



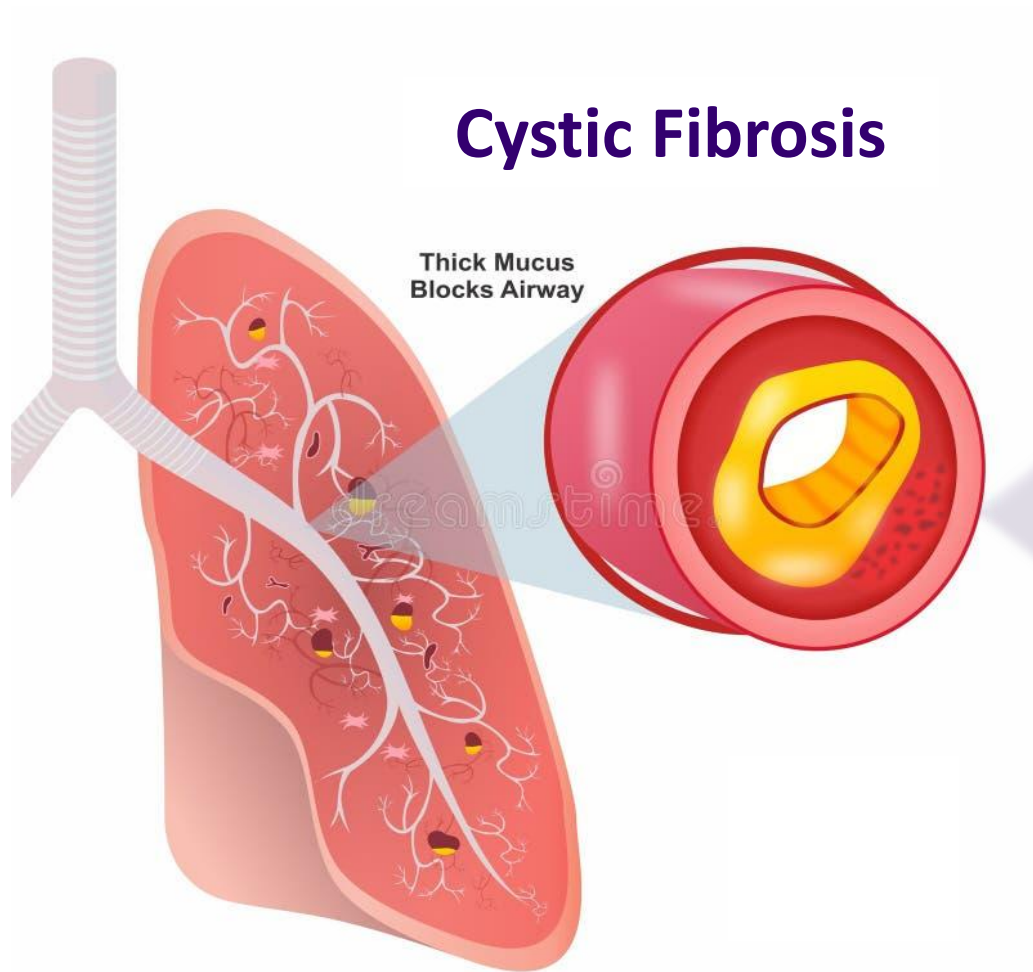
# Tile-based Analysis of GC×GC-TOFMS Data of SPME Sampled VOCs Produced from *Pseudomonas aeruginosa* and *Aspergillus fumigatus*

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Ashleigh B. Theberge and Robert E. Synovec**

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*17<sup>th</sup> Multidimensional Chromatography Workshop*

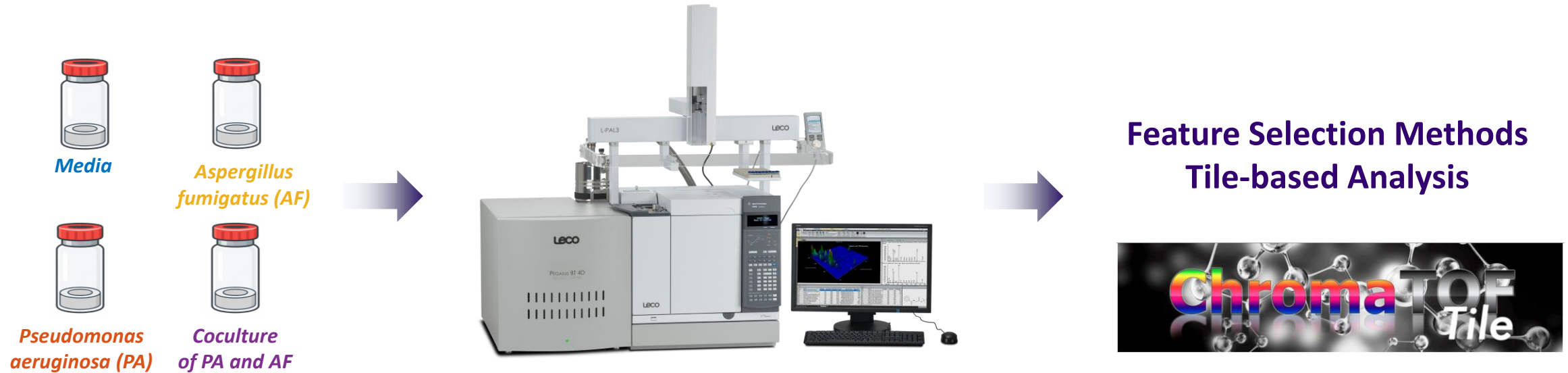
# Project Motivation



- *Pseudomonas aeruginosa* and *Aspergillus fumigatus* are major pathogens found in the lungs of patients with Cystic fibrosis.
- Their coexistence worsens lung function and leads to poor clinical outcomes.
- The project aims to investigate their metabolic interactions.

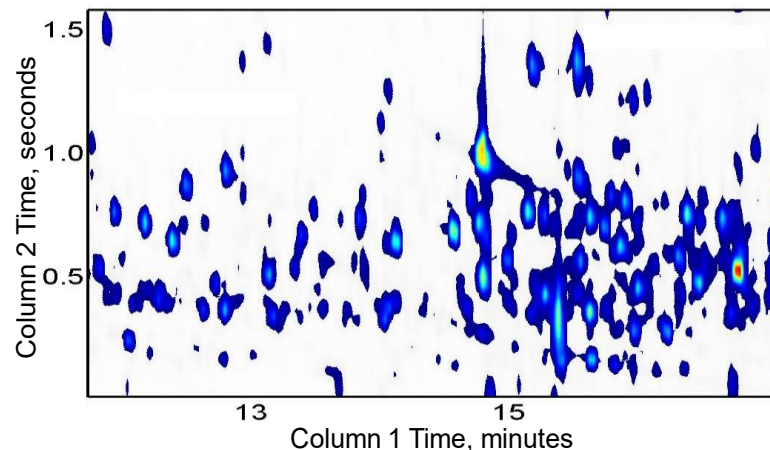
# Aim and Methodology

- To discover analytes that are **statistically different** in the headspace across all sample classes (Media, PA monoculture, AF monoculture, and their coculture) using comprehensive two-dimensional gas chromatography with time-of-flight mass spectrometry (GC×GC-TOFMS) and chemometrics.
- To explore appropriate experimental design approaches for generating high quality data and enabling high throughput experimentation.

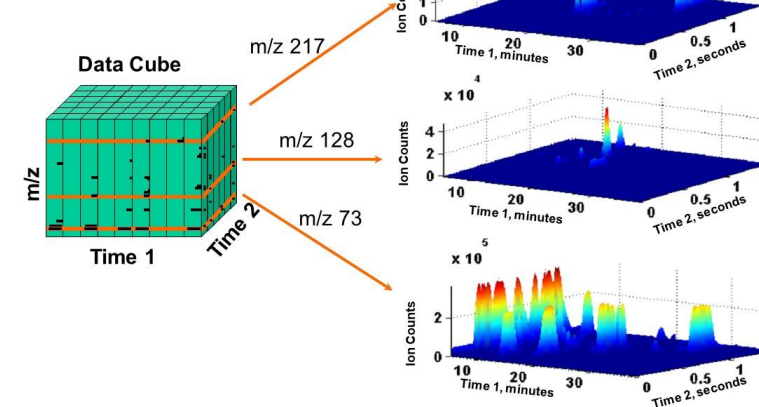


# GC×GC-TOFMS : Comprehensive Two-Dimensional Gas Chromatography with Time-of-Flight Mass Spectral Detection

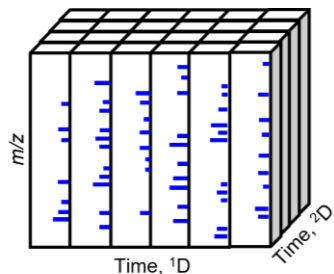
- Mass spectra with electron impact ionization and unit mass resolution  
→ peak identification
- Fast → 500 spectra / second  
Column Two peak widths:  
~ 50 ms to ~ 300 ms
- Adds another selective dimension  
→ 3<sup>rd</sup> - order data  
→ Provides informative data analysis



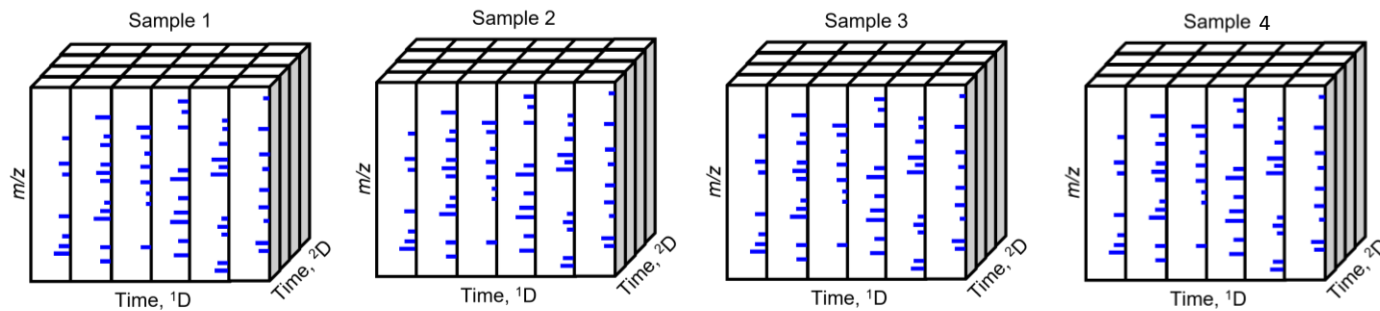
3<sup>rd</sup> Order Data... with TOFMS



# Methods of Handling GC×GC-TOFMS Data



Three-dimensional array  
(cube)



Four-dimensional array

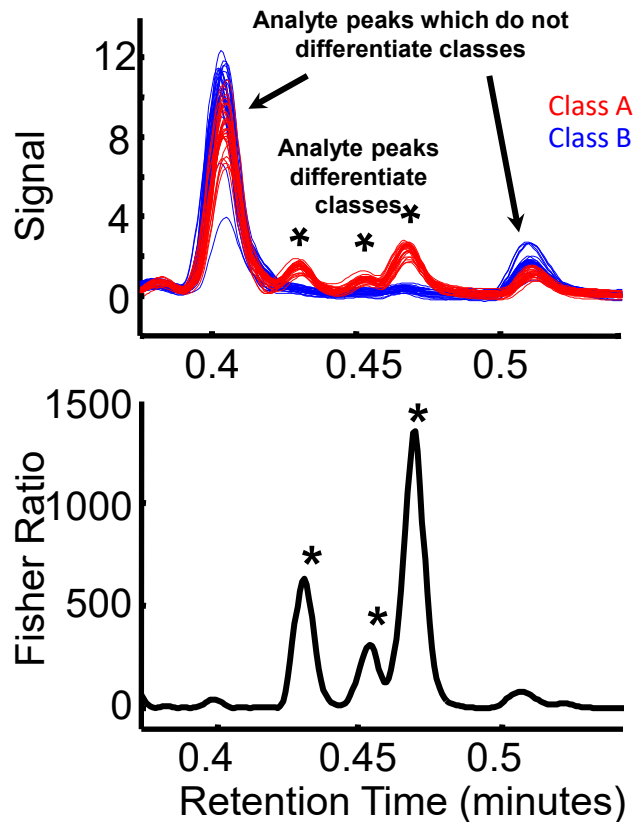
Use of a TOFMS with a high collection frequency  
can create a large amount of data  
**> 10<sup>6</sup> data points per chromatogram!**

## *Data reduction strategies*

- *Assemble peak tables*
- *Average the chromatographic signal (i.e., binning)*
- *Discovery-based Feature selection*

# Tile-based Fisher Ratio (F-ratio) Analysis

Shown for 1D data....



.... applied to **Class A** samples  
versus **Class B** samples

$$\text{Standard } F - \text{ratio} = \frac{\text{Between Class Variance}}{\sum(\text{Within Class Variance})}$$

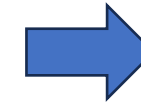
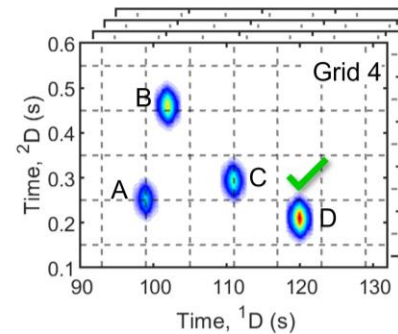
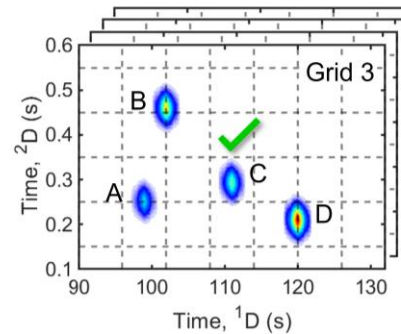
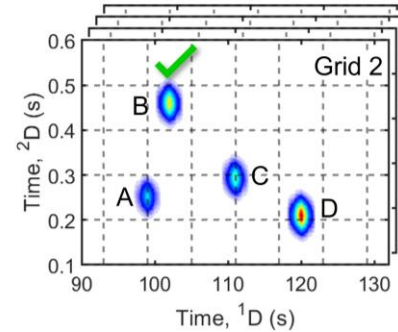
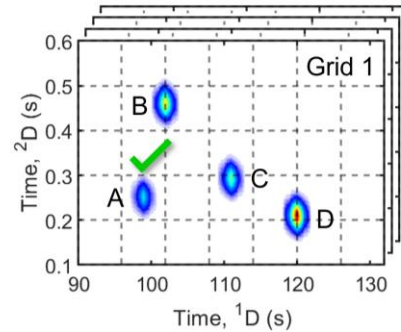
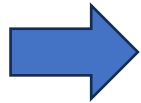
- K.J. Johnson, R.E. Synovec, J. Chromatogr. A, 2002, 977, 225-237.
- L.C. Marney, W.C. Siegler, B.A. Parsons, J.C. Hoggard, B.W. Wright, R.E. Synovec, Talanta 2013, 115, 887-895.
- B.A. Parsons, L.C. Marney, W.C. Siegler, J.C. Hoggard, B.W. Wright, R.E. Synovec, Anal. Chem. 2015, 87, 3812-3819.
- N.E. Watson, B.A. Parsons, R.E. Synovec, J. Chromatogr. A, 2016, 1459, 101-111.
- B.A. Parsons, D.K. Pinkerton, B.W. Wright, R.E. Synovec, J. Chromatogr. A, 2016, 1440, 179-190.
- B.C. Reaser, B.W. Wright, R.E. Synovec, Anal. Chem., 2017, 89, 3606-3612.

*F-ratio Analysis provides a ranked hitlist of analytes that are likely to be statistically different in concentration (p-value < 0.05) between sample classes.*

Hit List		
Hit #	Fisher Ratio	Analyte
1	High	AAA
↓	↓	↓
N	Low	ZZZ

# Tile-based Fisher Ratio (F-ratio) Analysis

Illustration of how 4-grid  
tile-based FRA works.



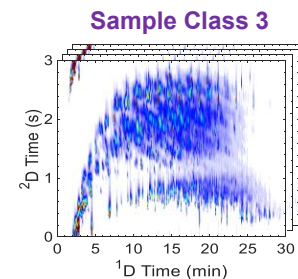
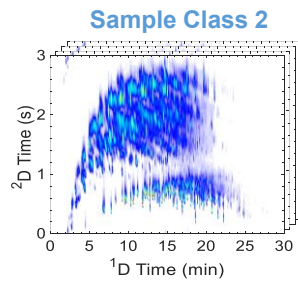
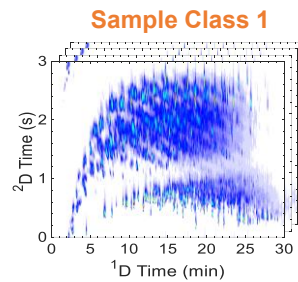
Hit List

Hit #	F-ratio	( <sup>1</sup> t <sub>R</sub> , <sup>2</sup> t <sub>R</sub> )
1	High	(x,y)
<hr/>		
$N$	Low	(x <sub>N</sub> ,y <sub>N</sub> )



# Software Development at UW

## Tile-based Fisher Ratio Analysis

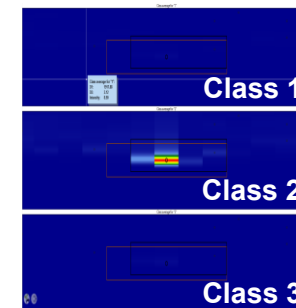


Apply  
ChromaTOF Tile

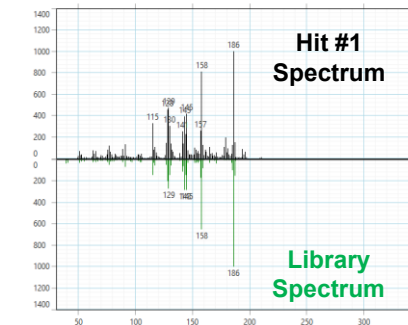
Hit Table

Hit	RT	Area	Intensity	Score	Class
1	1.12	1.0	1.0	1.0	Class 1
2	1.12	1.0	1.0	1.0	Class 1
3	1.12	1.0	1.0	1.0	Class 1
4	1.12	1.0	1.0	1.0	Class 1
5	1.12	1.0	1.0	1.0	Class 1
6	1.12	1.0	1.0	1.0	Class 1
7	1.12	1.0	1.0	1.0	Class 1
8	1.12	1.0	1.0	1.0	Class 1
9	1.12	1.0	1.0	1.0	Class 1
10	1.12	1.0	1.0	1.0	Class 1
11	1.12	1.0	1.0	1.0	Class 1
12	1.12	1.0	1.0	1.0	Class 1
13	1.12	1.0	1.0	1.0	Class 1
14	1.12	1.0	1.0	1.0	Class 1
15	1.12	1.0	1.0	1.0	Class 1
16	1.12	1.0	1.0	1.0	Class 1
17	1.12	1.0	1.0	1.0	Class 1
18	1.12	1.0	1.0	1.0	Class 1
19	1.12	1.0	1.0	1.0	Class 1
20	1.12	1.0	1.0	1.0	Class 1
21	1.12	1.0	1.0	1.0	Class 1
22	1.12	1.0	1.0	1.0	Class 1
23	1.12	1.0	1.0	1.0	Class 1
24	1.12	1.0	1.0	1.0	Class 1
25	1.12	1.0	1.0	1.0	Class 1
26	1.12	1.0	1.0	1.0	Class 1
27	1.12	1.0	1.0	1.0	Class 1
28	1.12	1.0	1.0	1.0	Class 1
29	1.12	1.0	1.0	1.0	Class 1
30	1.12	1.0	1.0	1.0	Class 1
31	1.12	1.0	1.0	1.0	Class 1
32	1.12	1.0	1.0	1.0	Class 1
33	1.12	1.0	1.0	1.0	Class 1
34	1.12	1.0	1.0	1.0	Class 1
35	1.12	1.0	1.0	1.0	Class 1
36	1.12	1.0	1.0	1.0	Class 1
37	1.12	1.0	1.0	1.0	Class 1
38	1.12	1.0	1.0	1.0	Class 1
39	1.12	1.0	1.0	1.0	Class 1
40	1.12	1.0	1.0	1.0	Class 1
41	1.12	1.0	1.0	1.0	Class 1
42	1.12	1.0	1.0	1.0	Class 1
43	1.12	1.0	1.0	1.0	Class 1
44	1.12	1.0	1.0	1.0	Class 1
45	1.12	1.0	1.0	1.0	Class 1
46	1.12	1.0	1.0	1.0	Class 1
47	1.12	1.0	1.0	1.0	Class 1
48	1.12	1.0	1.0	1.0	Class 1
49	1.12	1.0	1.0	1.0	Class 1
50	1.12	1.0	1.0	1.0	Class 1
51	1.12	1.0	1.0	1.0	Class 1
52	1.12	1.0	1.0	1.0	Class 1
53	1.12	1.0	1.0	1.0	Class 1
54	1.12	1.0	1.0	1.0	Class 1
55	1.12	1.0	1.0	1.0	Class 1
56	1.12	1.0	1.0	1.0	Class 1
57	1.12	1.0	1.0	1.0	Class 1
58	1.12	1.0	1.0	1.0	Class 1
59	1.12	1.0	1.0	1.0	Class 1
60	1.12	1.0	1.0	1.0	Class 1
61	1.12	1.0	1.0	1.0	Class 1
62	1.12	1.0	1.0	1.0	Class 1
63	1.12	1.0	1.0	1.0	Class 1
64	1.12	1.0	1.0	1.0	Class 1
65	1.12	1.0	1.0	1.0	Class 1
66	1.12	1.0	1.0	1.0	Class 1
67	1.12	1.0	1.0	1.0	Class 1
68	1.12	1.0	1.0	1.0	Class 1
69	1.12	1.0	1.0	1.0	Class 1
70	1.12	1.0	1.0	1.0	Class 1
71	1.12	1.0	1.0	1.0	Class 1
72	1.12	1.0	1.0	1.0	Class 1
73	1.12	1.0	1.0	1.0	Class 1
74	1.12	1.0	1.0	1.0	Class 1
75	1.12	1.0	1.0	1.0	Class 1
76	1.12	1.0	1.0	1.0	Class 1
77	1.12	1.0	1.0	1.0	Class 1
78	1.12	1.0	1.0	1.0	Class 1
79	1.12	1.0	1.0	1.0	Class 1
80	1.12	1.0	1.0	1.0	Class 1
81	1.12	1.0	1.0	1.0	Class 1
82	1.12	1.0	1.0	1.0	Class 1
83	1.12	1.0	1.0	1.0	Class 1
84	1.12	1.0	1.0	1.0	Class 1
85	1.12	1.0	1.0	1.0	Class 1
86	1.12	1.0	1.0	1.0	Class 1
87	1.12	1.0	1.0	1.0	Class 1
88	1.12	1.0	1.0	1.0	Class 1
89	1.12	1.0	1.0	1.0	Class 1
90	1.12	1.0	1.0	1.0	Class 1
91	1.12	1.0	1.0	1.0	Class 1
92	1.12	1.0	1.0	1.0	Class 1
93	1.12	1.0	1.0	1.0	Class 1
94	1.12	1.0	1.0	1.0	Class 1
95	1.12	1.0	1.0	1.0	Class 1
96	1.12	1.0	1.0	1.0	Class 1
97	1.12	1.0	1.0	1.0	Class 1
98	1.12	1.0	1.0	1.0	Class 1
99	1.12	1.0	1.0	1.0	Class 1
100	1.12	1.0	1.0	1.0	Class 1

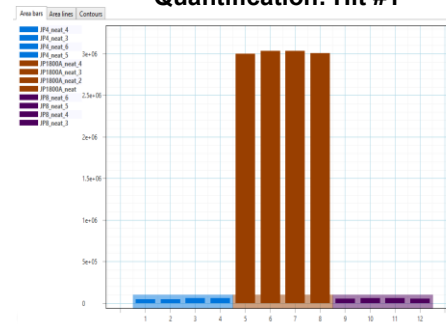
Hit #1 Selective Signal



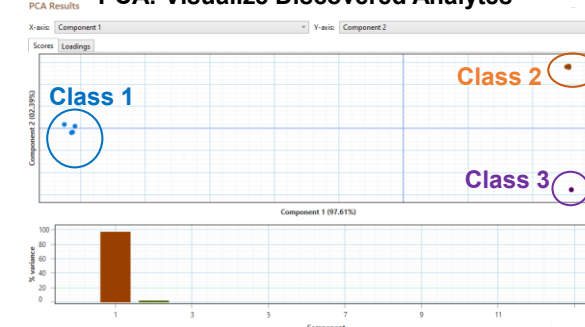
Identification: Hit #1



Quantification: Hit #1

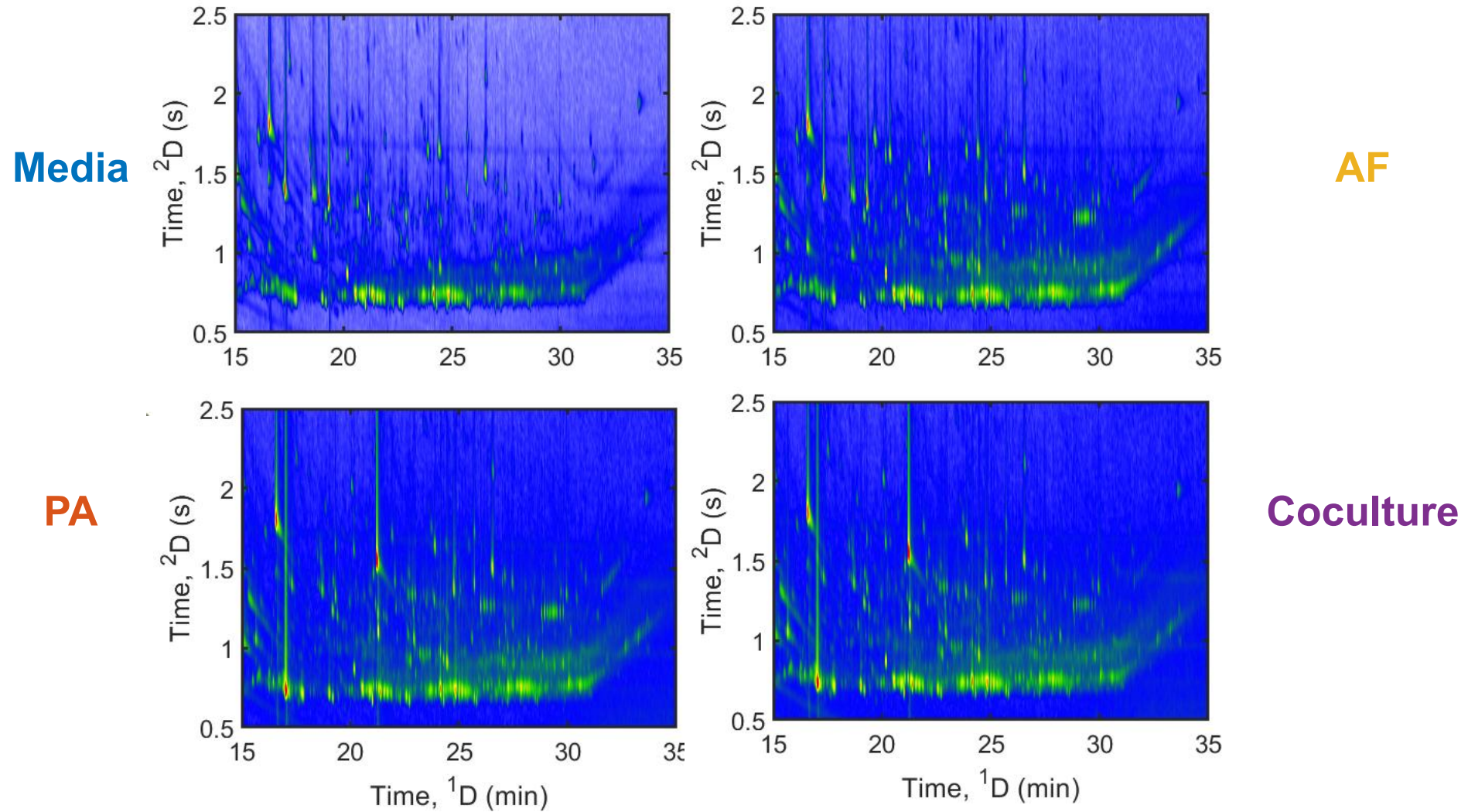


PCA: Visualize Discovered Analytes





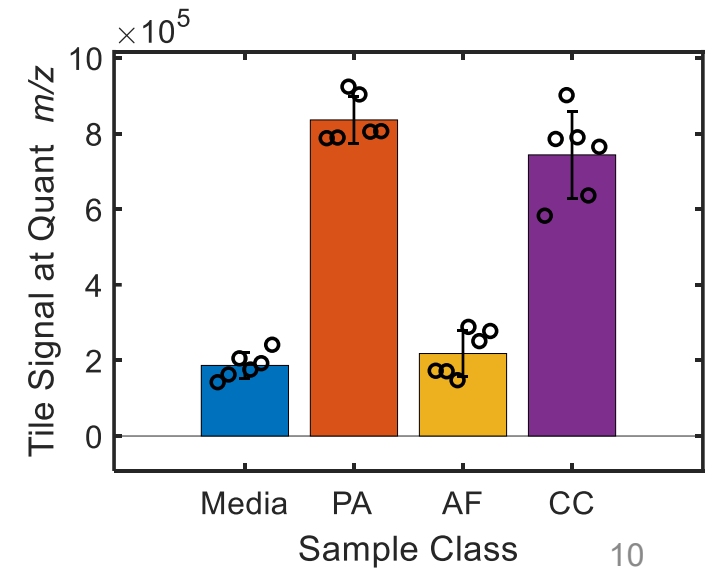
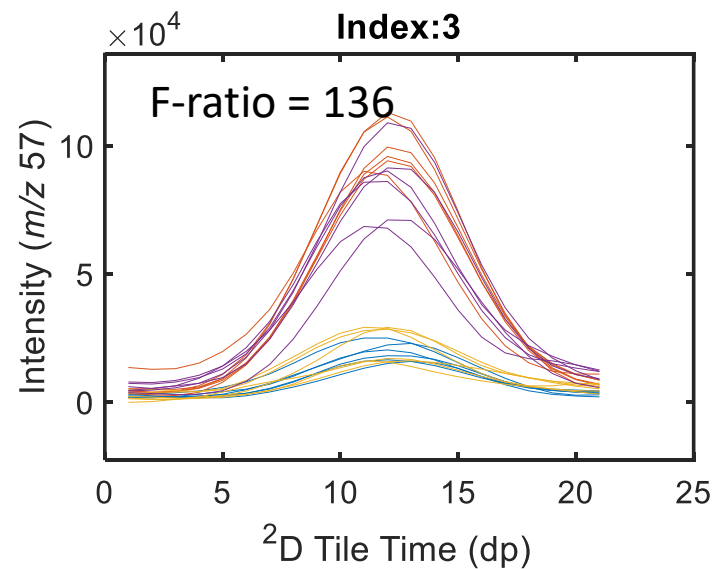
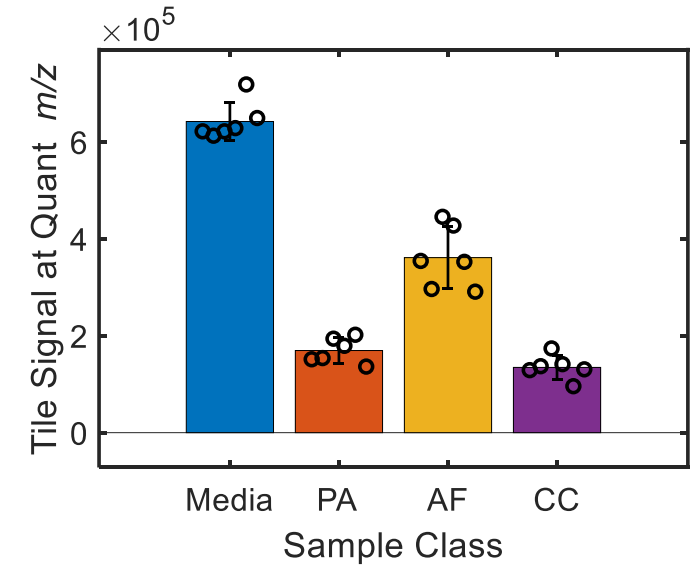
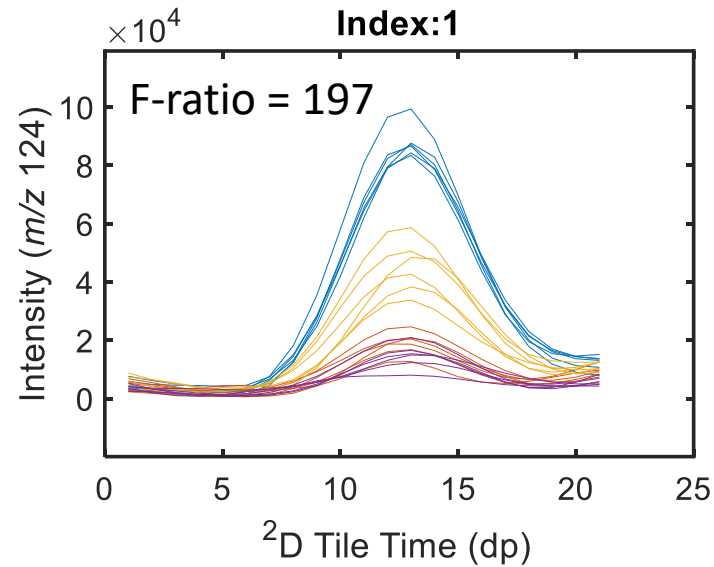
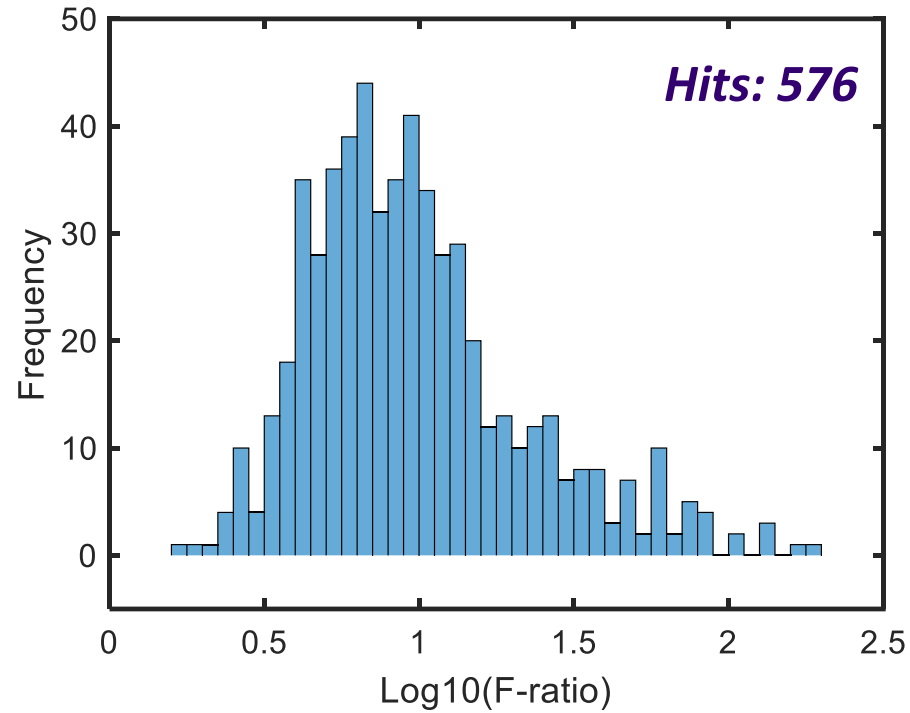
# Comparative Analysis of GC×GC-TOFMS Data



*~ 500 peaks detected in the TIC chromatogram*

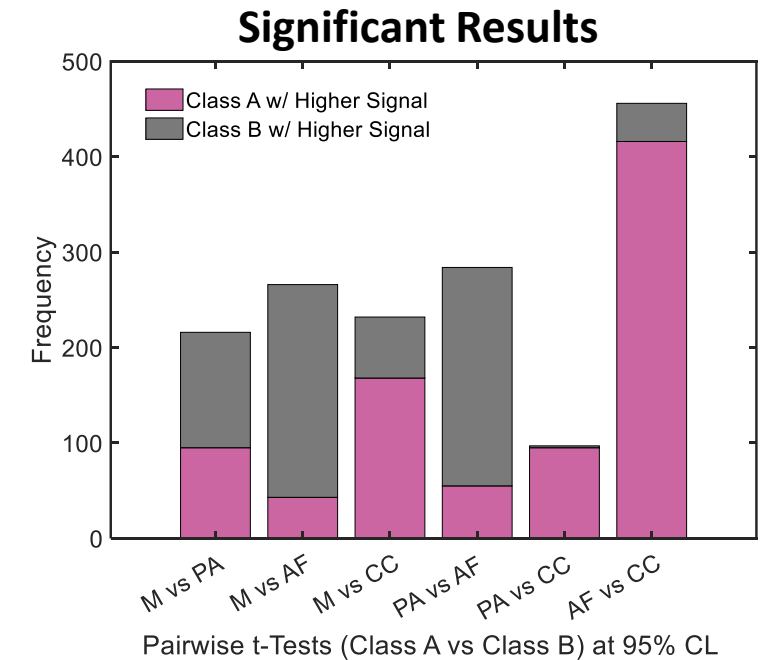
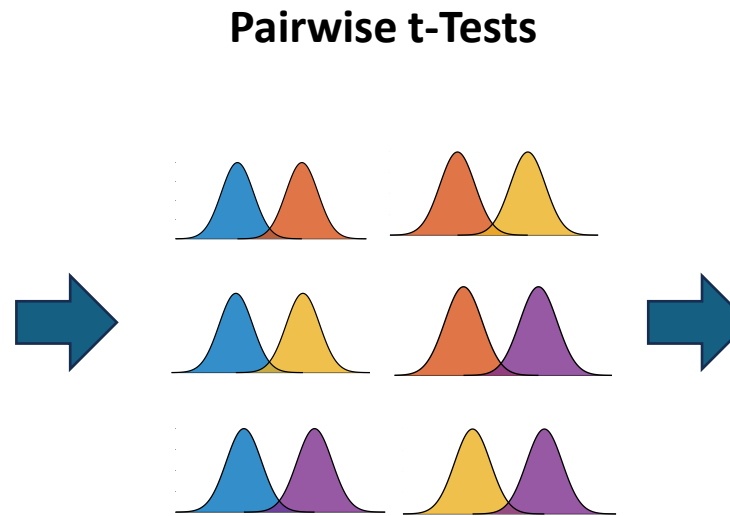
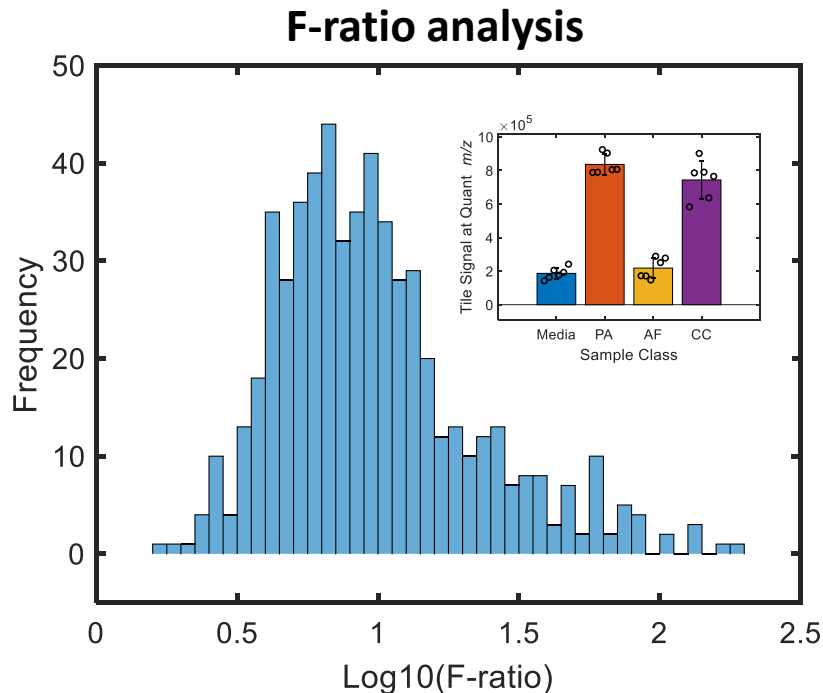
*The media sample appears to have less overall signal*

# Tile-based Fisher Ratio (F-ratio) Analysis



# Followed Up: Pairwise t-Test (95% CL)

- F-ratio analysis discovers analytes that are statistically different across all sample classes.
- Pairwise t-tests were formed to find out which classes differ.
- Significance set at  $p < 0.05$  (95% confidence level).
- For 4 classes, this results in 6 pairwise comparisons.



# Aim and Methodology

- To discover analytes that are **statistically different** in the headspace across all sample classes using comprehensive two-dimensional gas chromatography with time-of-flight mass spectrometry (GC×GC-TOFMS) and chemometrics
- To explore appropriate experimental design approaches for generating high quality data and enabling high throughput experimentation

**Feature Selection Methods**  
**Tile-based Analysis**



**Fisher Ratio**



**Coefficient of Variation**



**Fold Change**

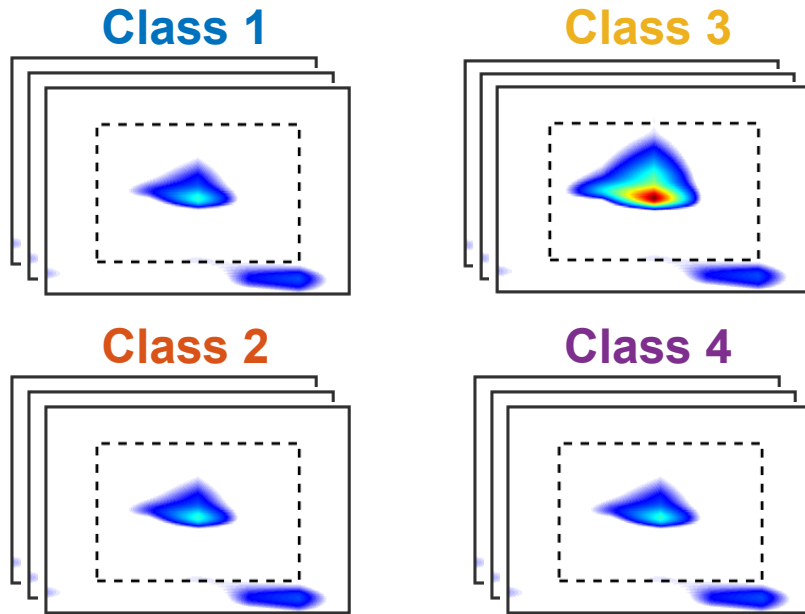
# Experimental Design Considerations Under Practical Constraints

- Replicates may not always be available due to sample, time, and/or cost limitations
- Replicates may not be reproducible: consistency across replicates is required
- Highly precision required during sample preparation for device fabrication
- Time sensitivity of sample preparation and data collection
  - SPME-GC×GC-TOFMS dataset collection required 24-hour spacing between the completion of sample preparation and the start of volatile absorption.

*Experimental Design Approaches for High-Quality Data  
via High Throughput Experimentation*

# Tile-Based Feature Selection Metrics

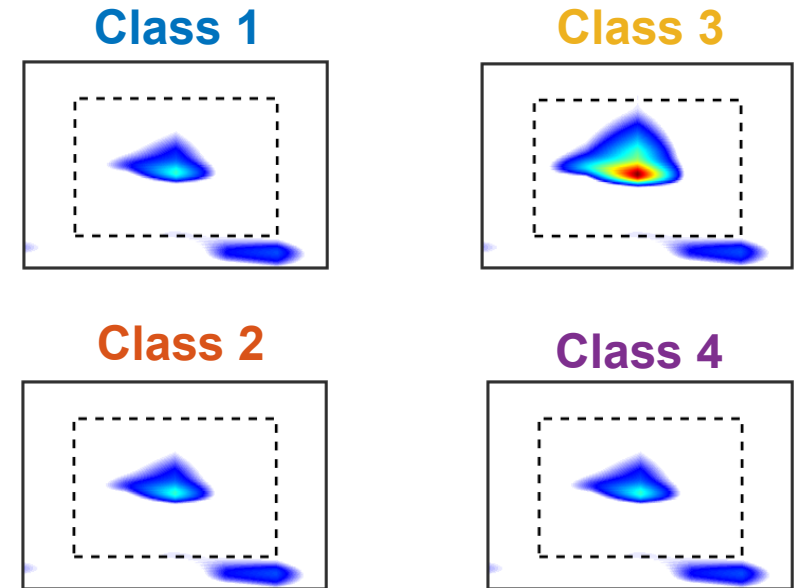
## Tile-Based F-ratio Analysis



$$F - ratio = \frac{\text{Between Class Variance}}{\sum(\text{Within Class Variance})}$$

*Replicates may not always be available due to sample, time, and/or expense limitations*

## Tile-Based Coefficient of Variation Analysis



$$CV = \frac{STD}{Mean}$$

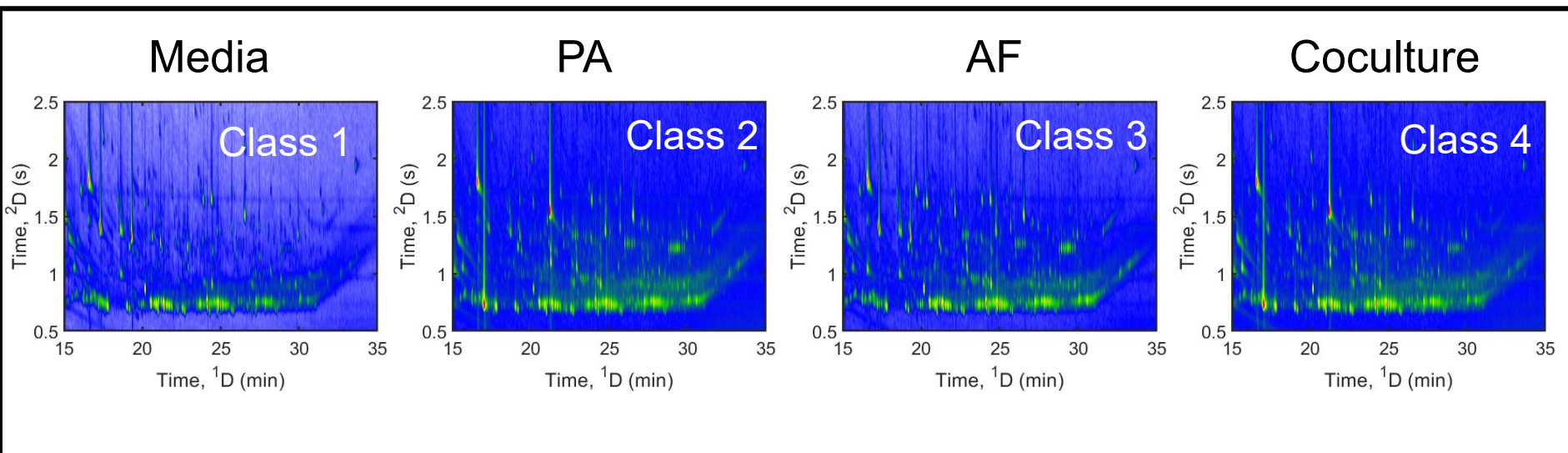
*Overcomes issues associated with pixel-based subtraction plots*



# Tile-Based Coefficient of Variation Analysis

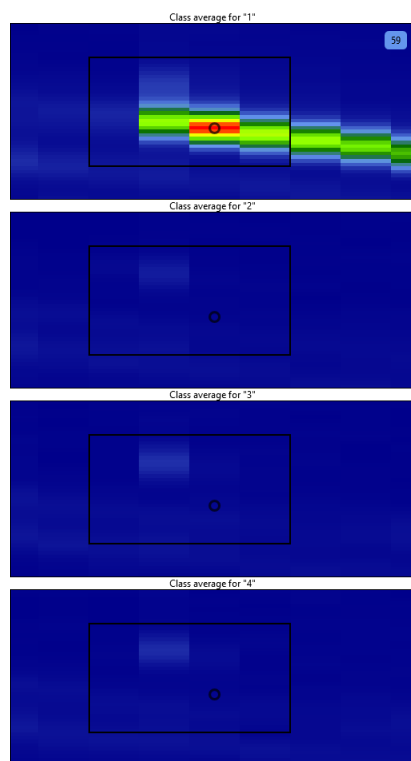
We applied ChromaTOF Tile (Coefficient of Variation method) to simultaneously obtain a single hitlist that relates all analytes in all samples in terms of up and down regulations of their concentrations.

This required only one replicate from each sample to obtain this comprehensive hitlist of relative concentration for each analyte.

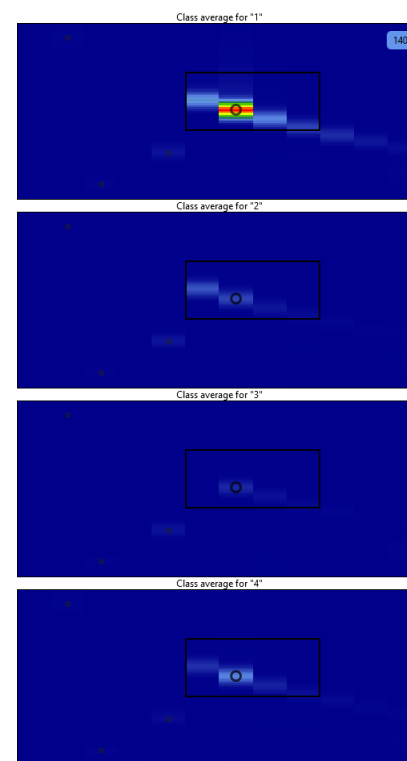
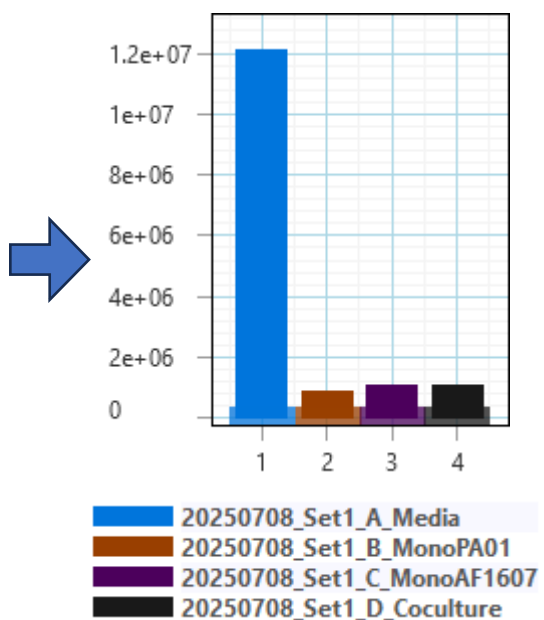


Hit List		
Hit #	Coefficient of Variation	Analyte
1	High	AAA
N	Low	ZZZ

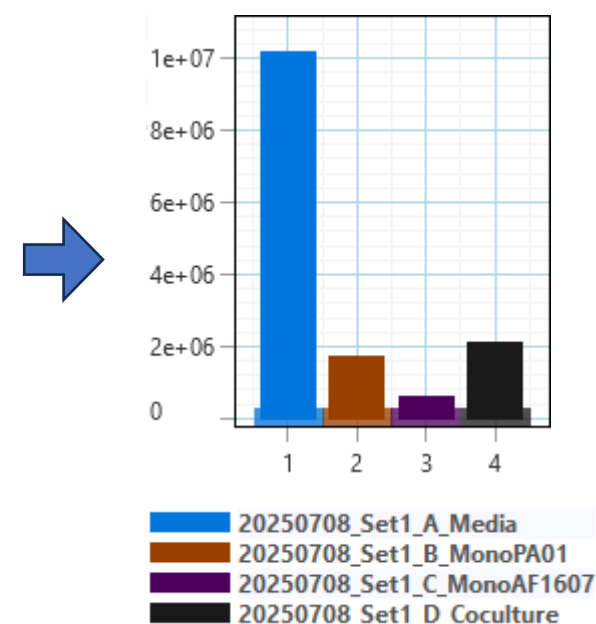
# Example Hits with Highest Signals in Class 1 – Media



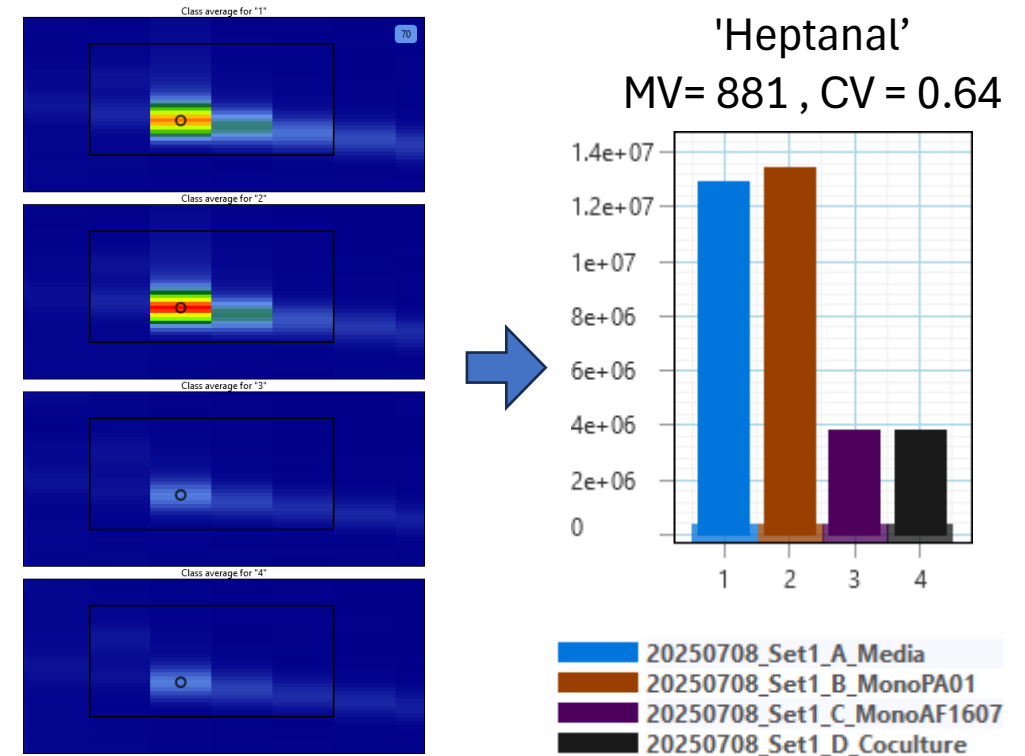
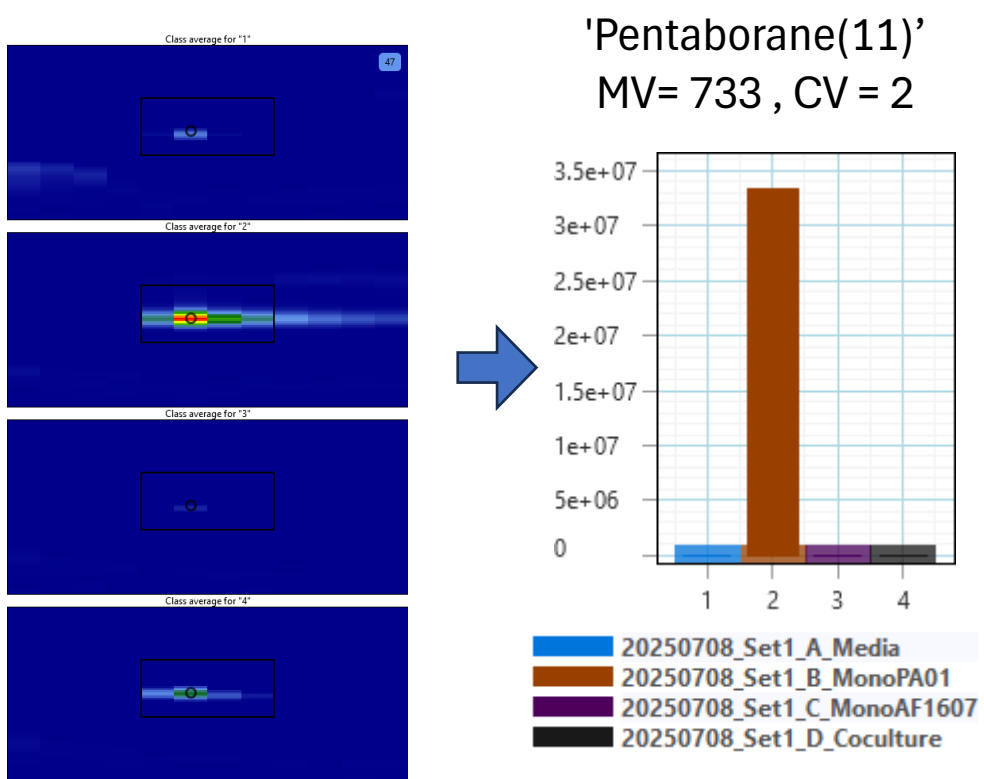
'2-Cyclobutyl-2-propanol'  
MV=741 , CV = 1.48



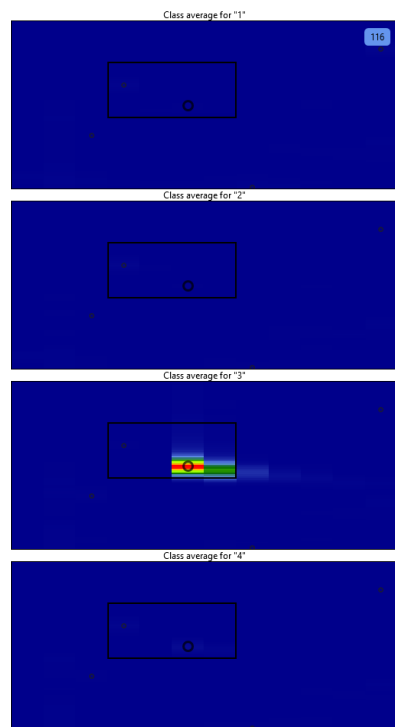
'4-Piperidinone, 2,2,6,6-tetramethyl-'  
MV = 821 , CV = 1.2



# Example Hits with Highest Signals in Class 2 – PA monoculture

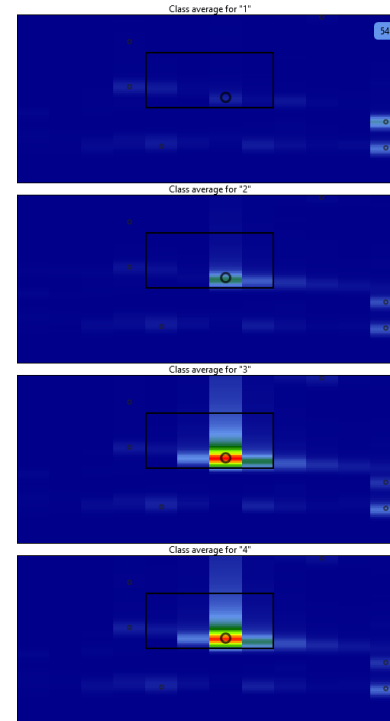
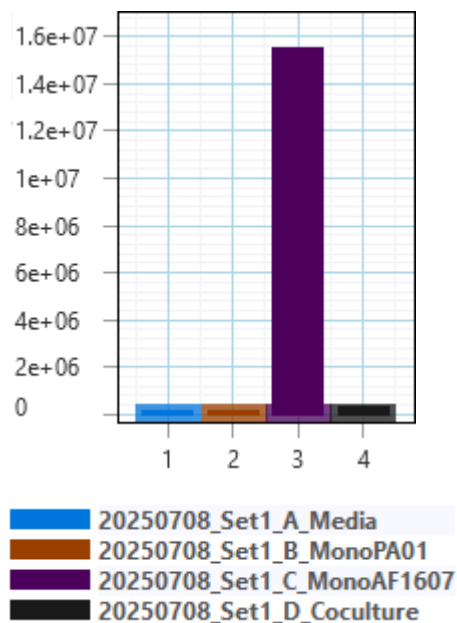


# Example Hits with Highest Signals in Class 3 – AF monoculture



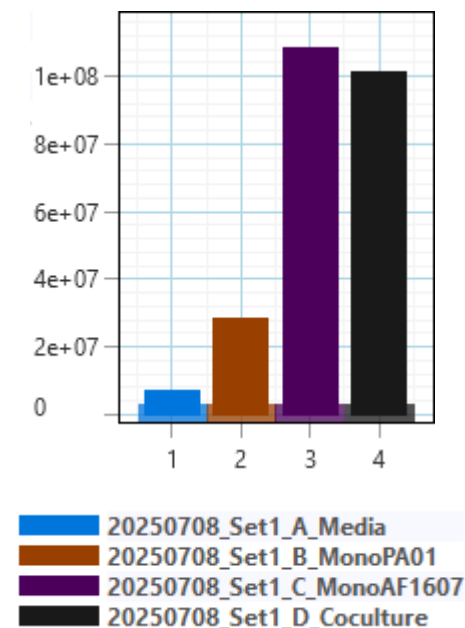
'3(2H)-Thiophenone, dihydro-2-methyl-'

MV = 818, CV = 1.9

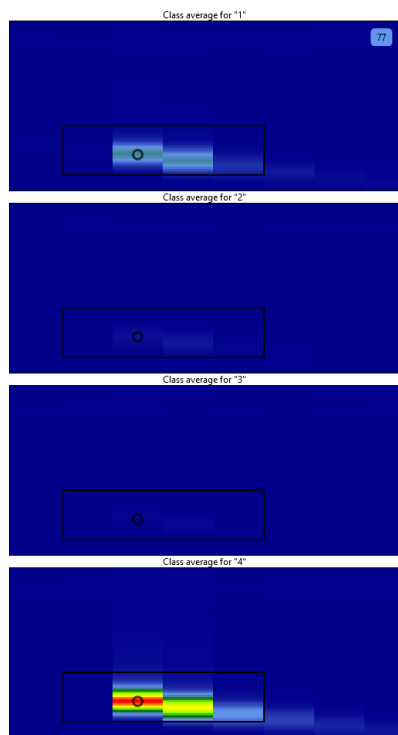


'1-Octen-3-ol'

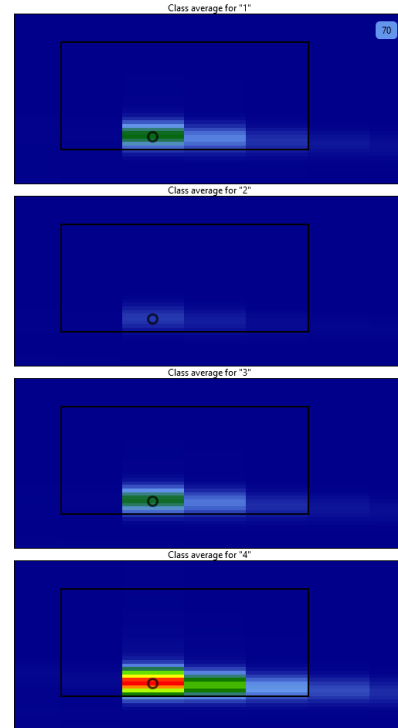
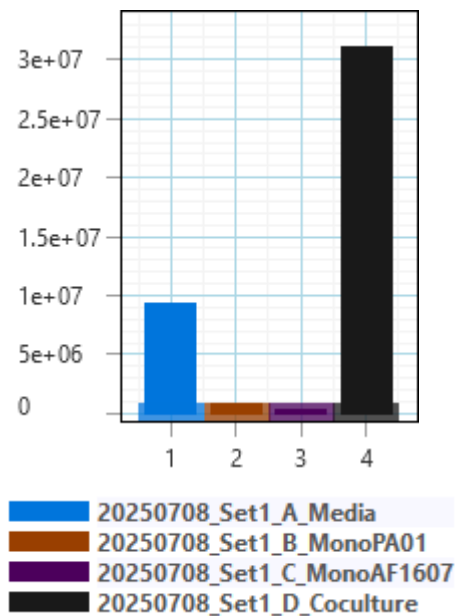
MV = 837, CV = 0.83



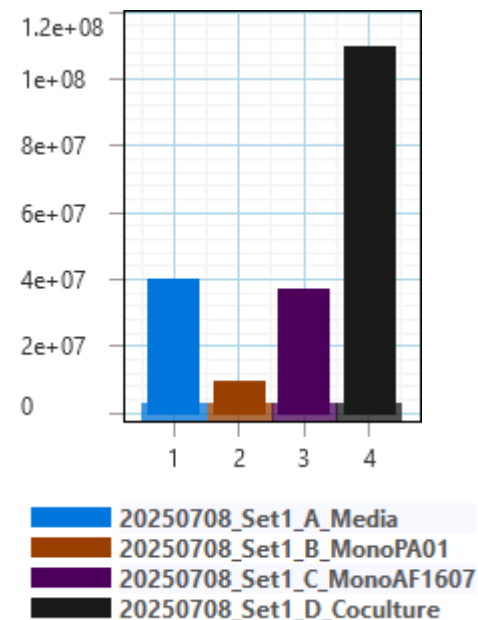
# Example Hits with Highest Signals in Class 4 - Coculture



'1H,1H,2H-Perfluoro-1-octene'  
MV = 798, CV = 1.39



'2,4-Dimethyl-1-heptene'  
MV = 915, CV = 0.87



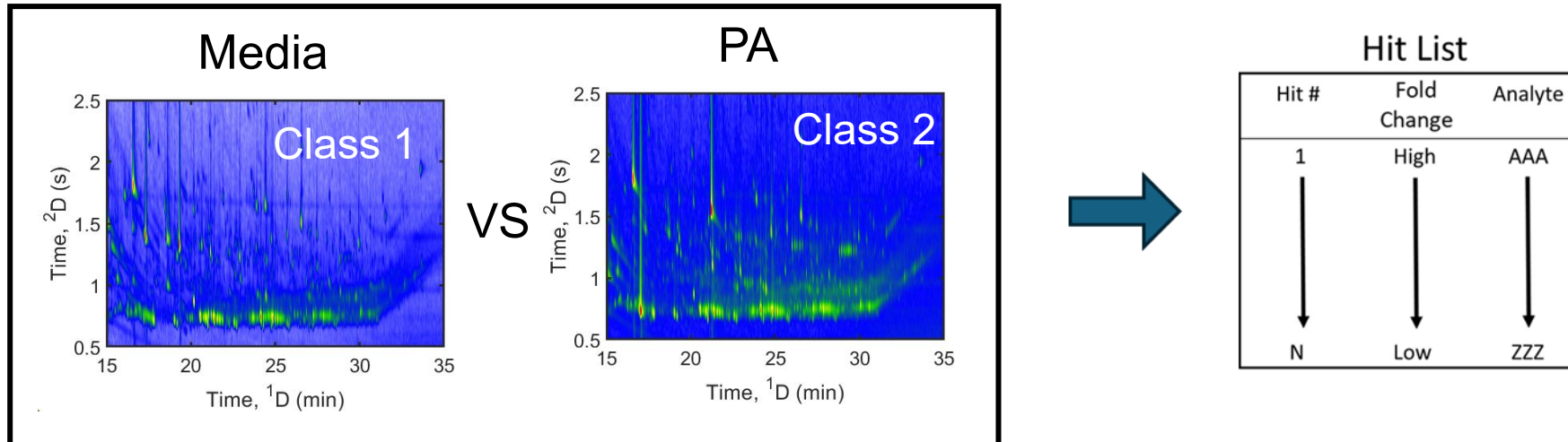
# Tile-based Pairwise Analysis

## *Non-Targeted Discovery Analysis Comparing Two Chromatograms*

Utilize a tile-based relative change method that discovers analytes that are different in concentration between two samples with only one replicate.

$$\text{Fold Change} = \left( \frac{\text{Class 1 Tile Signal Sum}}{\text{Class 2 Tile Signal Sum}} \right)$$

Discover any hits with specified fold change (FC) threshold.





# Conclusions and Next Steps

- Tile-based F-ratio analysis discovered 576 sample class distinguishing analytes.
- Additional pairwise t-tests can further determine which sample classes differ.
- Under constrained experimental conditions, the tile-based coefficient of variation (CV) method is more suitable for achieving high-quality data in high-throughput experimentation.
- Appropriate feature selection methods (F-ratio, CV, and FC) should be selected based on the specific experimental design.
- Further analyte identification can be performed using the chemometric tool PARAFAC.

# Acknowledgements

## Principal Investigator

- Dr. Robert Synovec

## Synovec Lab Members

- Rachel Halvorsen
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- Cassandra Padilla
- Peri Abdigali
- Valencia Parker
- Jungho Ahn
- Stephanie Nguyen

Synovec Lab

Gas Chromatography, Liquid Chromatography,  
and Mass Spectrometry, with Multi-Dimensional  
Data Analysis

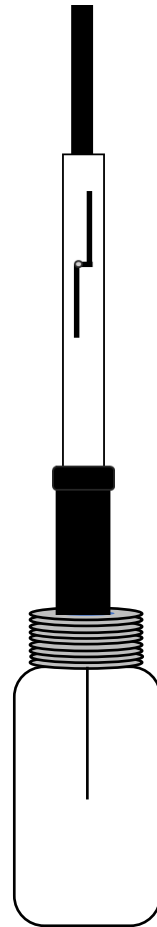


Seattle's Best  
Chromatography



*Thank you for listening! Any questions?*

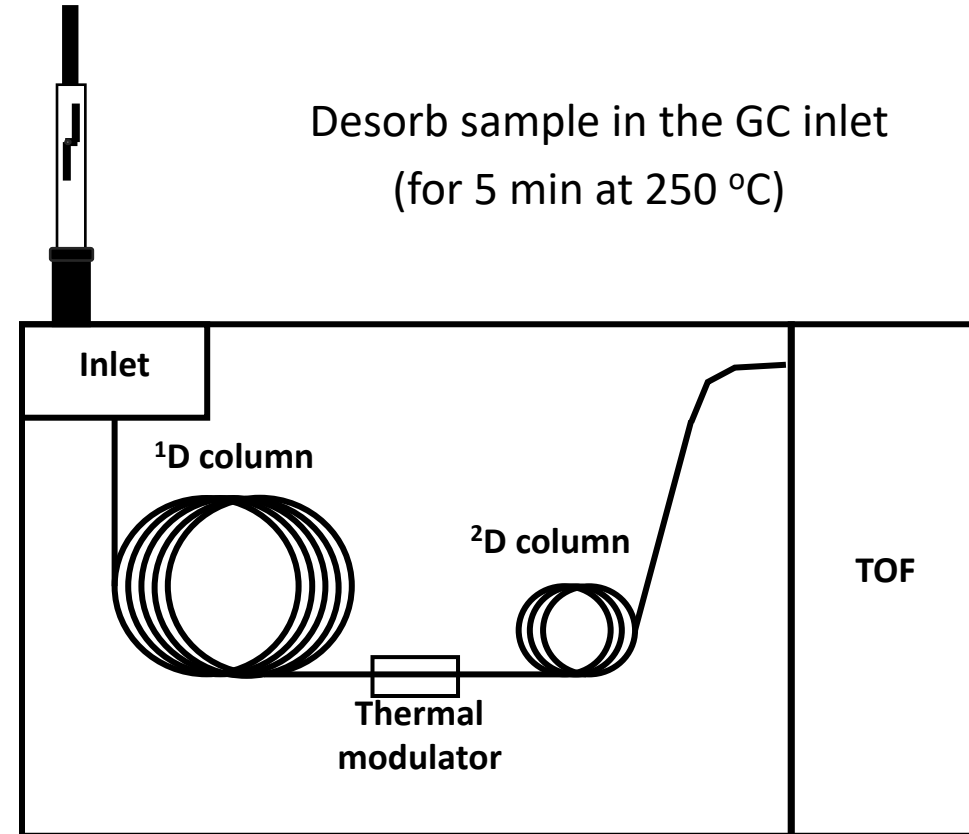
SPME Tool



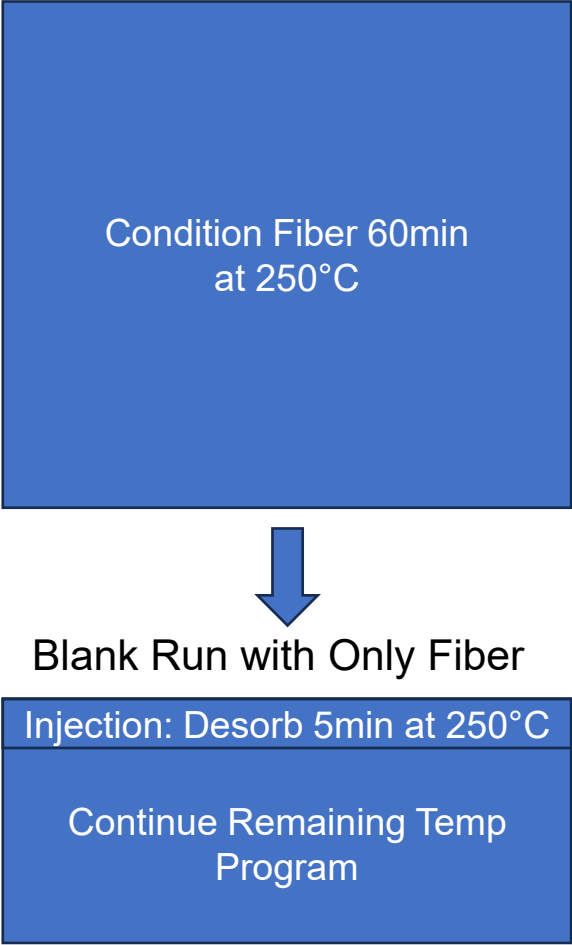
SPME  
Fiber

Expose SPME to sample  
(for 30 min at 37 °C)

Desorb sample in the GC inlet  
(for 5 min at 250 °C)



**Condition Workflow**



**Run Sample Workflow**

