (.clf) file to classify
- Each unknown will generate a probability to be in each class, and a decision regions plot will show the locations of unknowns relative to the classifying regions
- NOTE: if the classifying scheme used Gaussian data, the unknowns must have Gaussian feature detection performed prior to classification
- NOTE: The unknowns ONLY need to have data at the voltages selected in the classification scheme (but can be full fingerprints as well)



Stars correspond to unknowns,
squares to training data

6. Tips and Tricks

- The parameters used in analysis are saved into the .ciu file – so to see how any particular data was analyzed, use the ‘print parameters from file’ button.
 - NOTE: these are updated every time the .ciu file is saved (which is after most analyses), so it is possible in some cases to overwrite them after the fact
- If you want to save parameters so that you don’t have to keep entering them, use the ‘update default parameters’ button, which will save all current parameter values to be the defaults.
- Use an automated extractor to generate _raw.csv files for analysis. There are several available for Waters data (including ours, called TWIMExtract) and one being built for Agilent data which should be available soon.

6. Tips and Tricks – Feature Detection

- Interpolation can be very helpful for feature detection, especially if you want to detect features that only show up at a few collision voltages
 - Interpolating the activation axis can increase the effective length of short features, making them easier to fit

7. Troubleshooting

- Problems and bugs can be reported to us at ciusuite-ruotololab@umich.edu
 - Please include as much information as possible, particularly including:
 - Any error message(s) that print on the program console (the black window in the background)
 - The .ciu file that triggered the error if possible
 - What were trying to do (and with what parameters) when the problem occurred.
- The program is still in beta testing and we very much appreciate your patience with any issues that arise!