

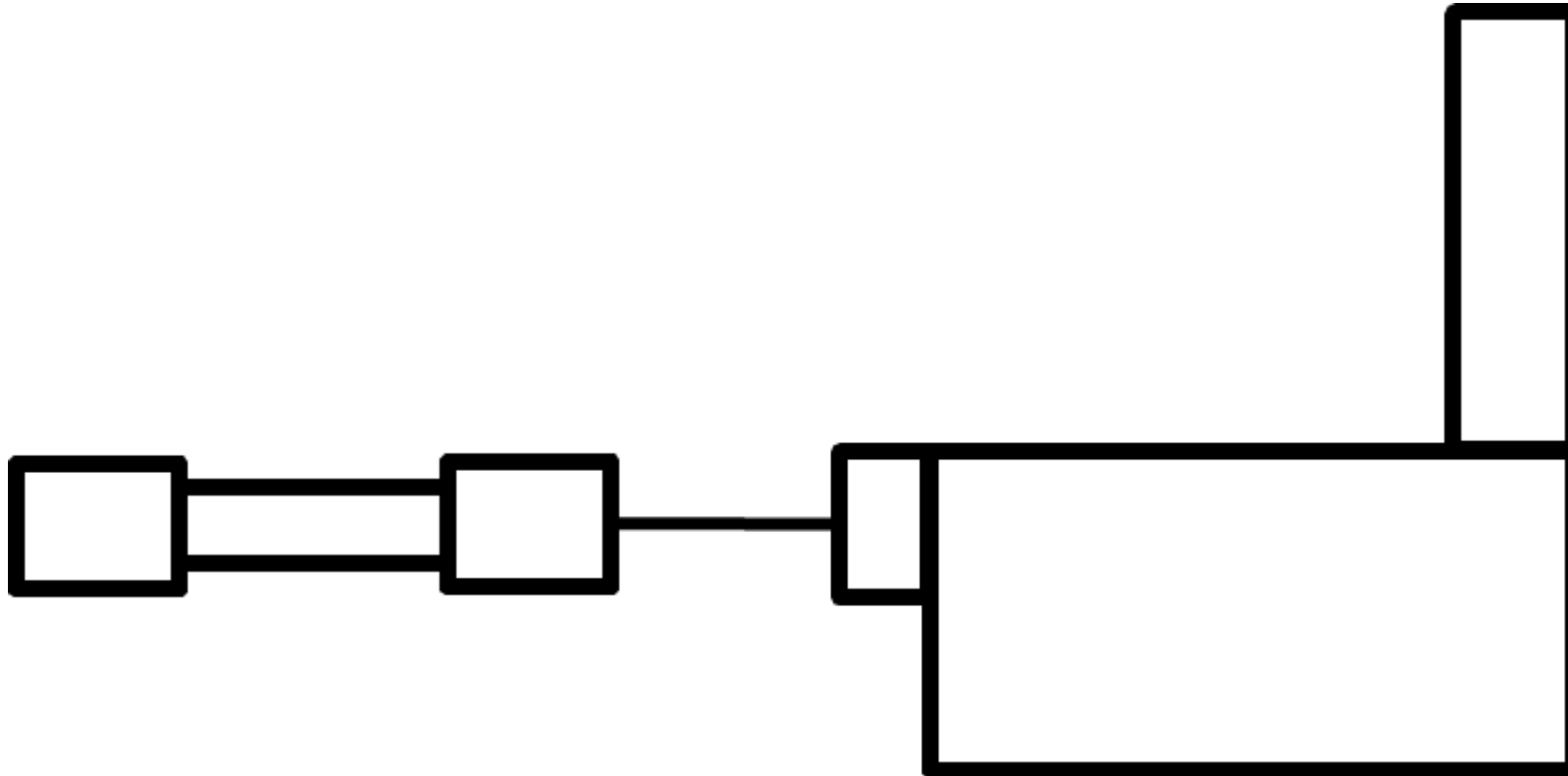
MS2Tox & MS2Quant: automated prediction of toxicity and concentration

anneli kruve
anneli.kruve@su.se
kruvelab.com

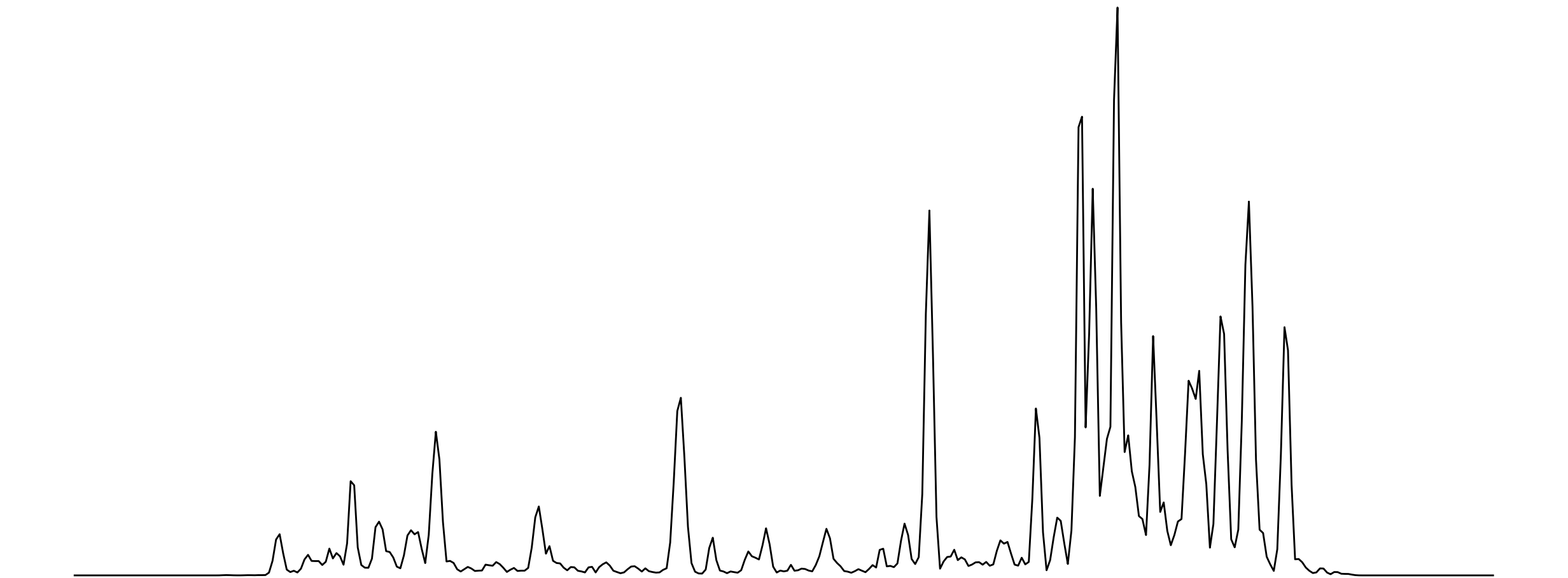
water analysis



nontarget screening with LC/HRMS



nontarget screening with LC/HRMS



0

5

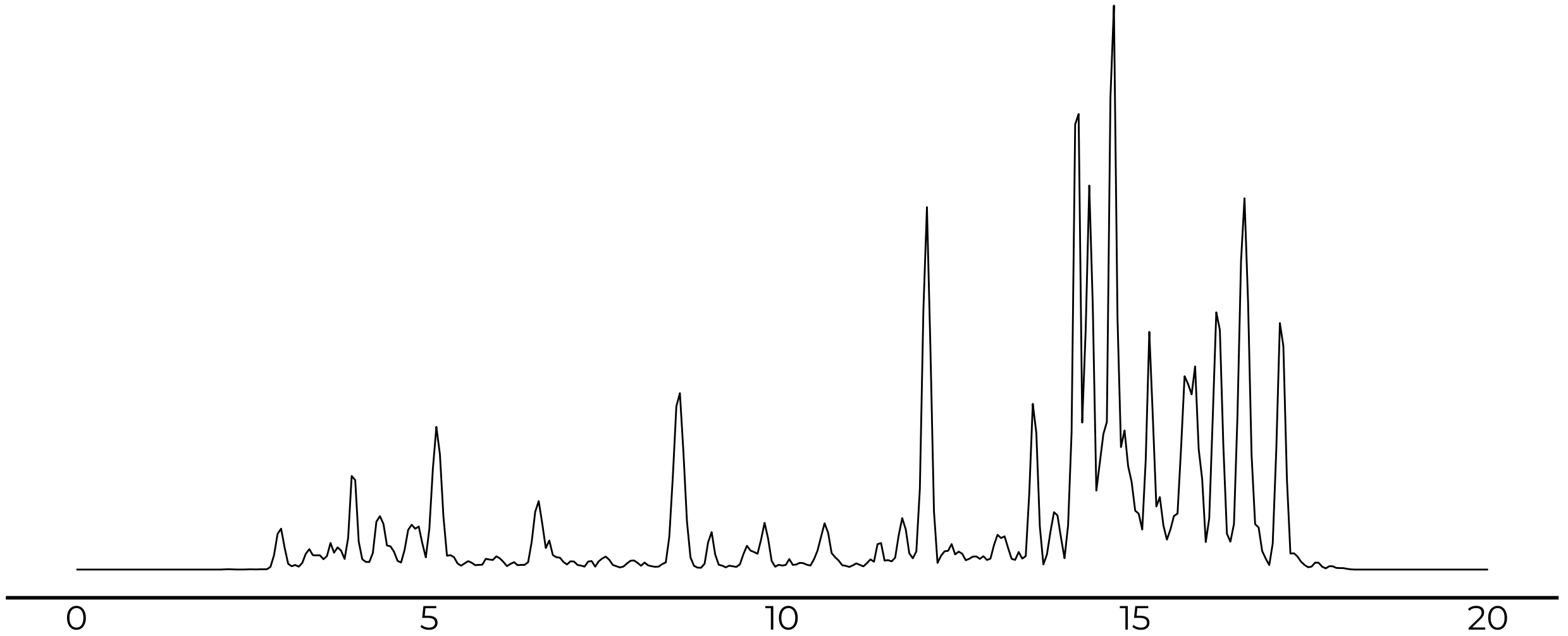
10

15

20

time

what next?



prioritization



toxicity

prioritization



toxicity



concentration

prioritization



toxicity



concentration



risk

prioritization



toxicity



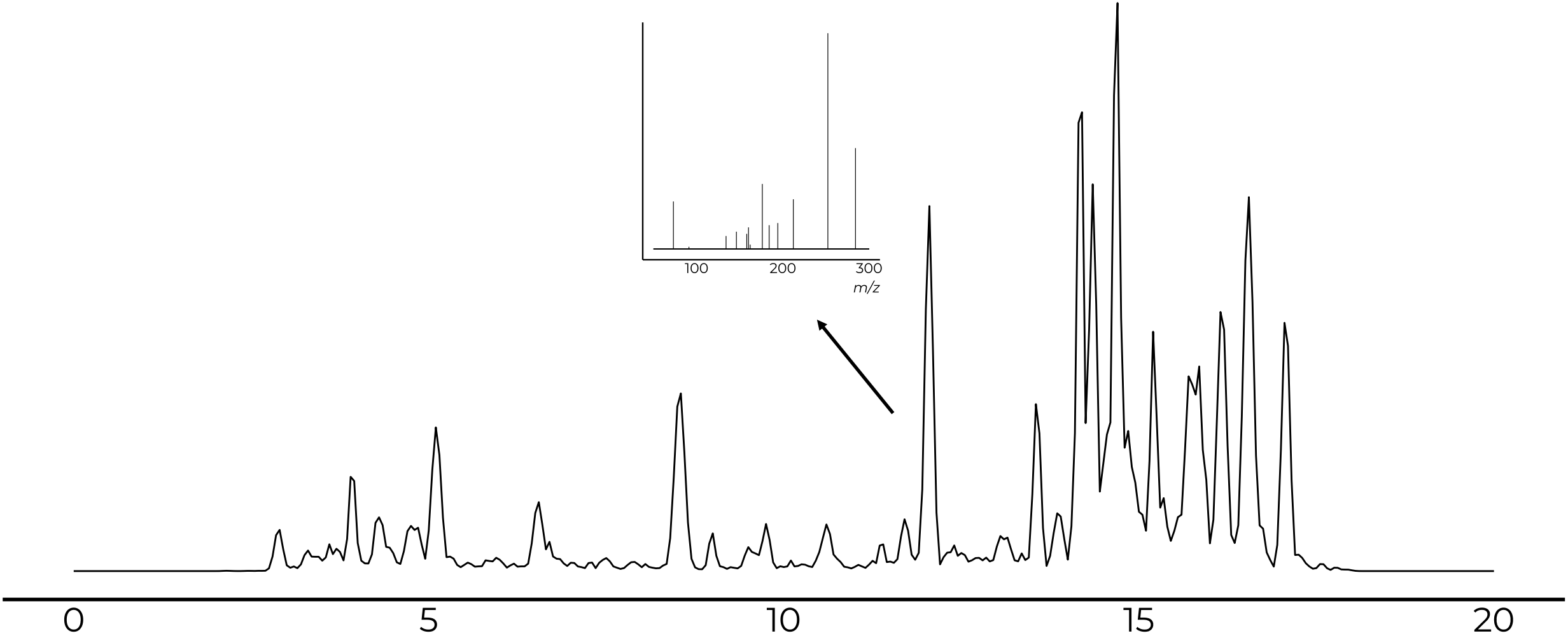
concentration



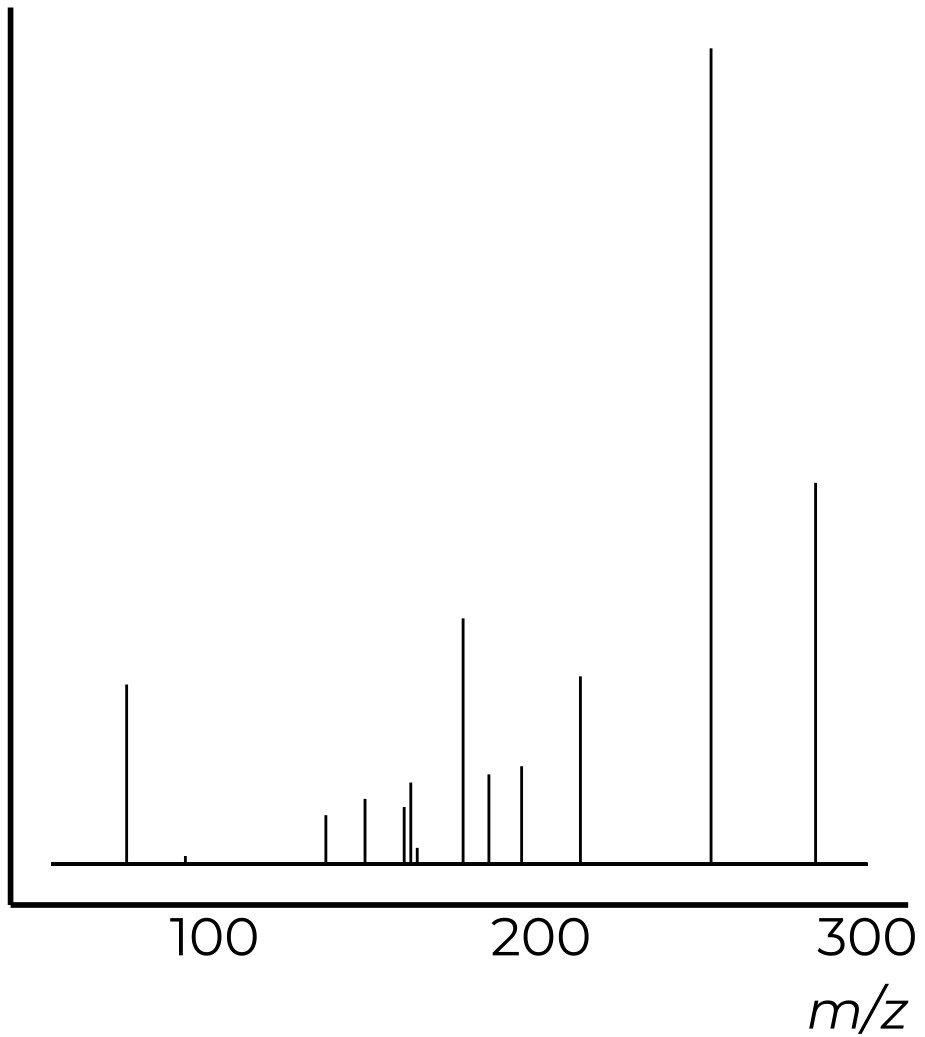
risk

$$\text{PriorityScore} = \frac{C_{\text{predicted}}}{AC_{50}^{\text{5th percentile}}}$$

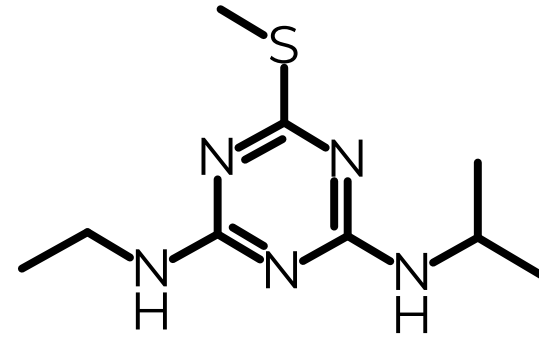
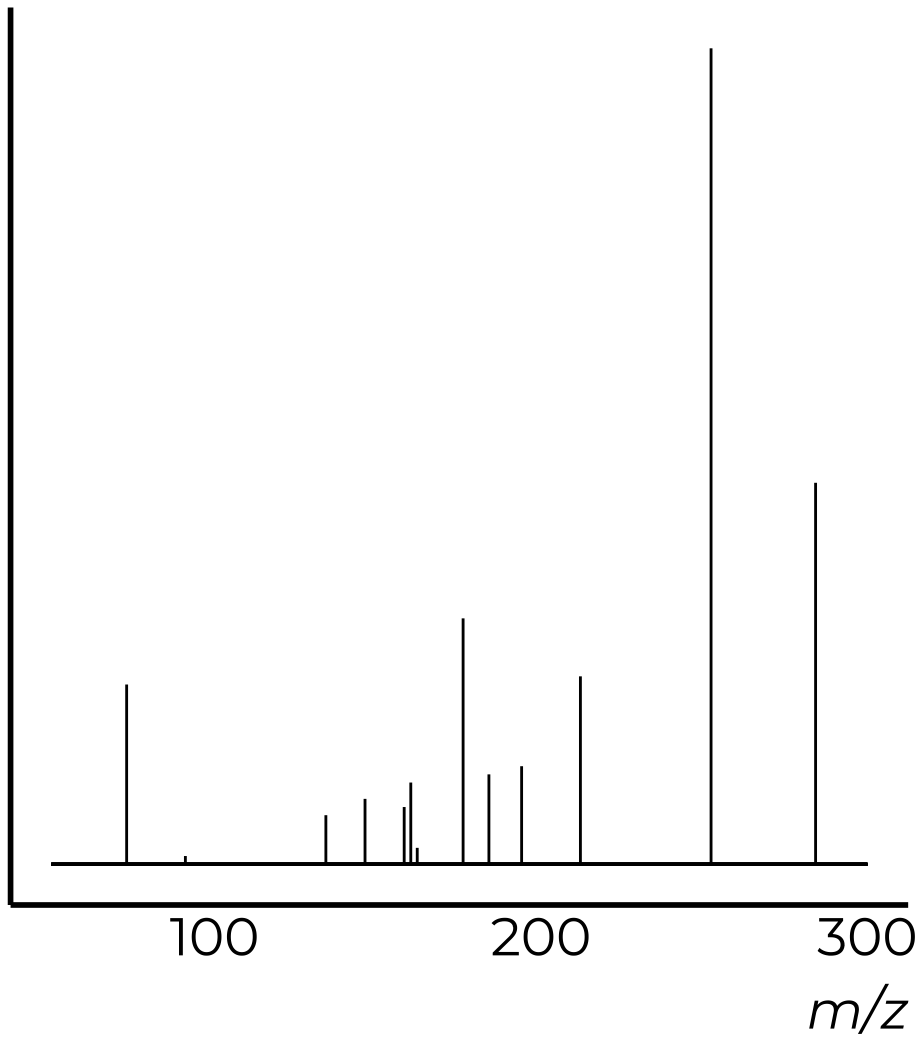
nontarget screening with LC/HRMS



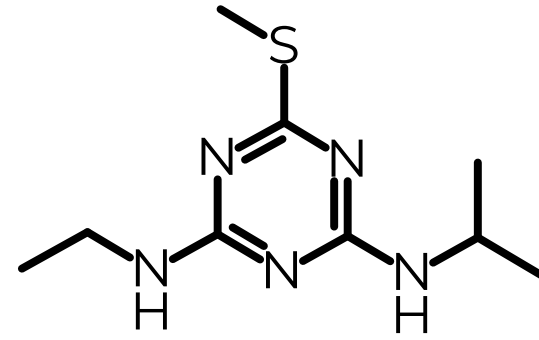
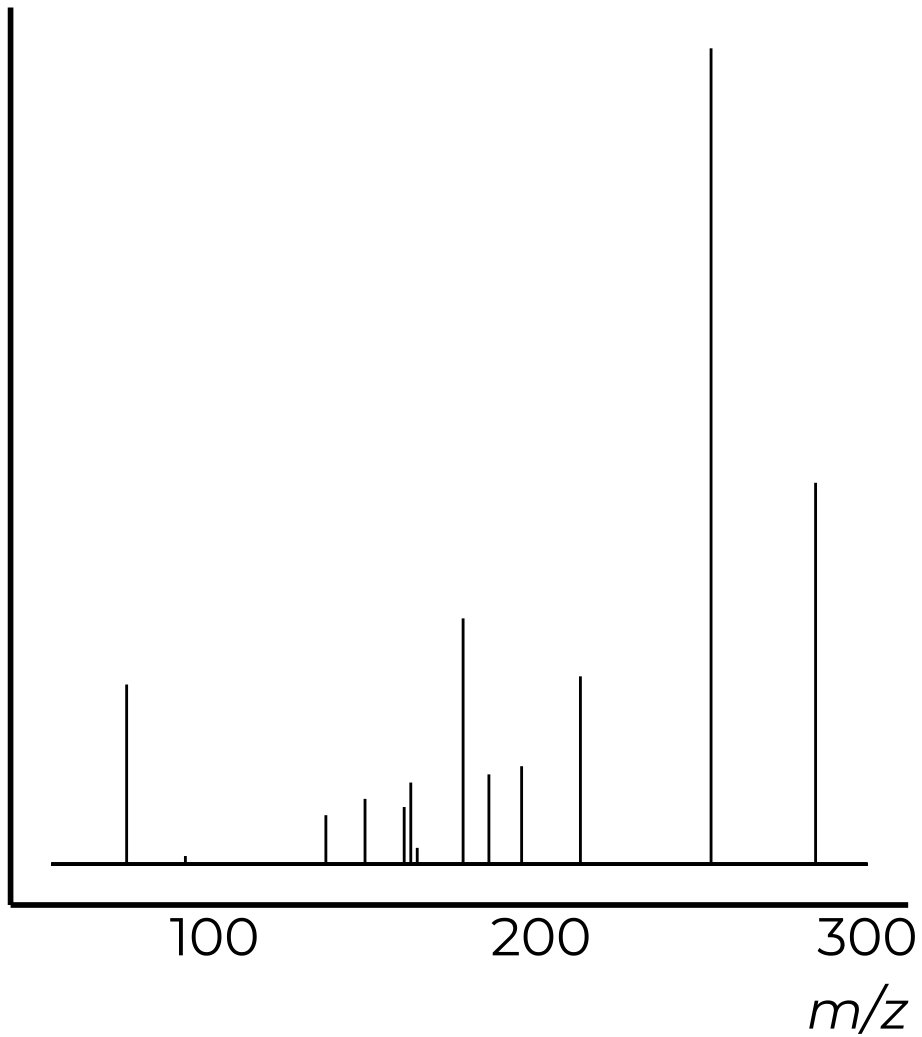
toxicity assessment



toxicity assessment

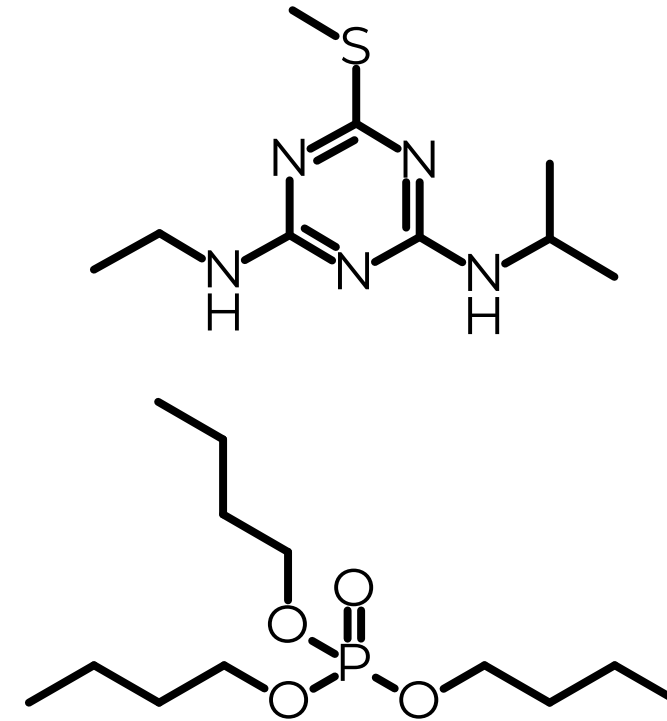
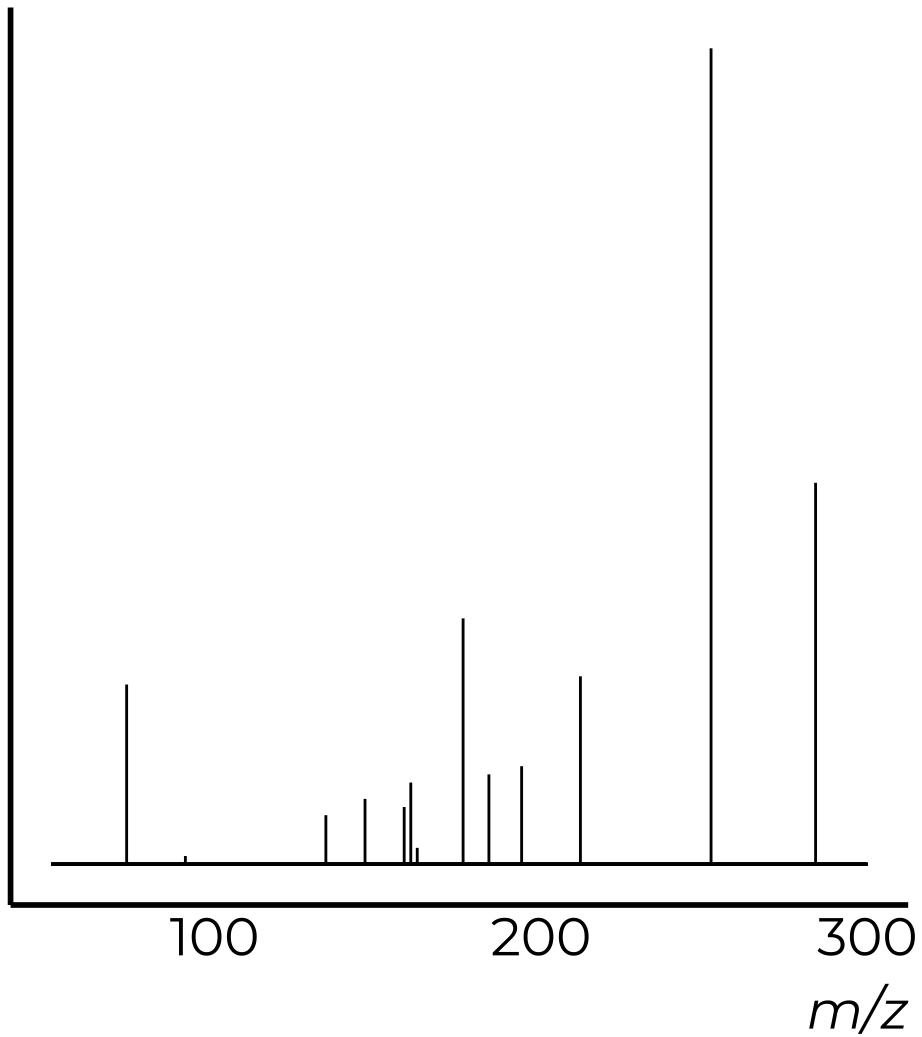


toxicity assessment



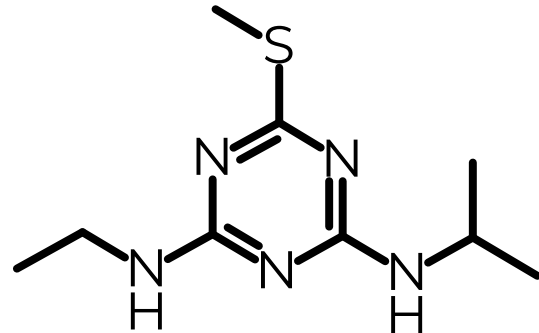
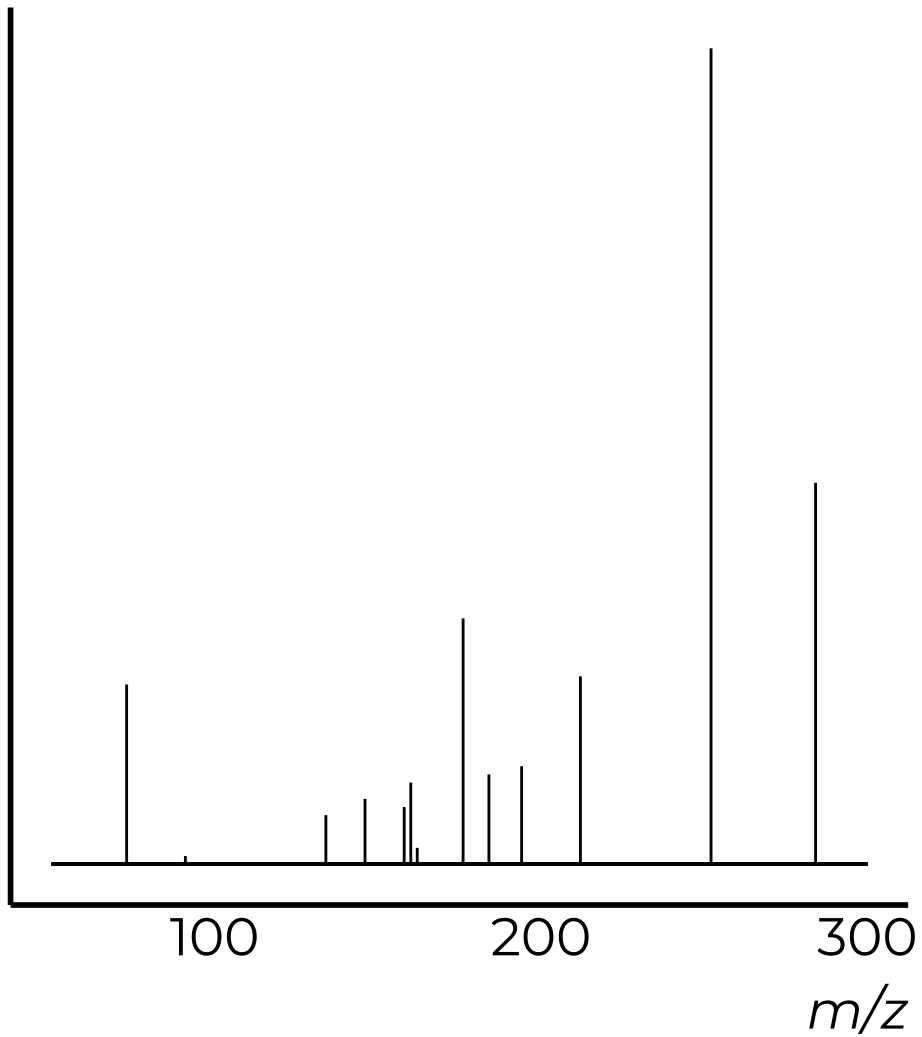
LC₅₀ = 9.3 mg/L

toxicity assessment

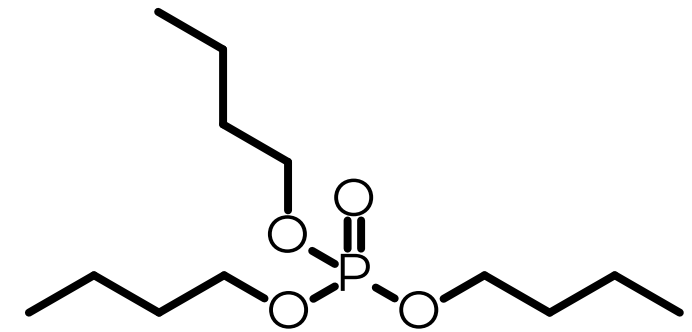


LC₅₀ = 9.3 mg/L

toxicity assessment

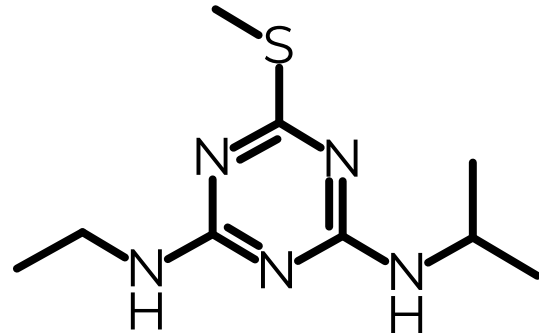
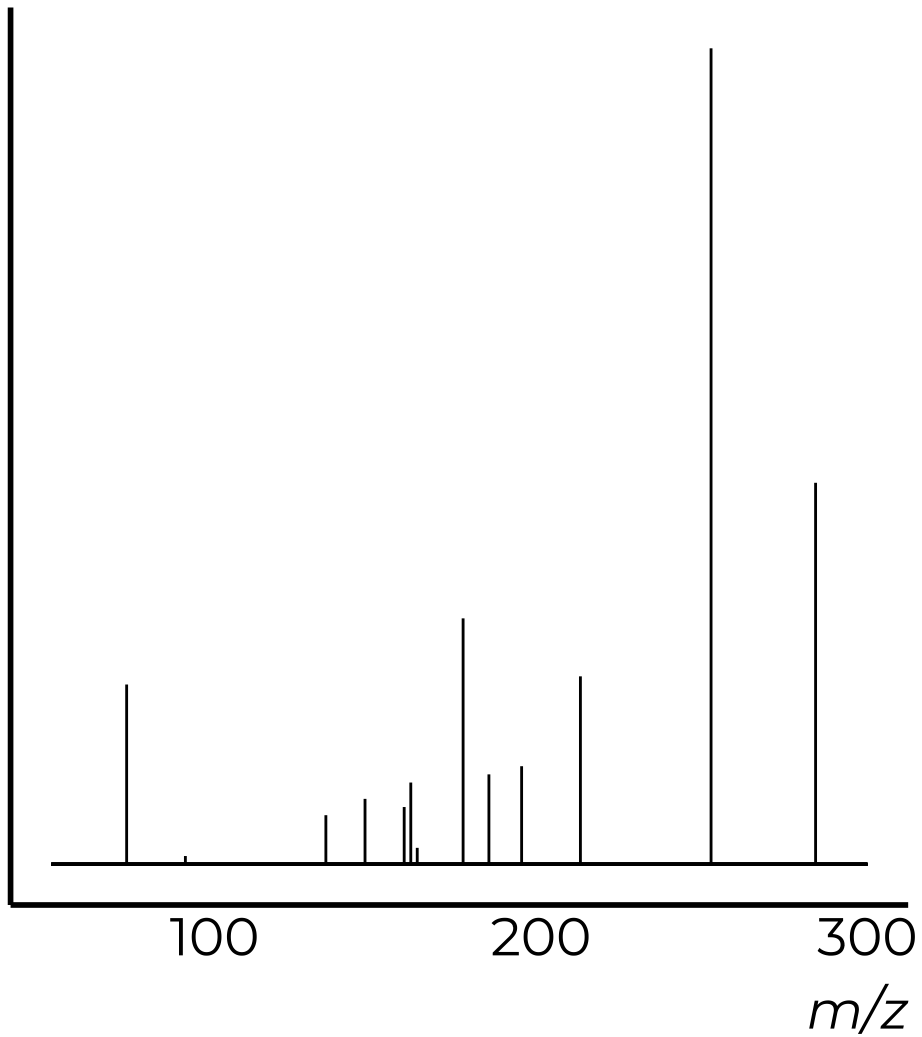


LC₅₀ = 9.3 mg/L

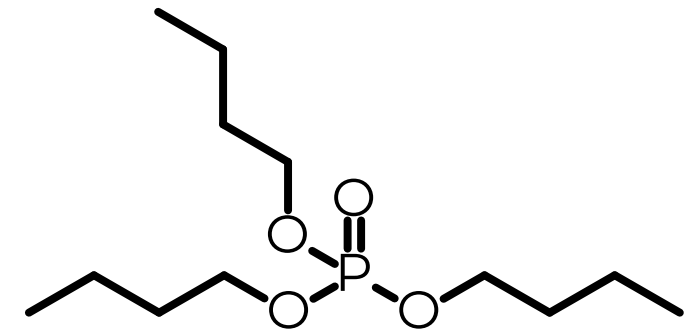


LC₅₀ = ? mg/L

toxicity assessment



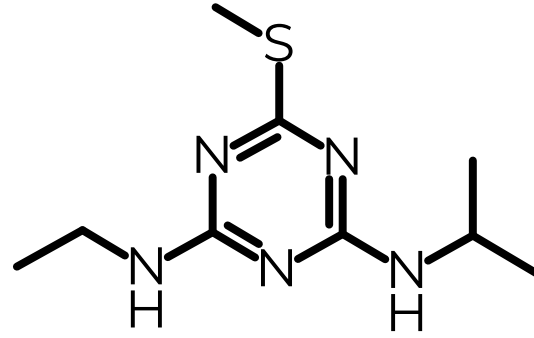
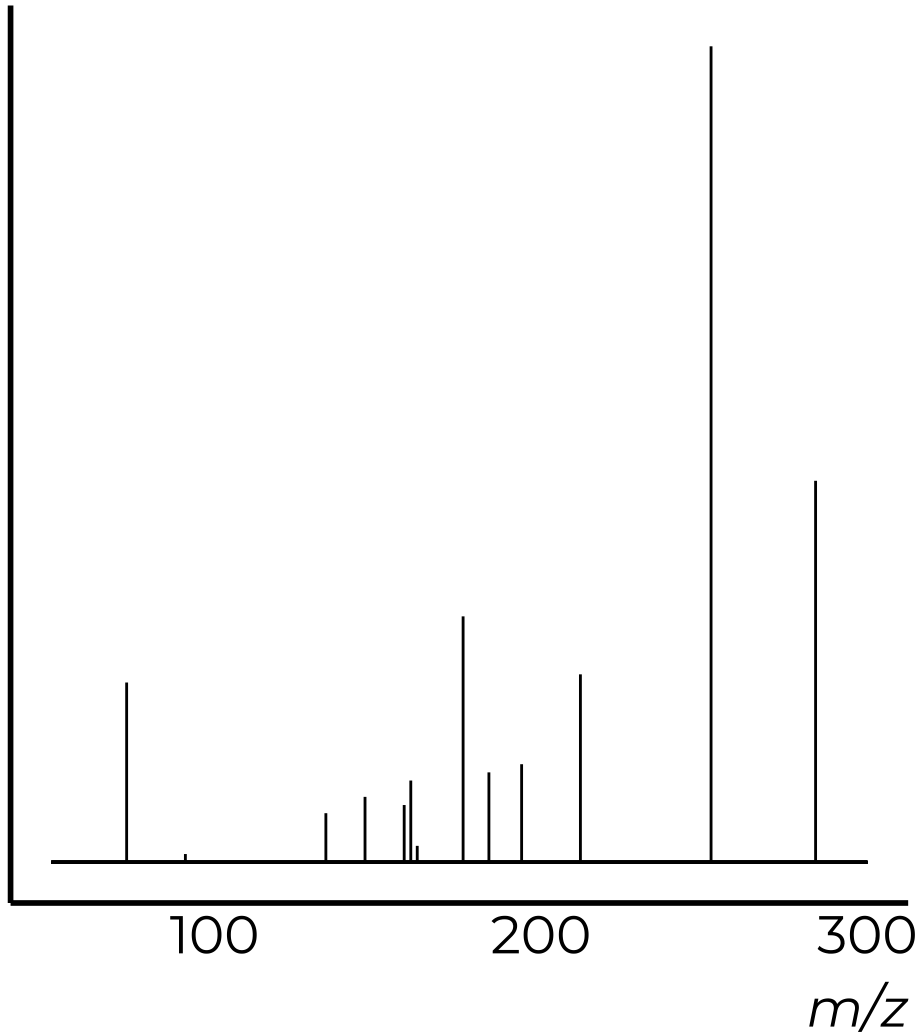
LC₅₀ = 9.3 mg/L



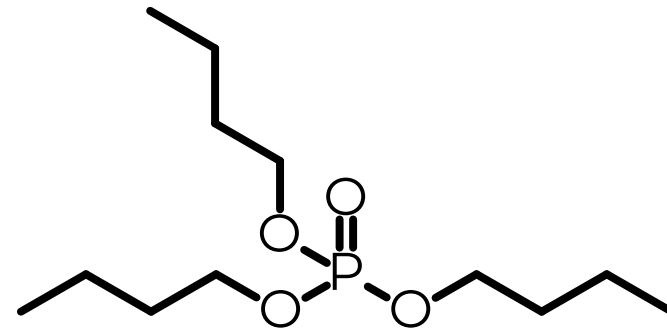
LC₅₀ = ? mg/L

?

toxicity assessment



$LC_{50} = 9.3 \text{ mg/L}$

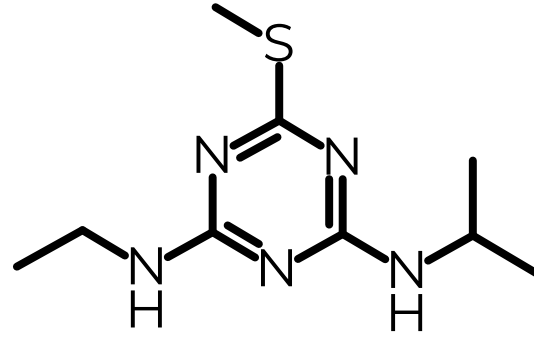


$LC_{50} = ? \text{ mg/L}$

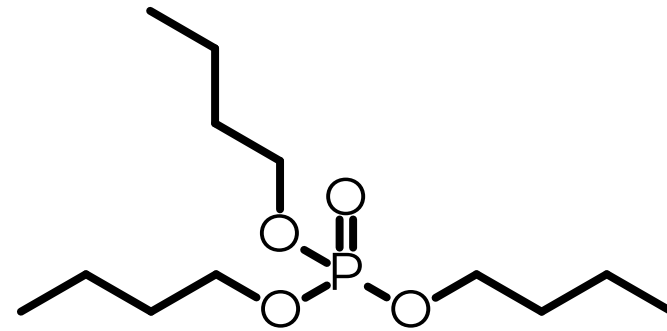
?

$LC_{50} = ? \text{ mg/L}$

toxicity assessment



LC₅₀ = 9.3 mg/L



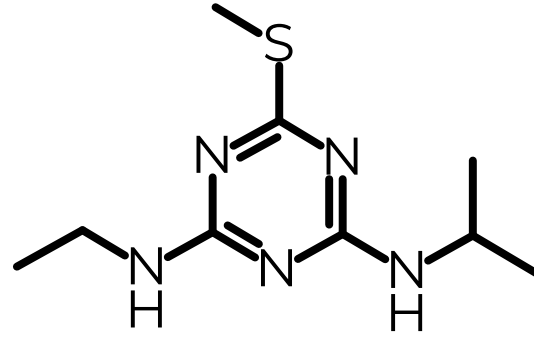
LC₅₀ = ? mg/L

?

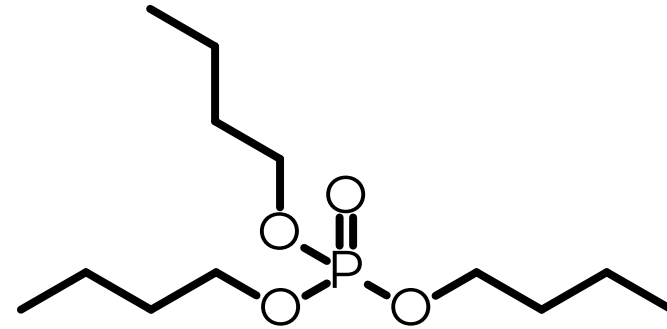
LC₅₀ = ? mg/L

toxicity assessment

<1%



LC₅₀ = 9.3 mg/L



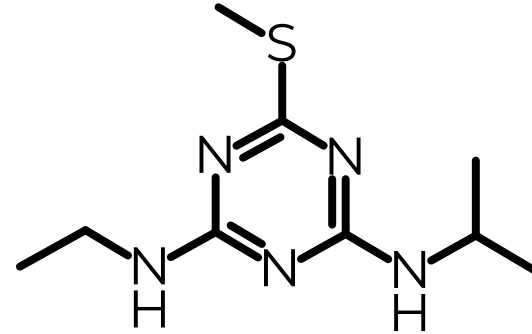
LC₅₀ = ? mg/L

?

LC₅₀ = ? mg/L

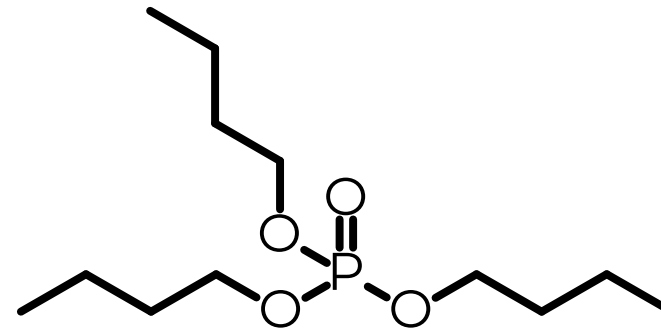
toxicity assessment

<1%



LC₅₀ = 9.3 mg/L

<2%



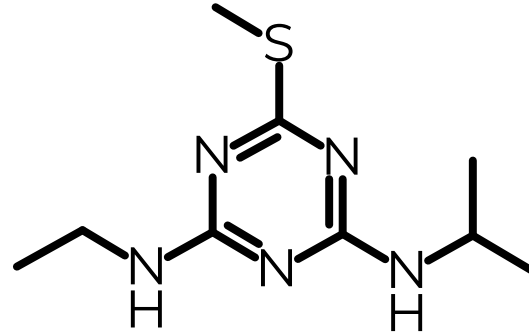
LC₅₀ = ? mg/L

?

LC₅₀ = ? mg/L

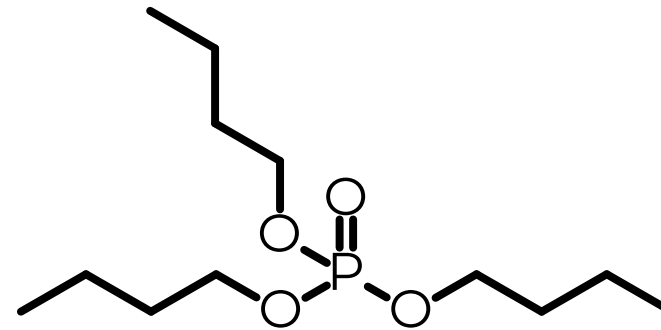
toxicity assessment

<1%



LC₅₀ = 9.3 mg/L

<2%



LC₅₀ = ? mg/L

~98%

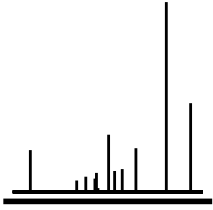
?

LC₅₀ = ? mg/L

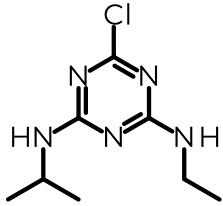
predicting toxicity

for detected chemicals

workflow



MS² spectra



structure as SMILES

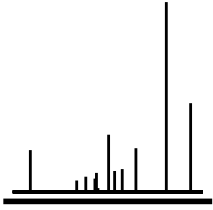


molecular descriptors



predict toxicity

workflow



MS² spectra



molecular descriptors

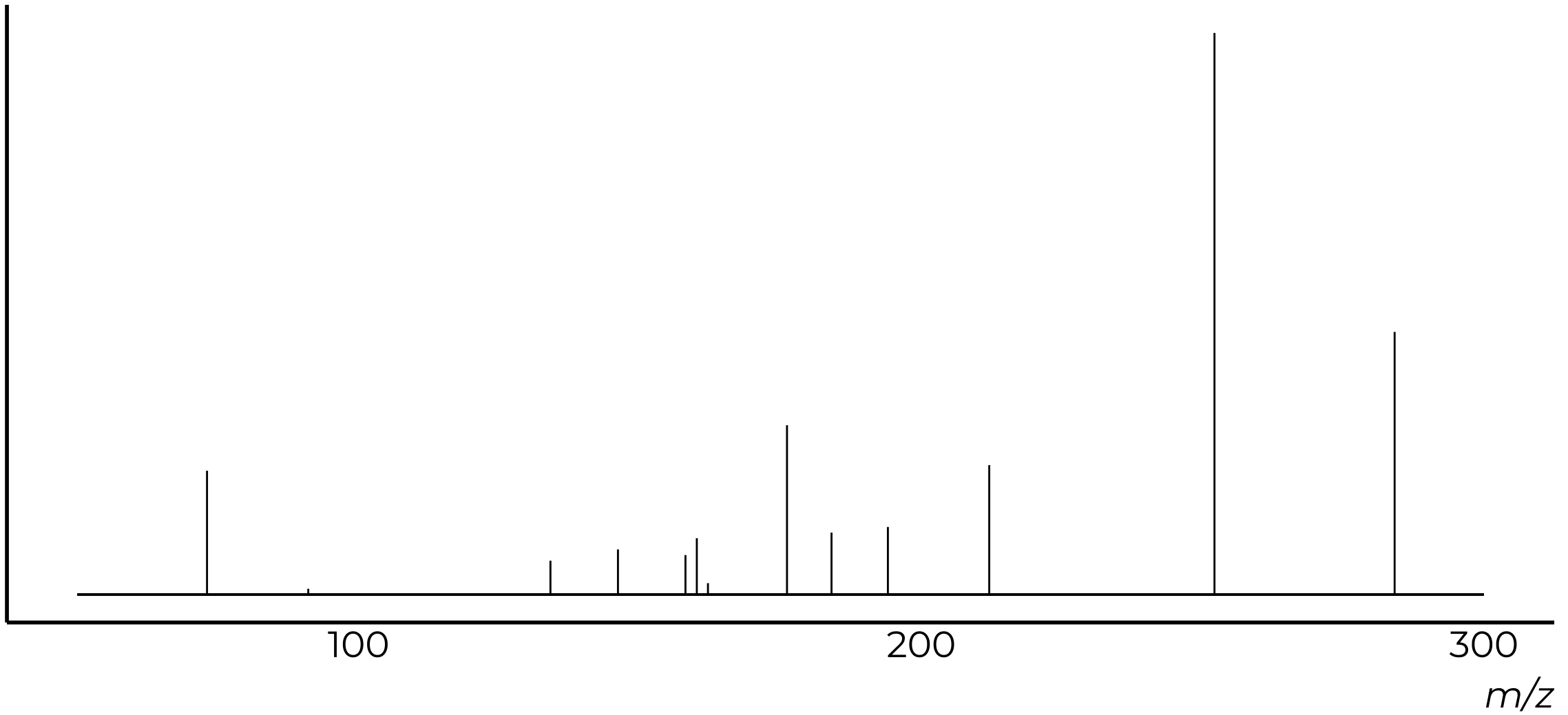


predict toxicity

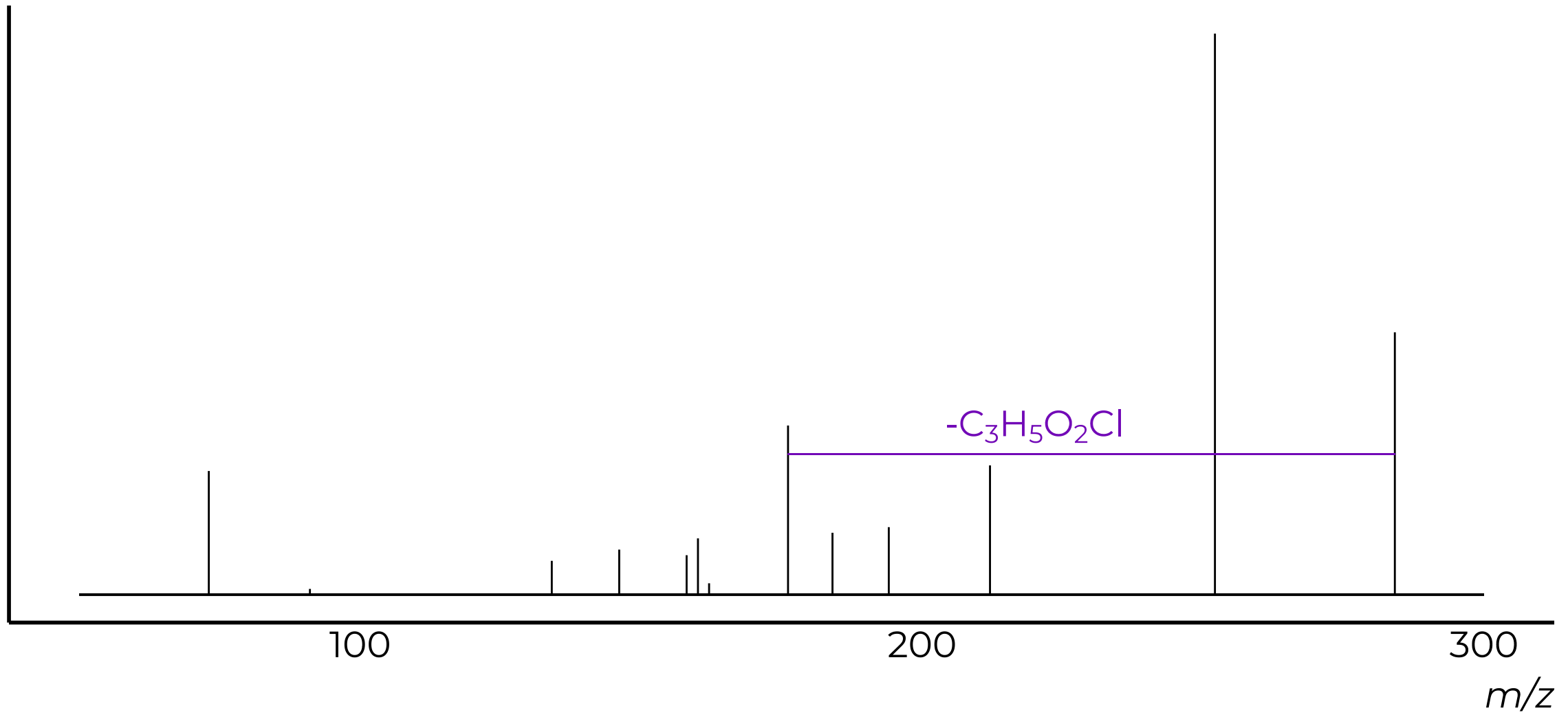
information available

in MS² spectra

MS² spectra



MS² spectra

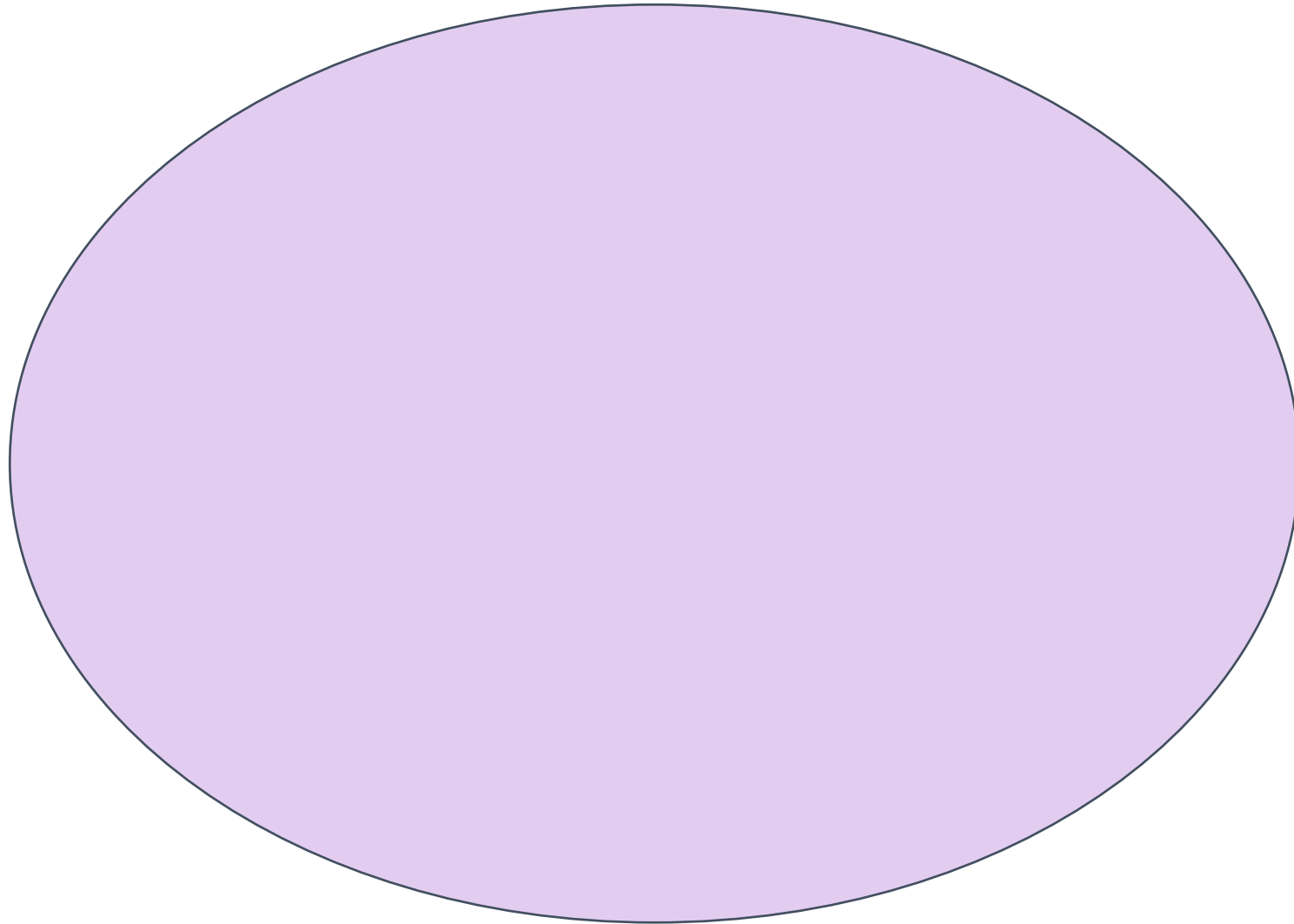


data for machine learning models

data for machine learning models

CompTox

all toxicity
values



data for machine learning models

CompTox

all toxicity values

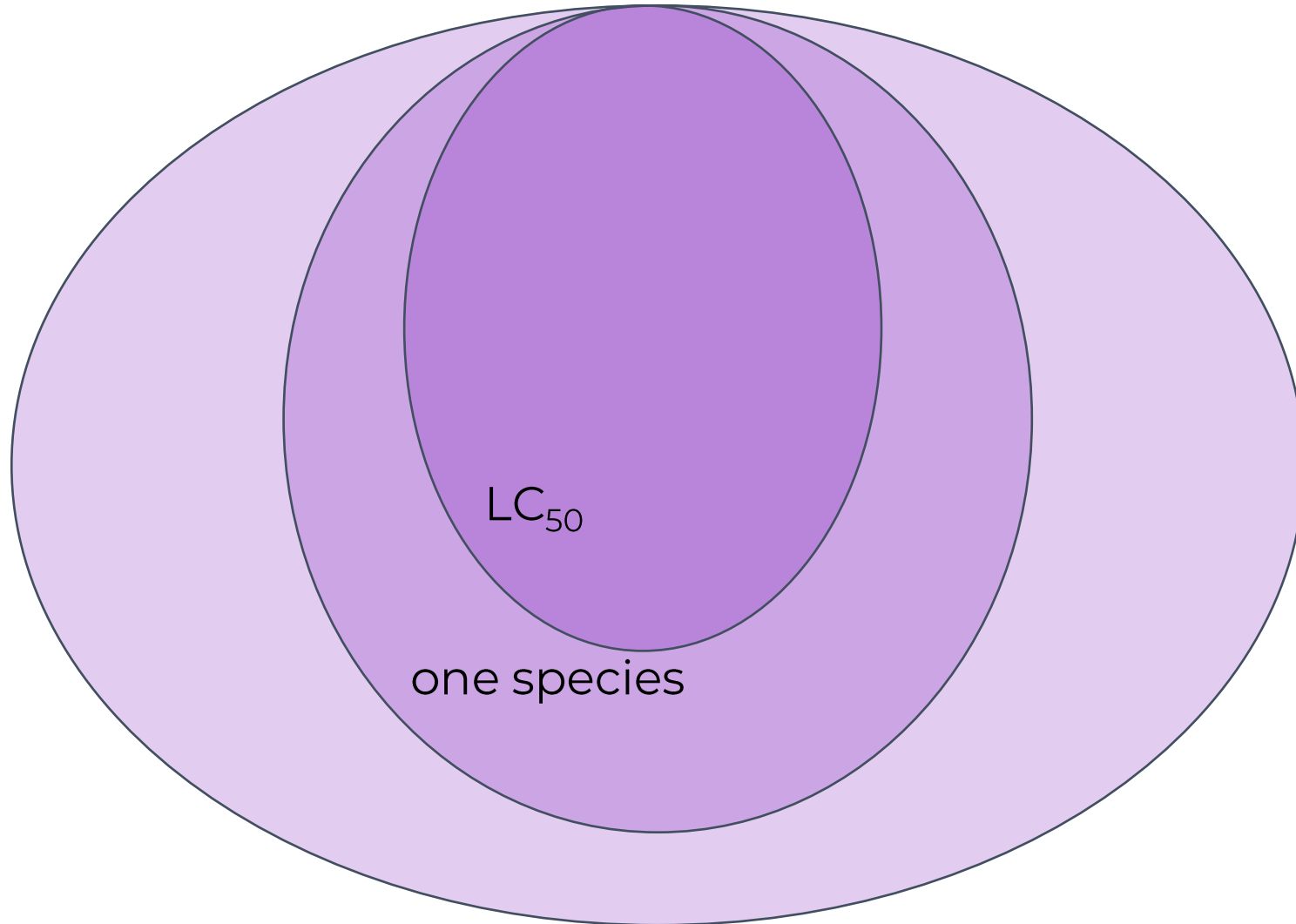


one species

data for machine learning models

CompTox

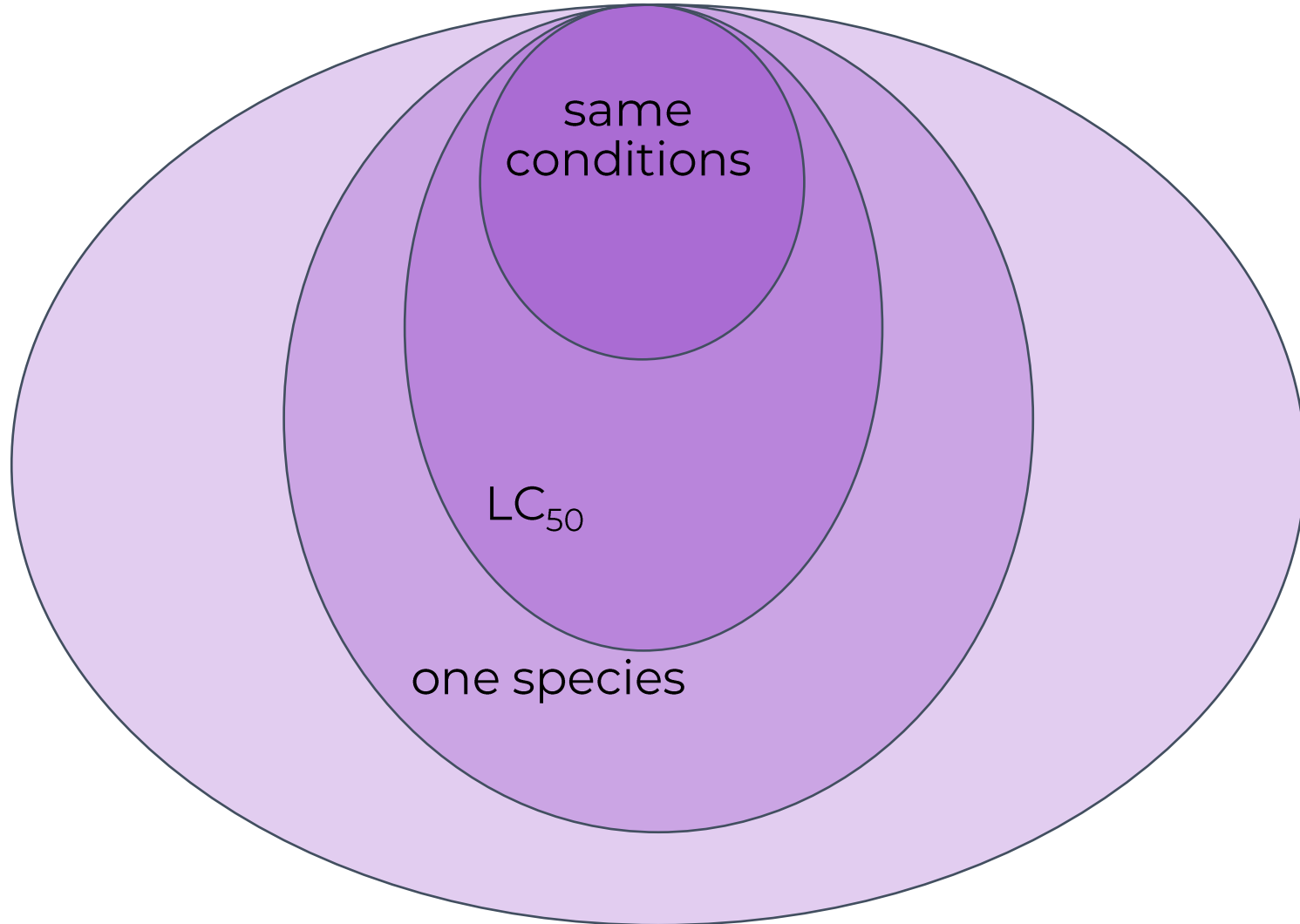
all toxicity values



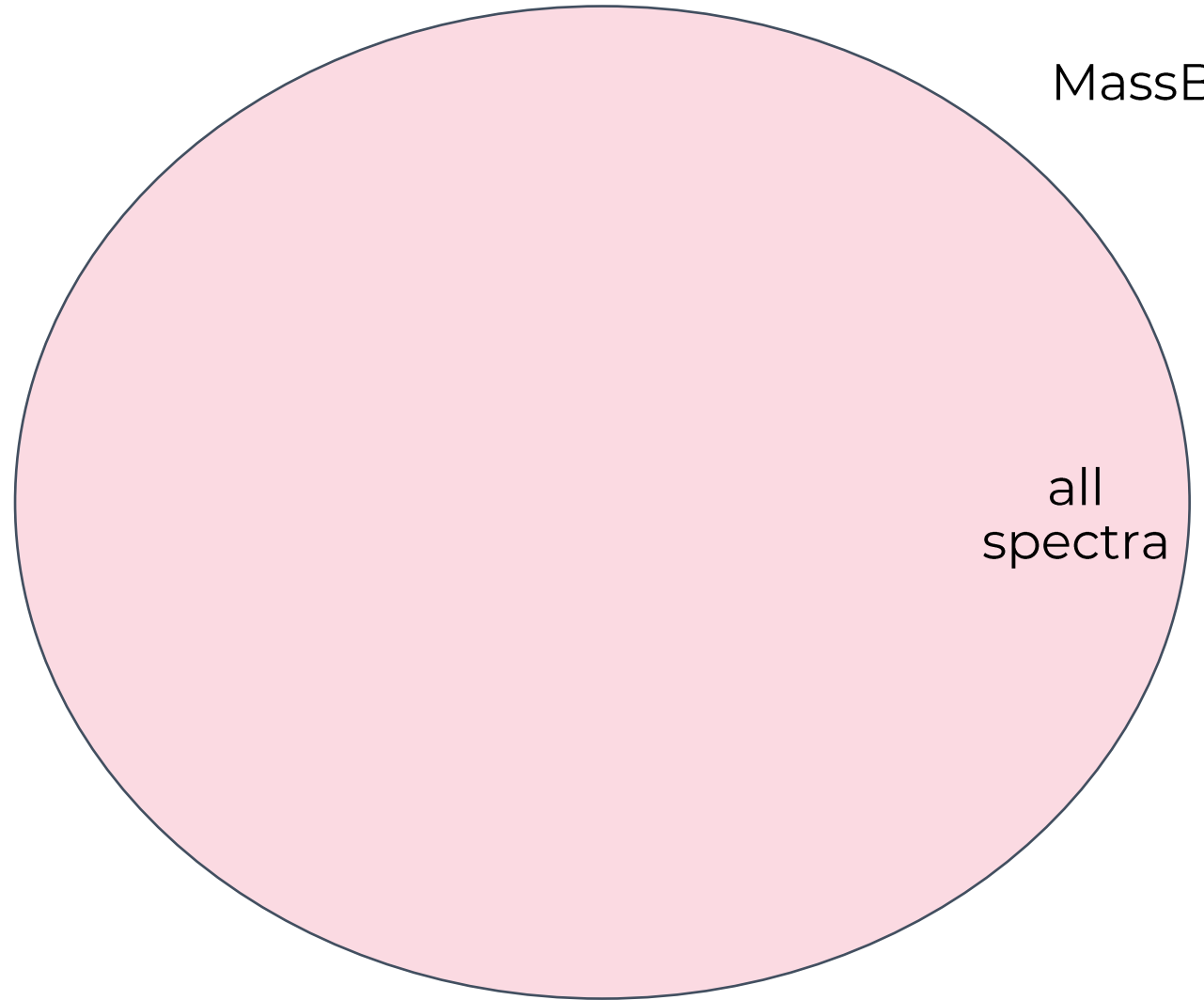
data for machine learning models

CompTox

all toxicity values



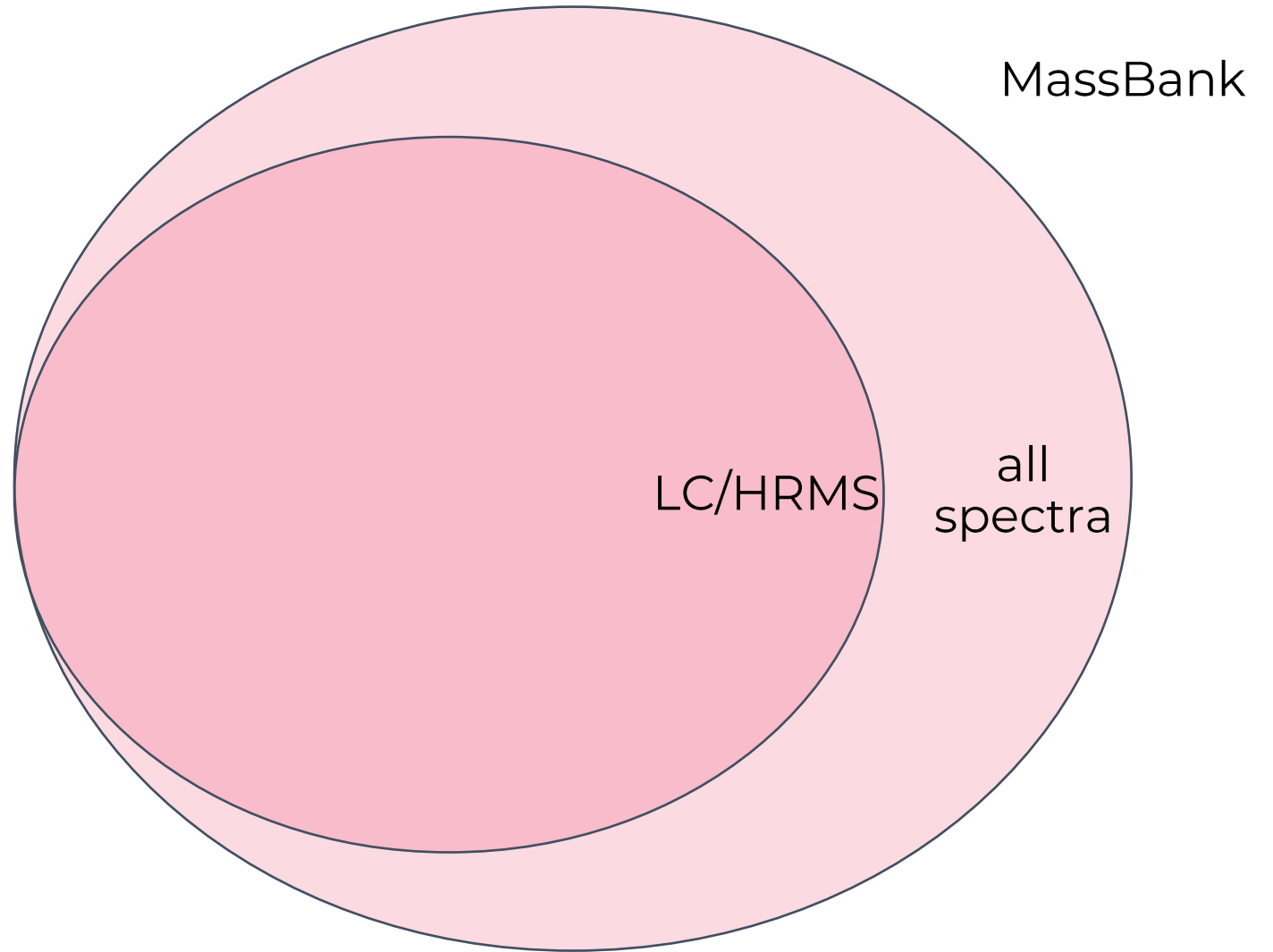
data for machine learning models



MassBank

all
spectra

data for machine learning models

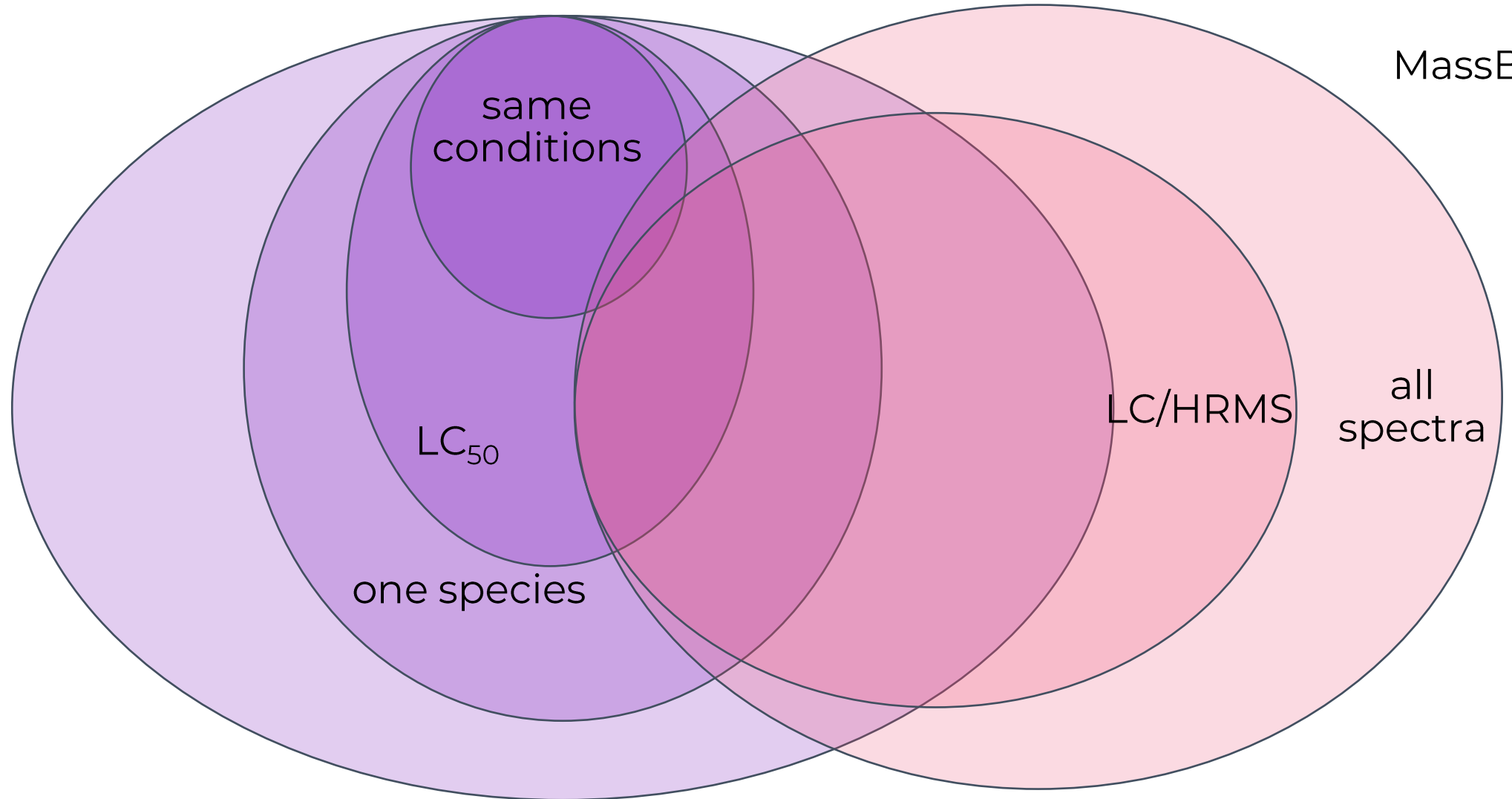


data for machine learning models

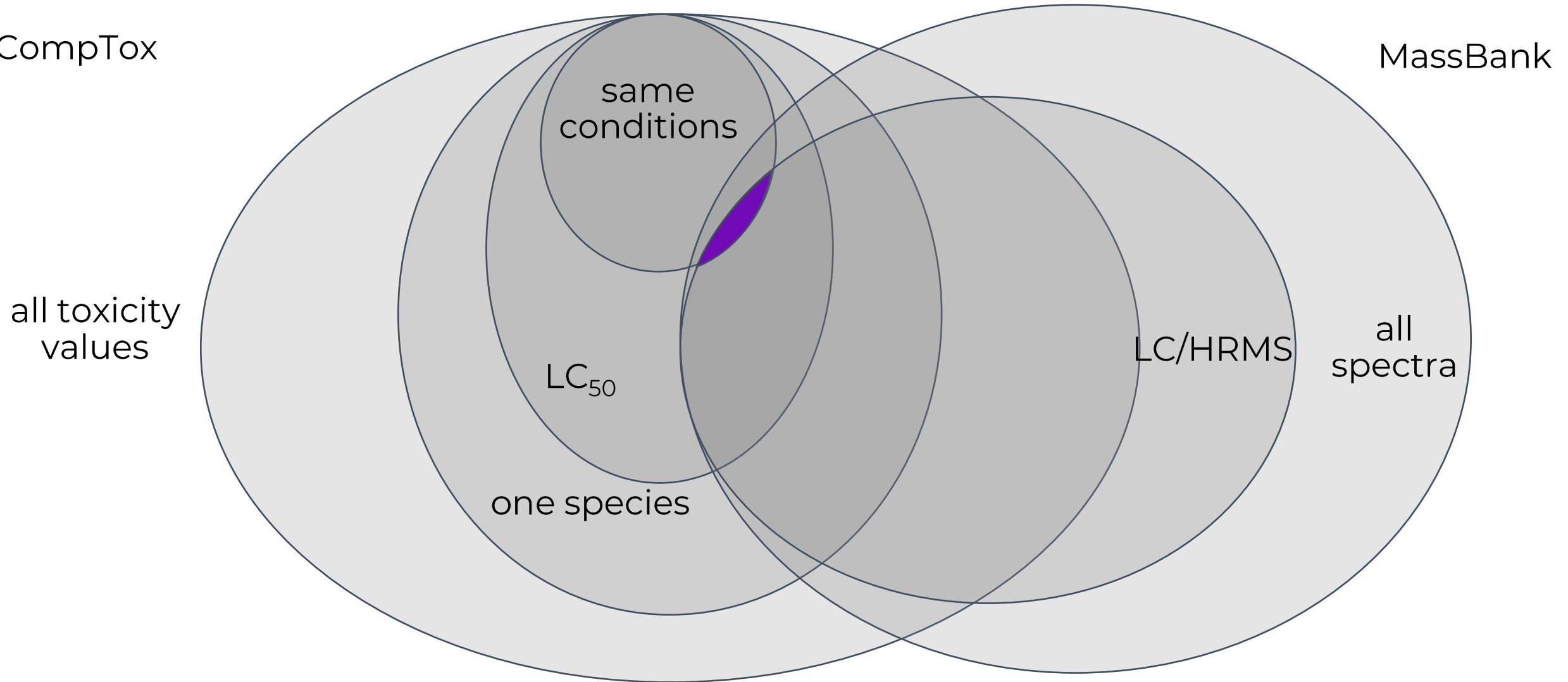
CompTox

MassBank

all toxicity values



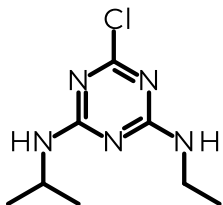
data for machine learning models



predicting toxicity

from the structure

workflow



structure as SMILES



molecular fingerprints



machine learning for predicting toxicity

selected endpoint

selected endpoint



fathead minnow, bluegill, and rainbow trout

selected endpoint



fathead minnow, bluegill, and rainbow trout



water flea

selected endpoint



fathead minnow, bluegill, and rainbow trout

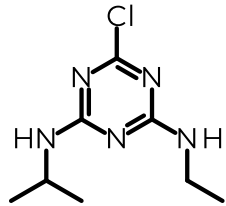


water flea



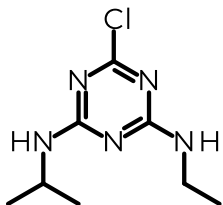
algae

workflow



structure as SMILES

workflow

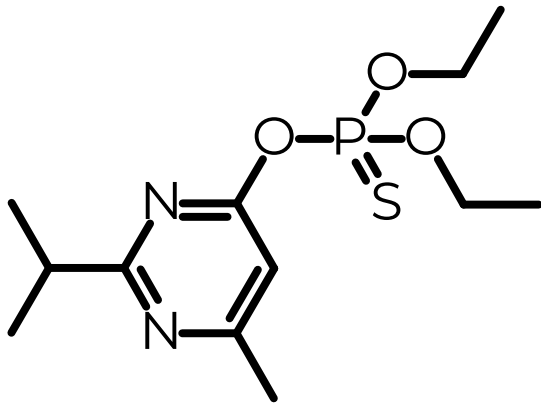


structure as SMILES

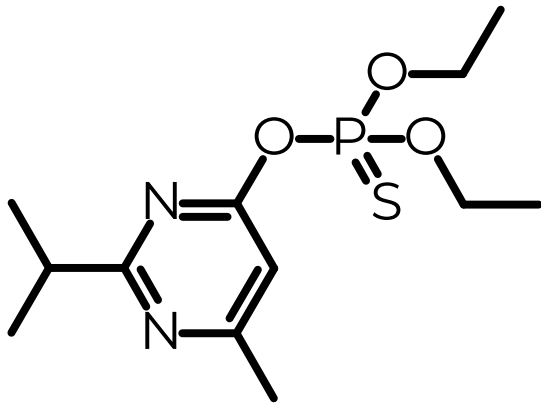


molecular fingerprints

structural fingerprints

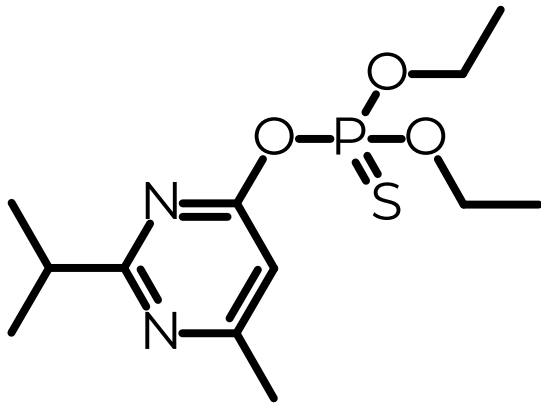


structural fingerprints



R: rcdk
→

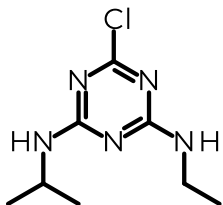
structural fingerprints



R: rcdk
→

0	
1	
1	
0	
1	

workflow



structure as SMILES



molecular fingerprints



machine learning for predicting LC_{50}

model training

mass (Da)	fp1	...	fp243
317.32000	0	...	0
208.26100	1	...	0
240.21499	1	...	0
300.57998	0	...	0
201.22500	0	...	0

model training

mass (Da)	fp1	...	fp243
317.32000	0	...	0
208.26100	1	...	0
240.21499	1	...	0
300.57998	0	...	0
201.22500	0	...	0

training set
517
chemicals

test set
130
chemicals

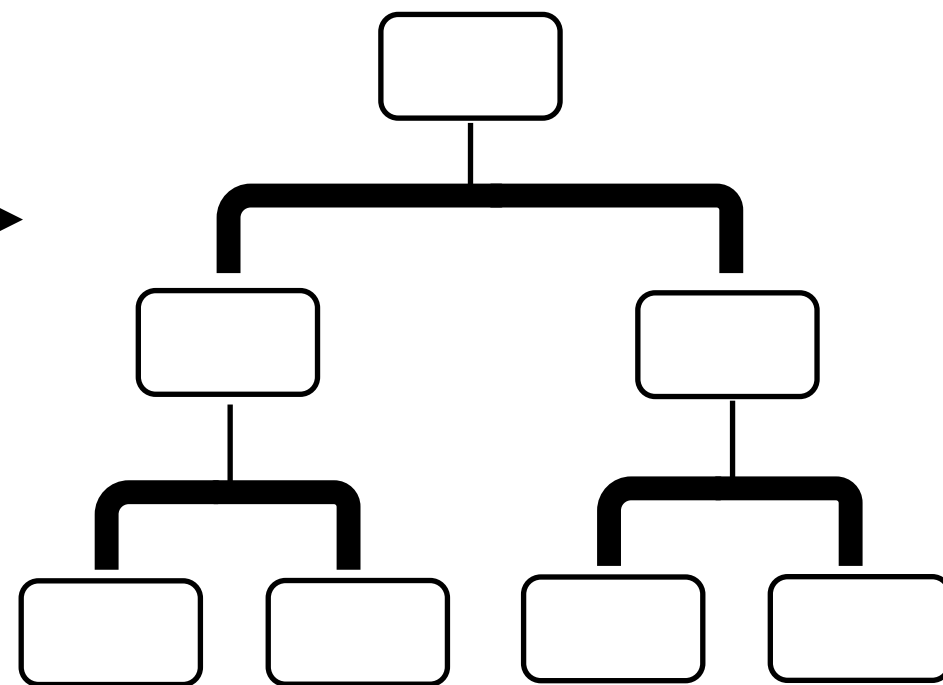
model training

mass (Da)	fp1	...	fp243
317.32000	0	...	0
208.26100	1	...	0
240.21499	1	...	0
300.57998	0	...	0
201.22500	0	...	0

training set
517
chemicals

test set
130
chemicals

gradient
boosting



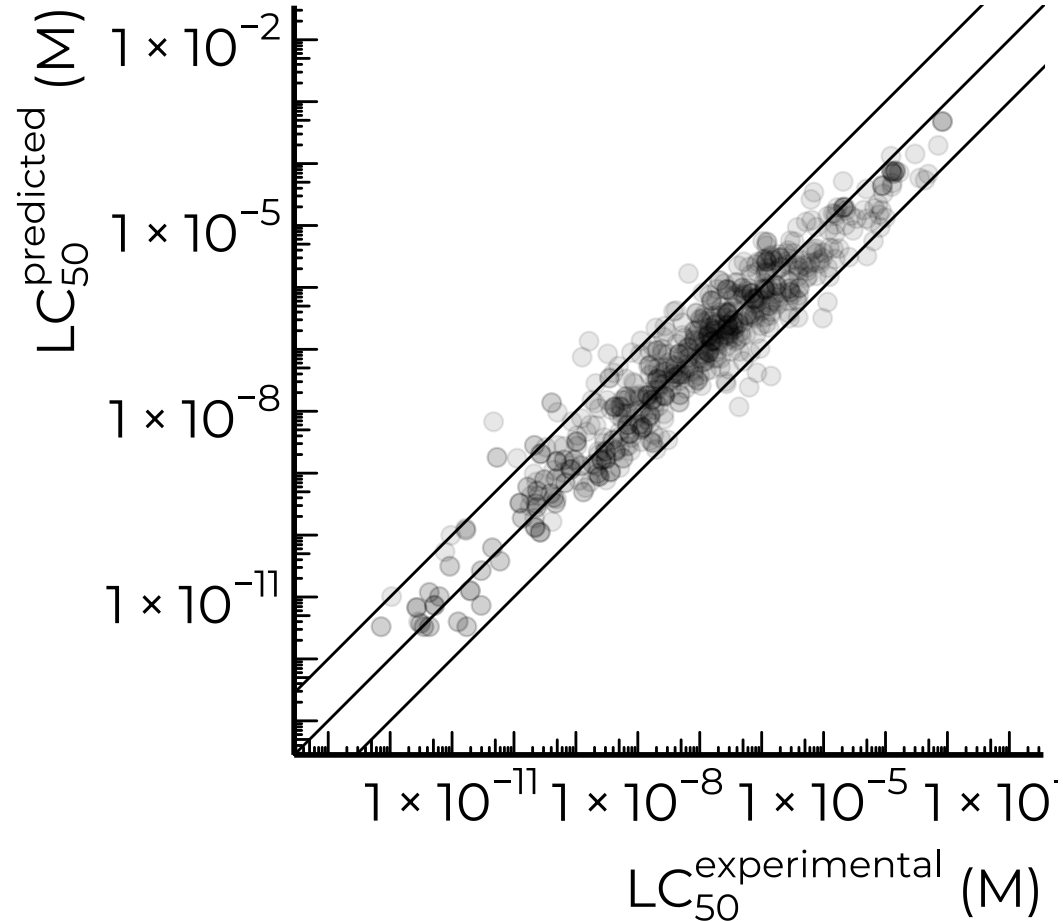
performance

of LC₅₀ predictions with molecular fingerprints

LC₅₀ predictions

Peets et al. ES&T 2022

fish LC₅₀



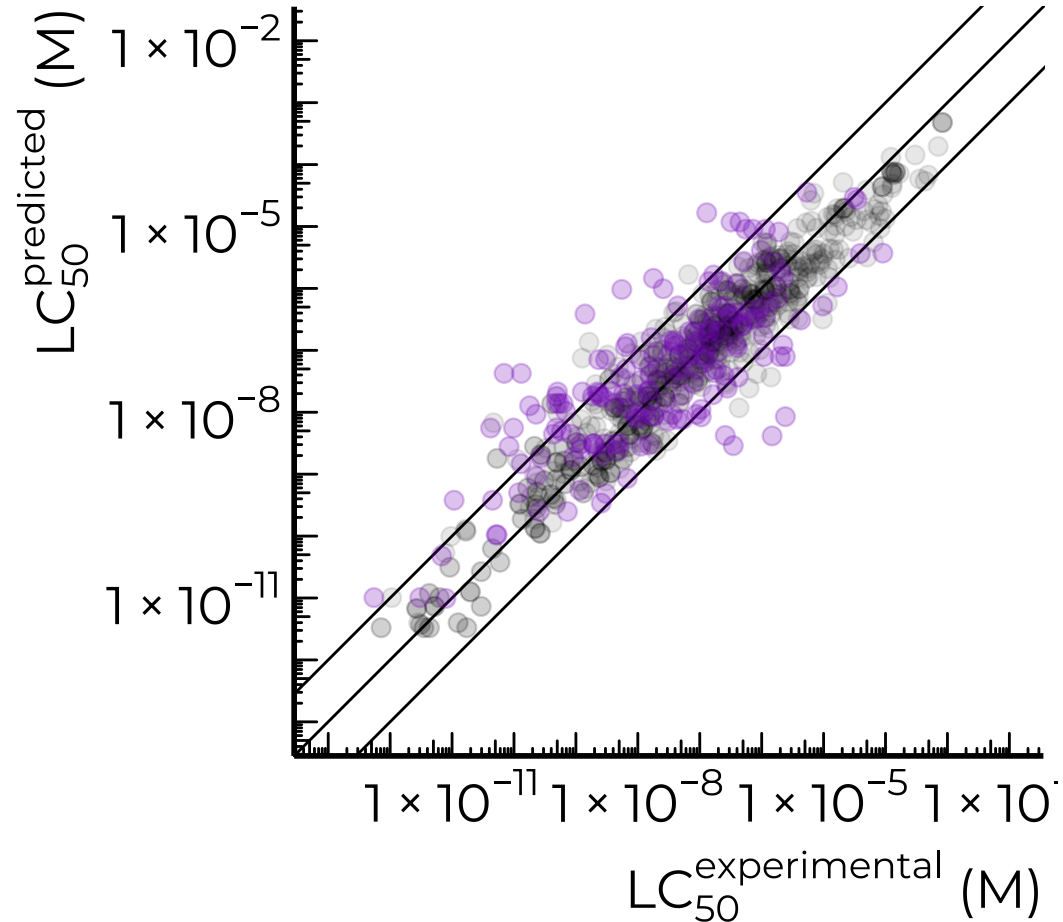
training set

RMSE 0.52 log(M)

LC₅₀ predictions

Peets et al. ES&T 2022

fish LC₅₀



training set

RMSE 0.52 log(M)

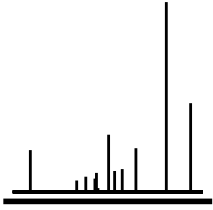
test set

RMSE 0.78 log(M)

unidentified chemicals

from MS² spectra

workflow



MS² spectra

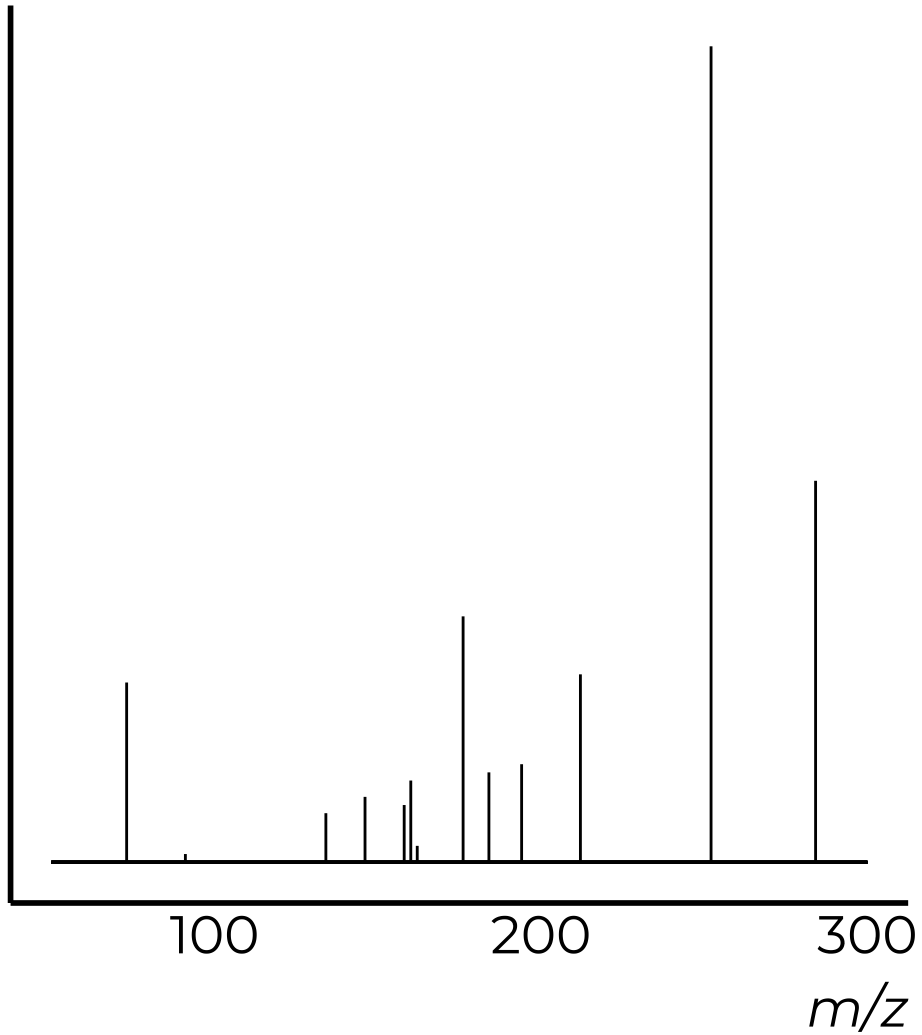


molecular fingerprints with SIRIUS+CSI:FingerID



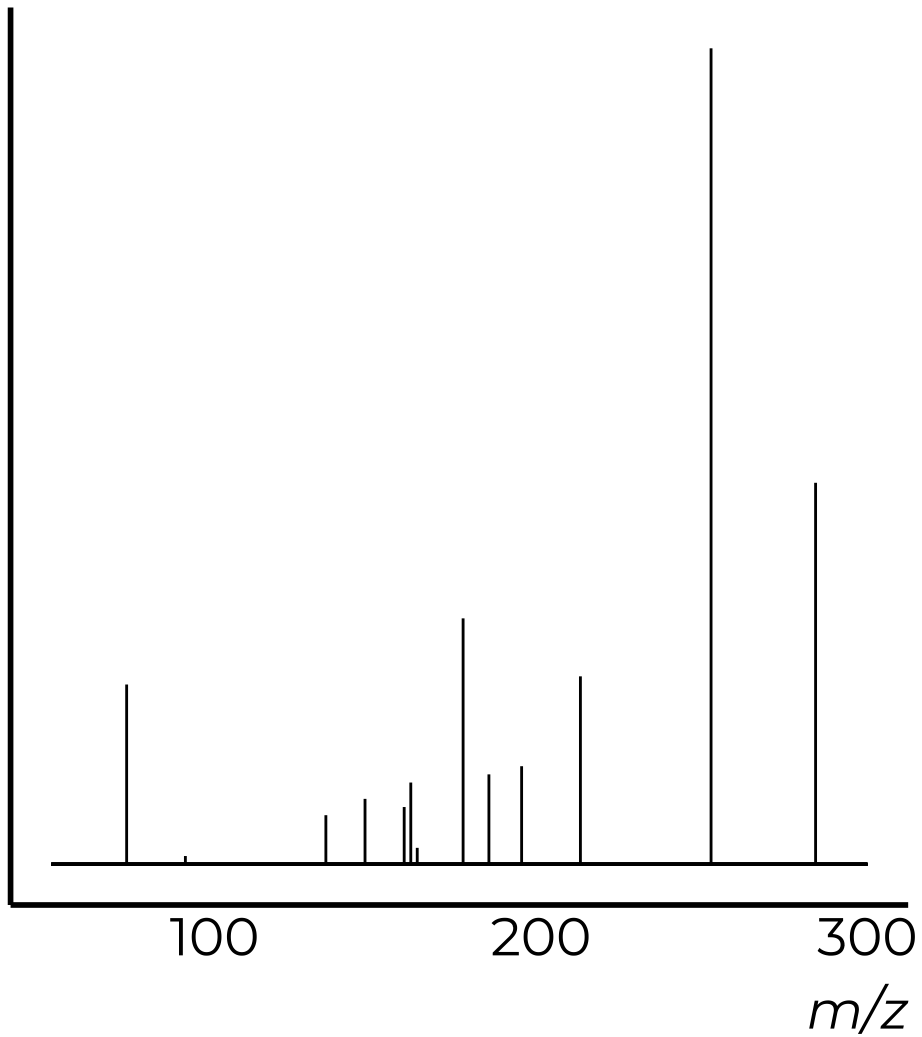
predict LC₅₀ with pretrained gradient boosting

predict for unknown chemicals



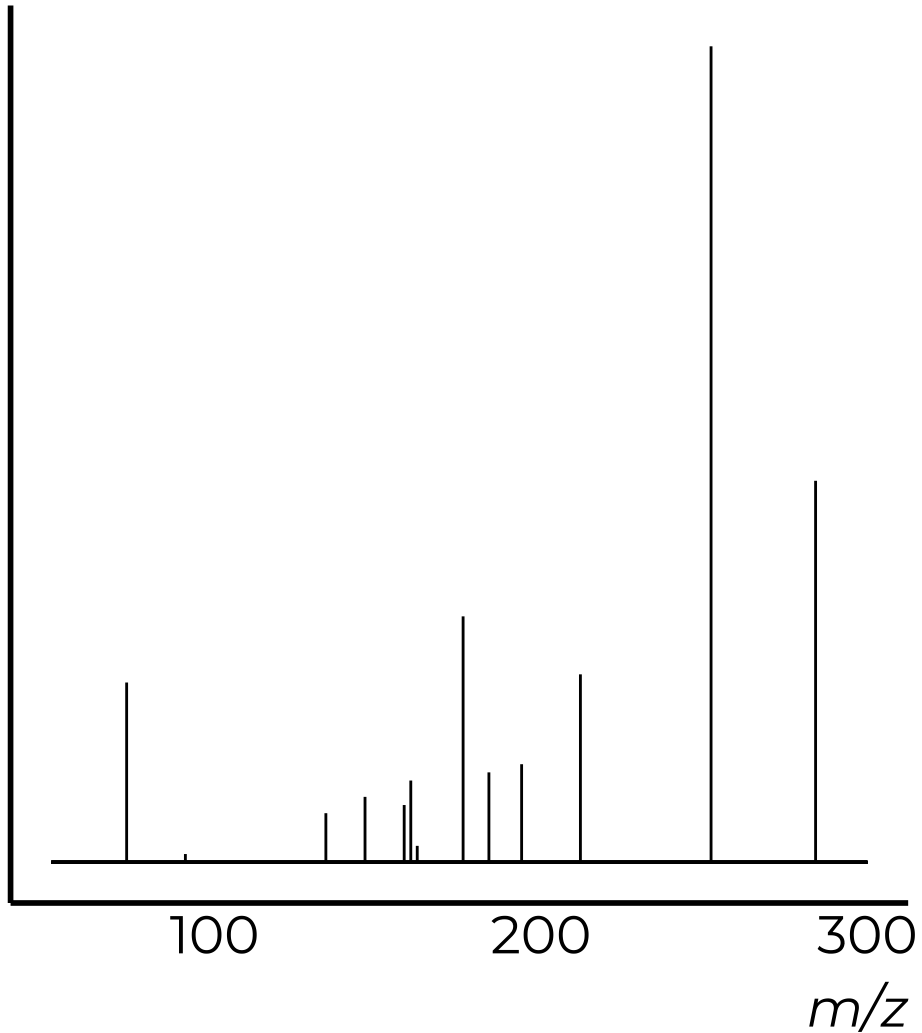
?

predict for unknown chemicals

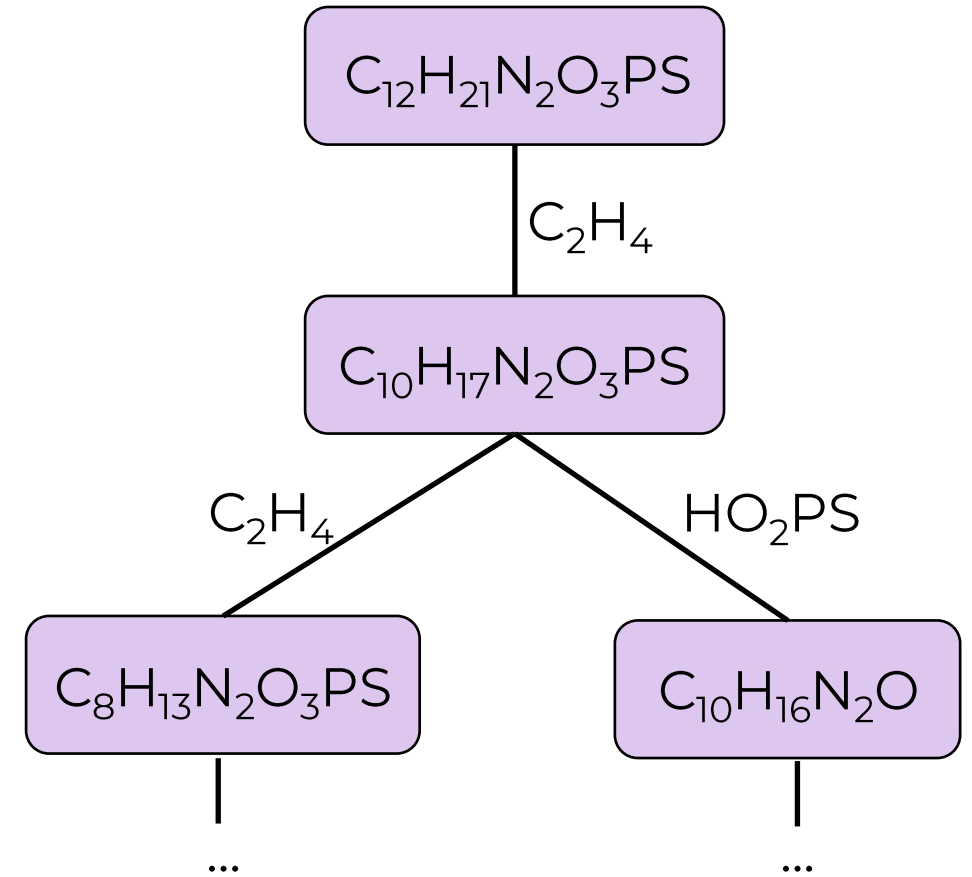


- C1CCOCC1
- O=P
- N
- N
- C1=CN=CN=C1

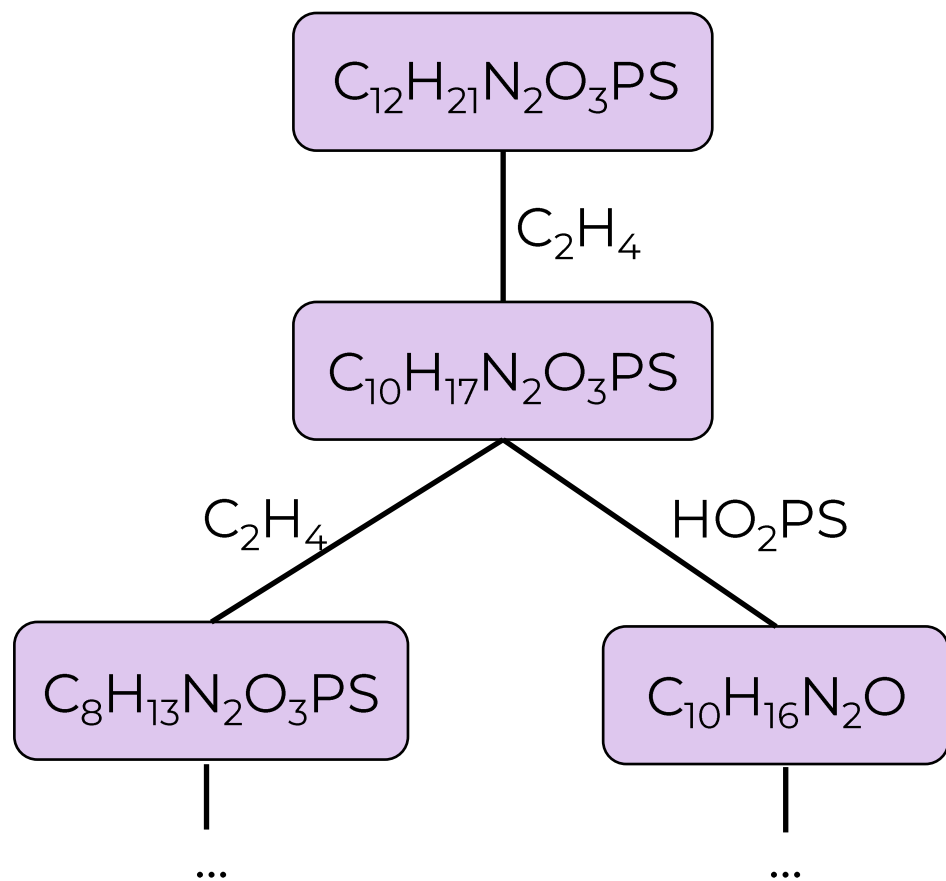
predict for unknown chemicals



SIRIUS+
CSI:FingerID
→



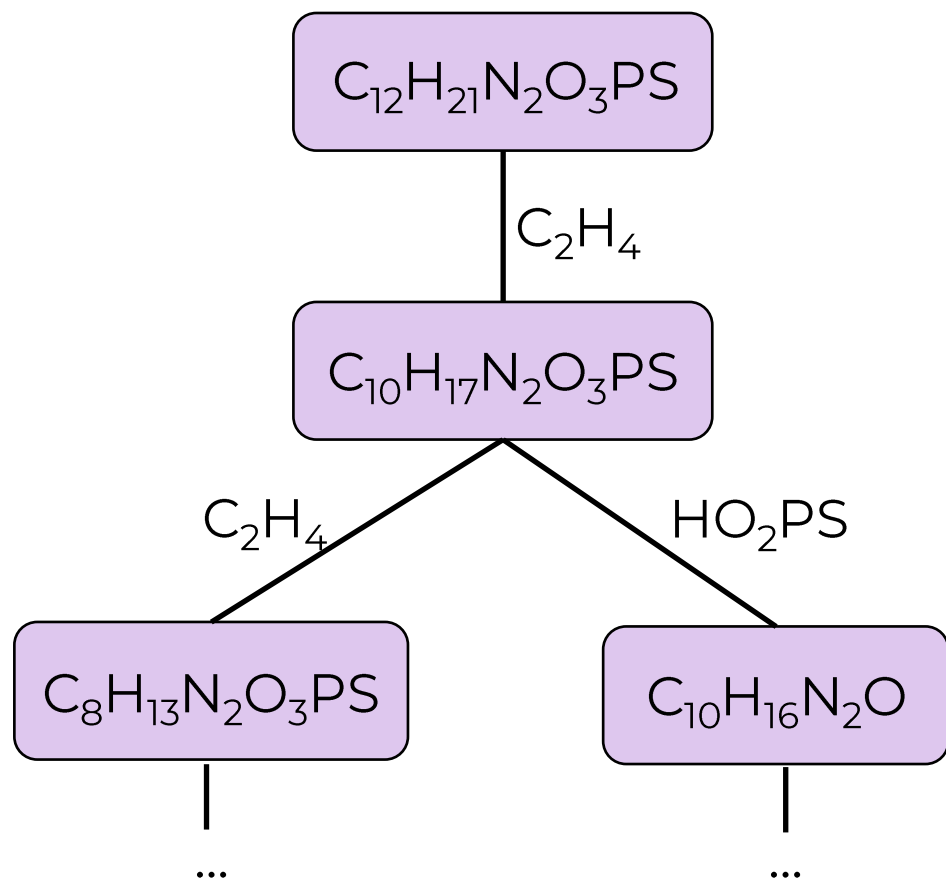
predict for unknown chemicals



SIRIUS+
CSI:FingerID
→

0.001	
0.999	$O-P$
0.999	$-N$
0.198	$-NH_2$
0.988	

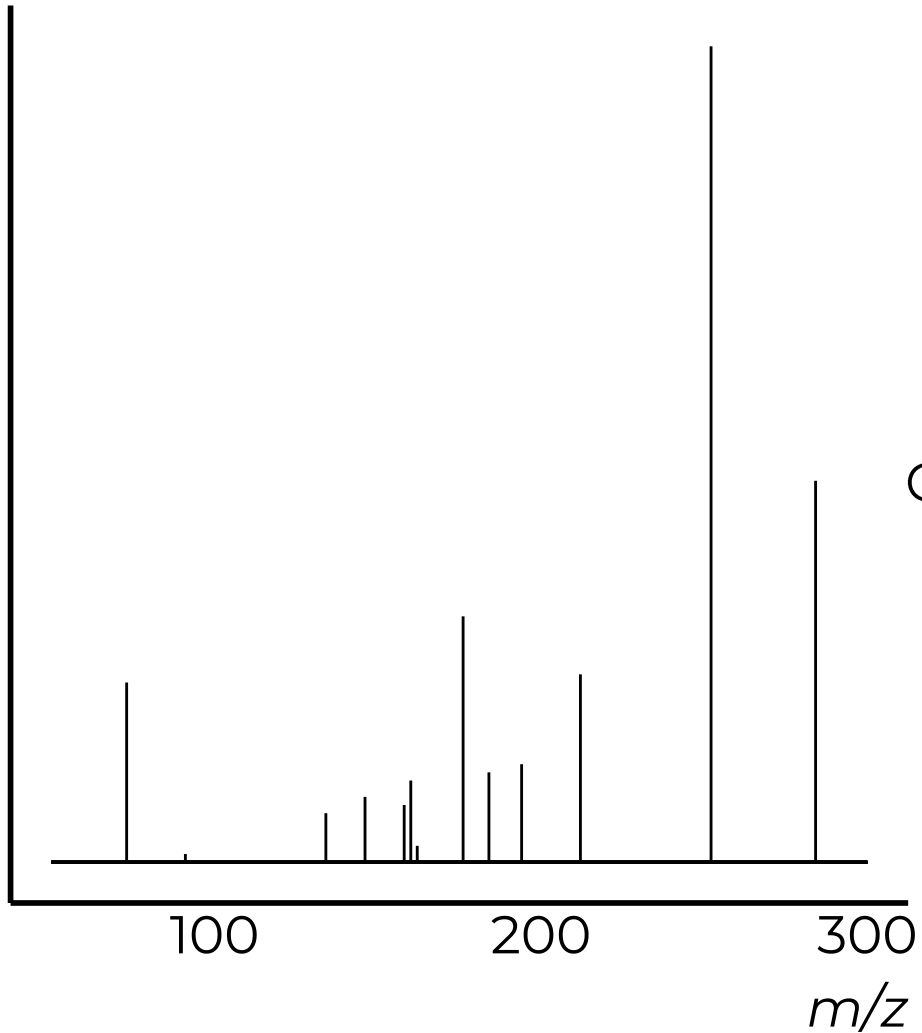
predict for unknown chemicals



SIRIUS+
CSI:FingerID
→

0	
1	
1	
0	
1	

predict for unknown chemicals



SIRIUS+
CSI:FingerID
→

0	
1	
1	
0	
1	

gradient
boosting
→

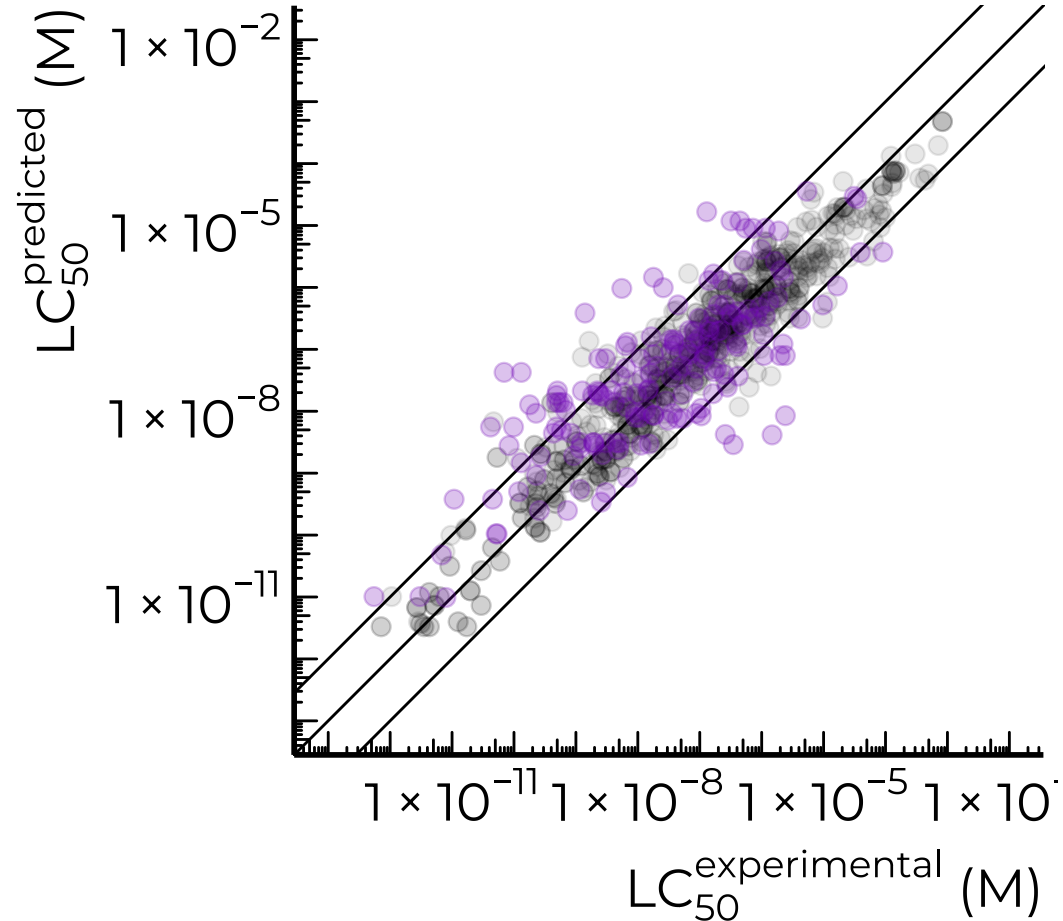
$LC_{50} = -2.2 \log(\text{mM})$

LC₅₀ predictions

LC₅₀ predictions

Peets et al. ES&T 2022

fish LC₅₀



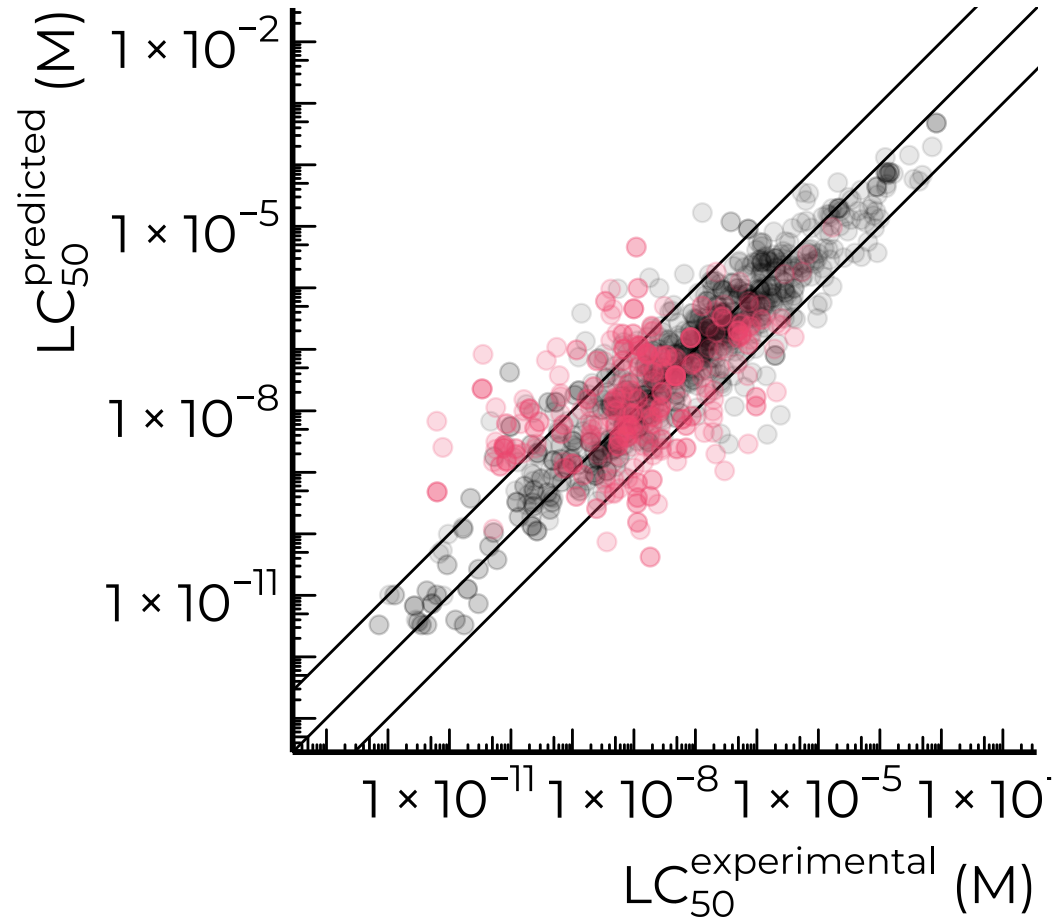
test set on structures

RMSE 0.78 log(M)

LC₅₀ predictions

Peets et al. ES&T 2022

fish LC₅₀



test set on structures

RMSE 0.78 log(M)

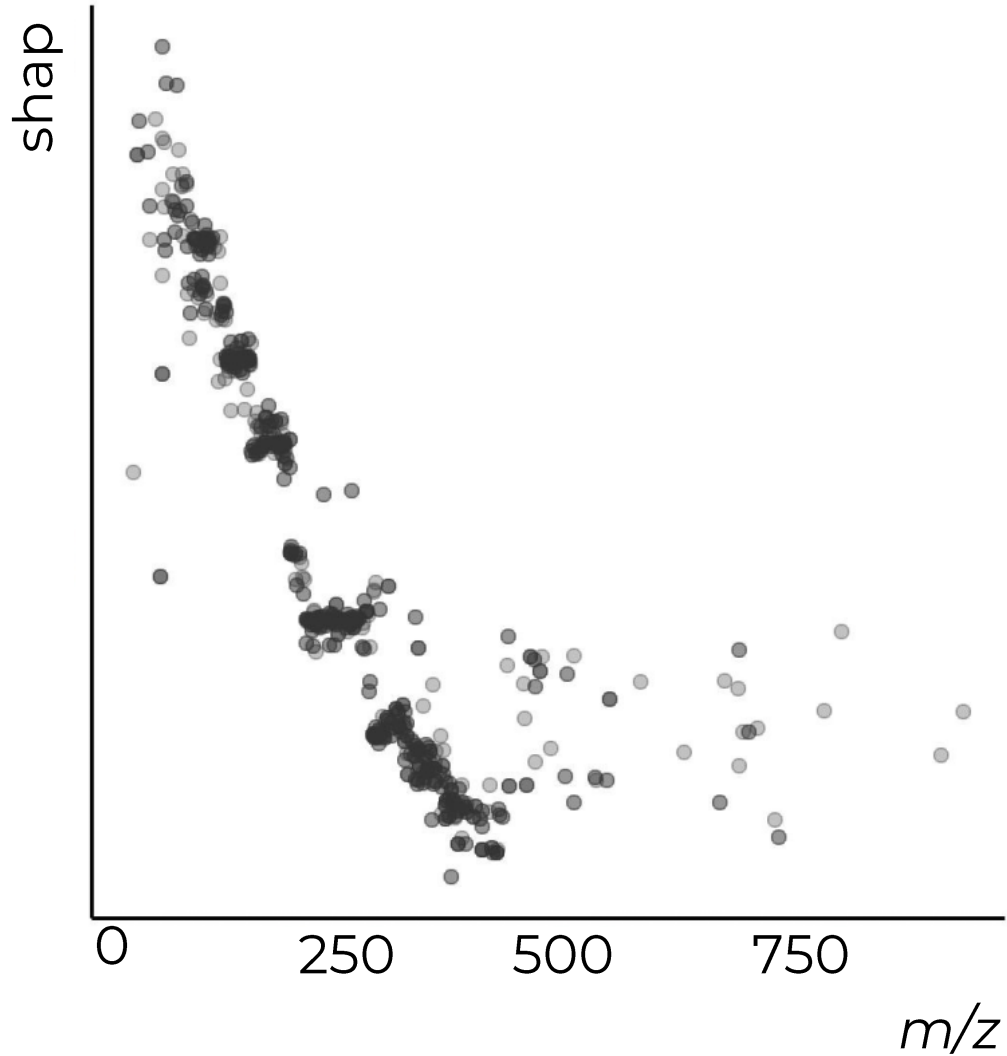
validation on MassBank

RMSE_{model} 0.88 log(M)

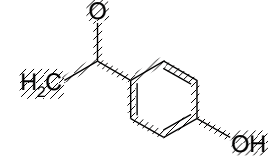
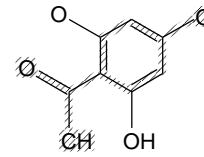
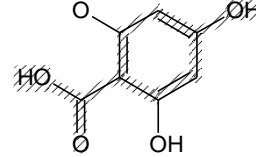
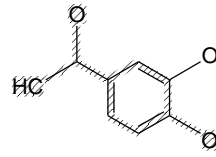
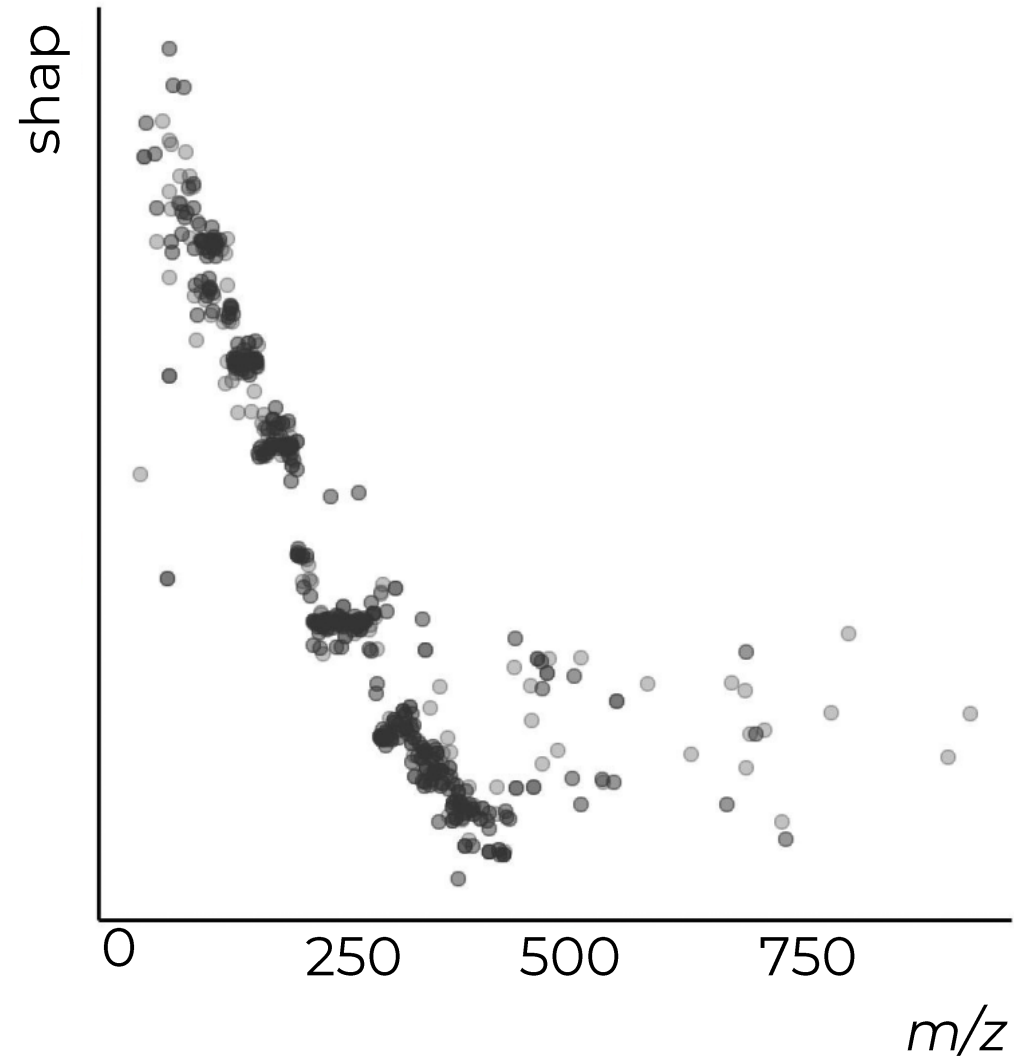
SD_{experimental} 0.44 log(mM)

model interpretation

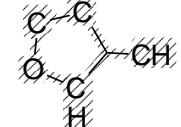
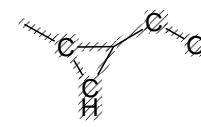
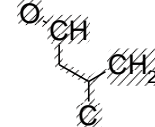
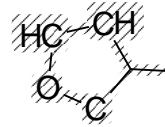
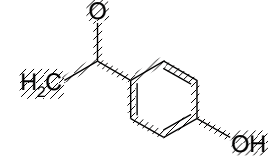
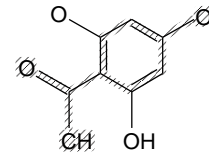
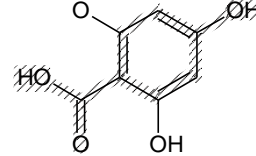
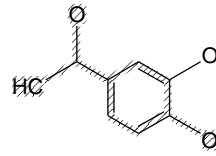
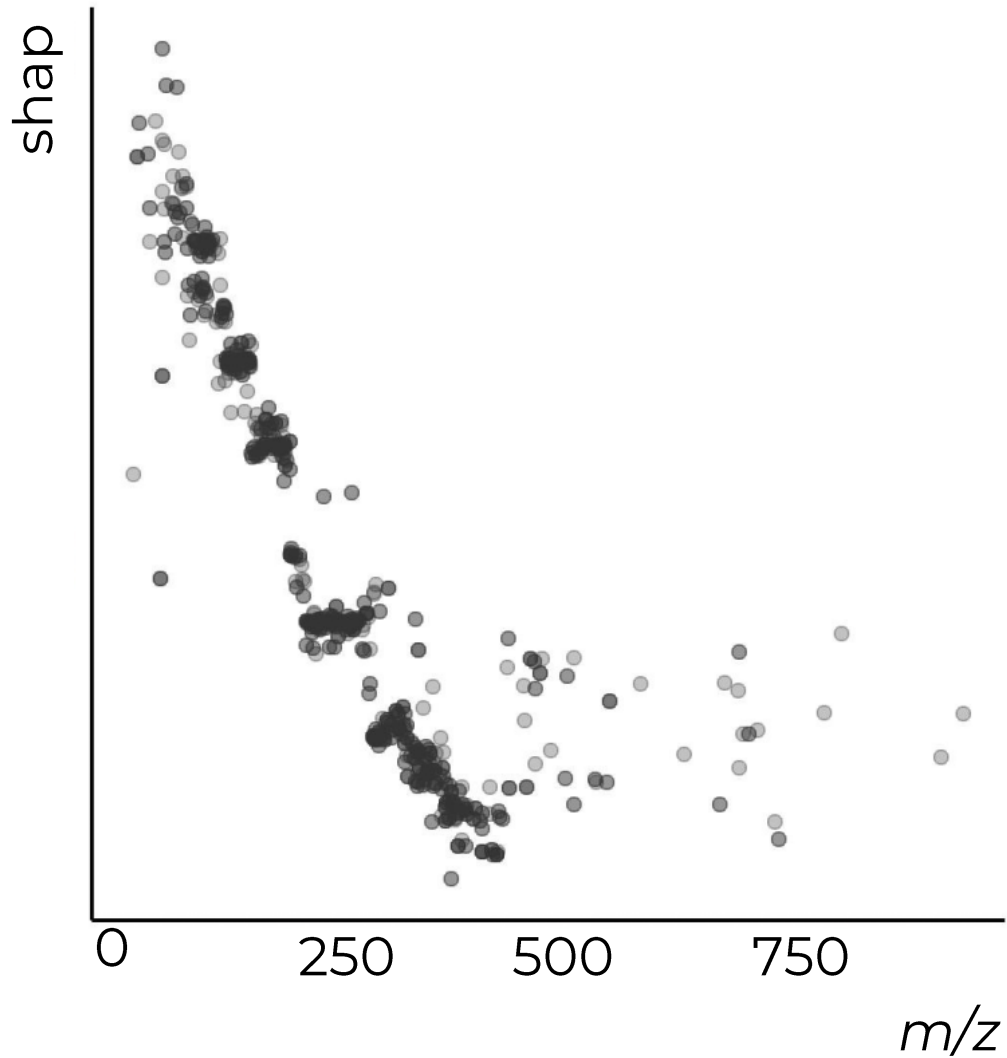
model interpretation



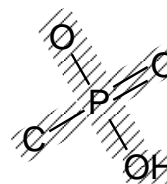
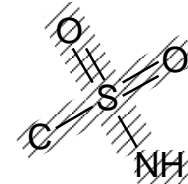
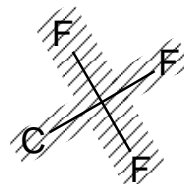
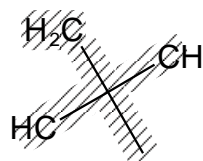
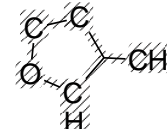
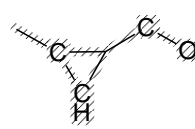
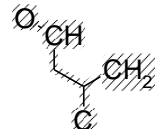
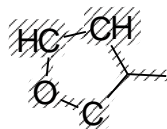
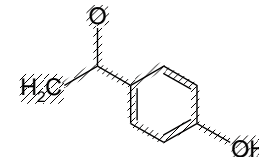
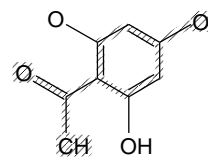
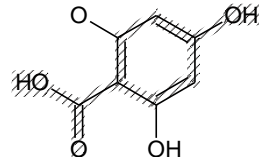
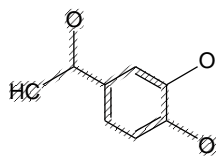
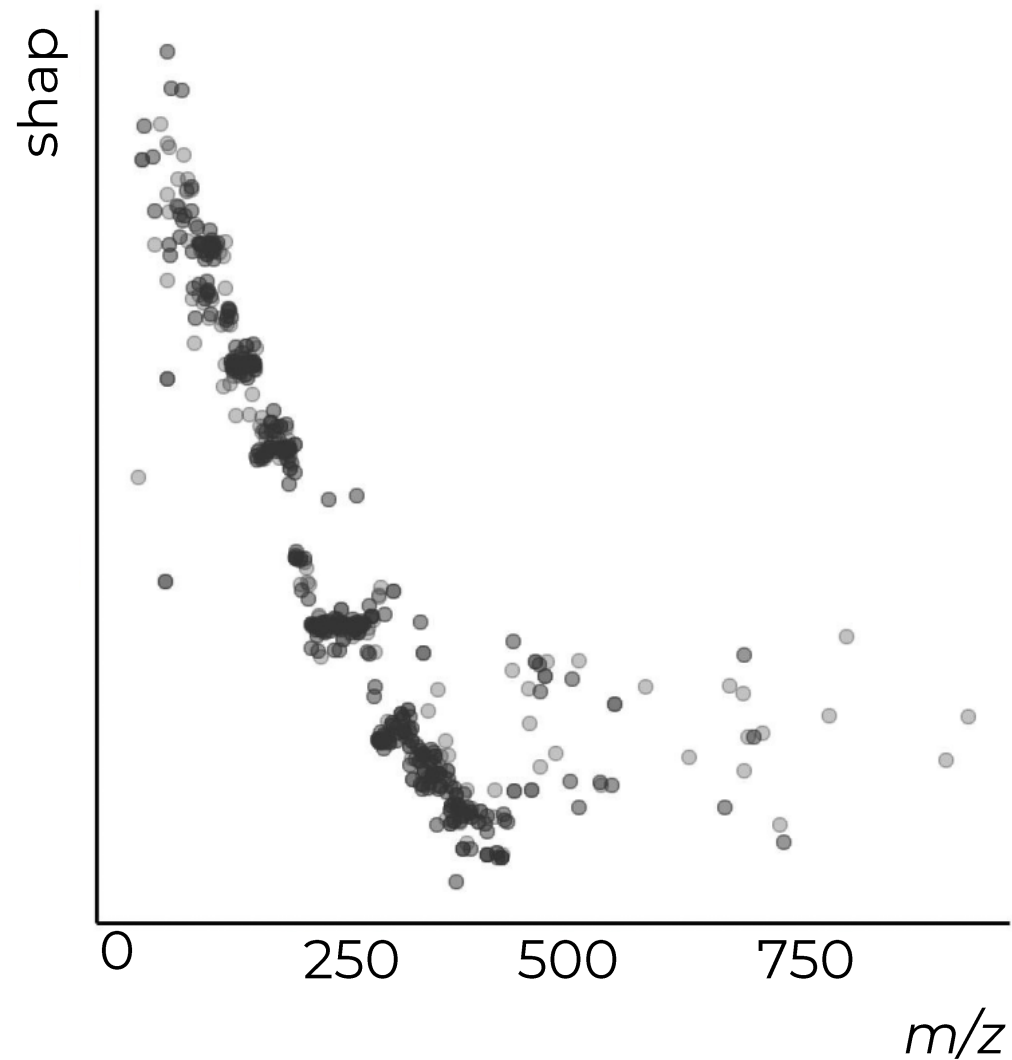
model interpretation



model interpretation



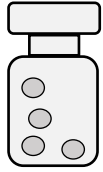
model interpretation



toxic chemicals

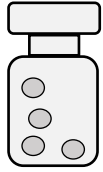
in wastewater

case study on wastewater

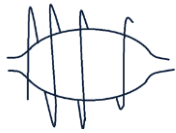


wastewater samples

case study on wastewater

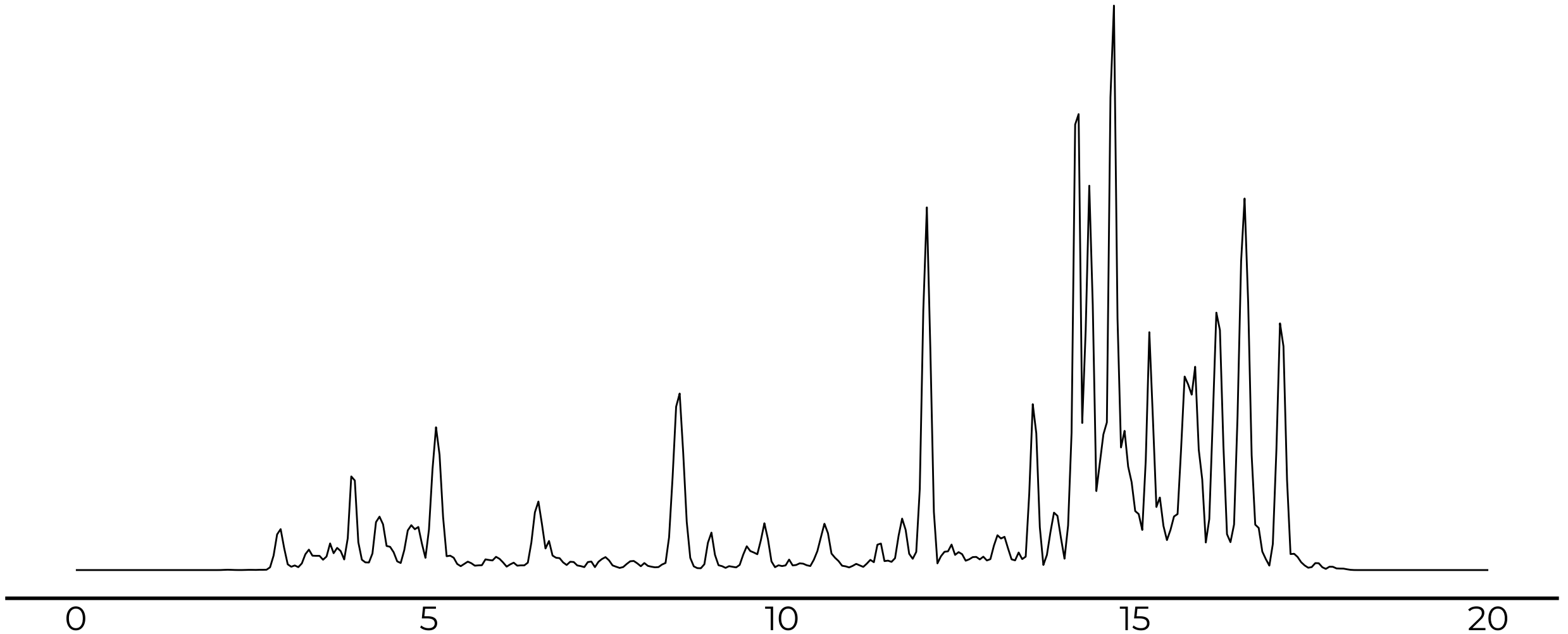


wastewater samples

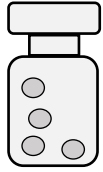


LC/HRMS analysis

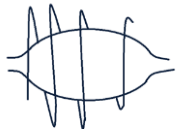
case study on wastewater



case study on wastewater



wastewater samples

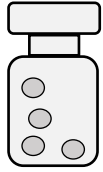


LC/HRMS analysis

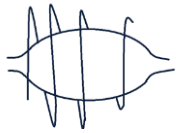


molecular fingerprints with SIRIUS+CSI:FingerID

case study on wastewater



wastewater samples



LC/HRMS analysis



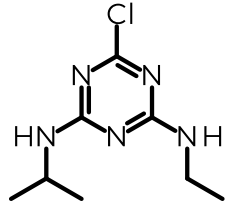
molecular fingerprints with SIRIUS+CSI:FingerID



predict LC_{50} with pretrained gradient boosting

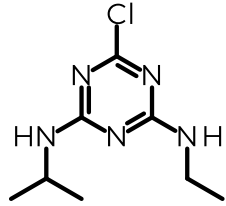
quality control

quality control

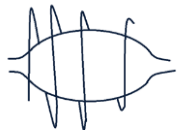


216 analytical standard

quality control

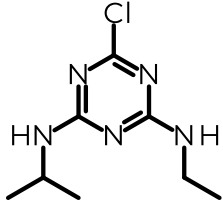


216 analytical standard

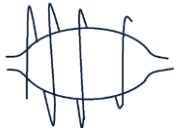


DIA and DDA MS² data

quality control



216 analytical standard

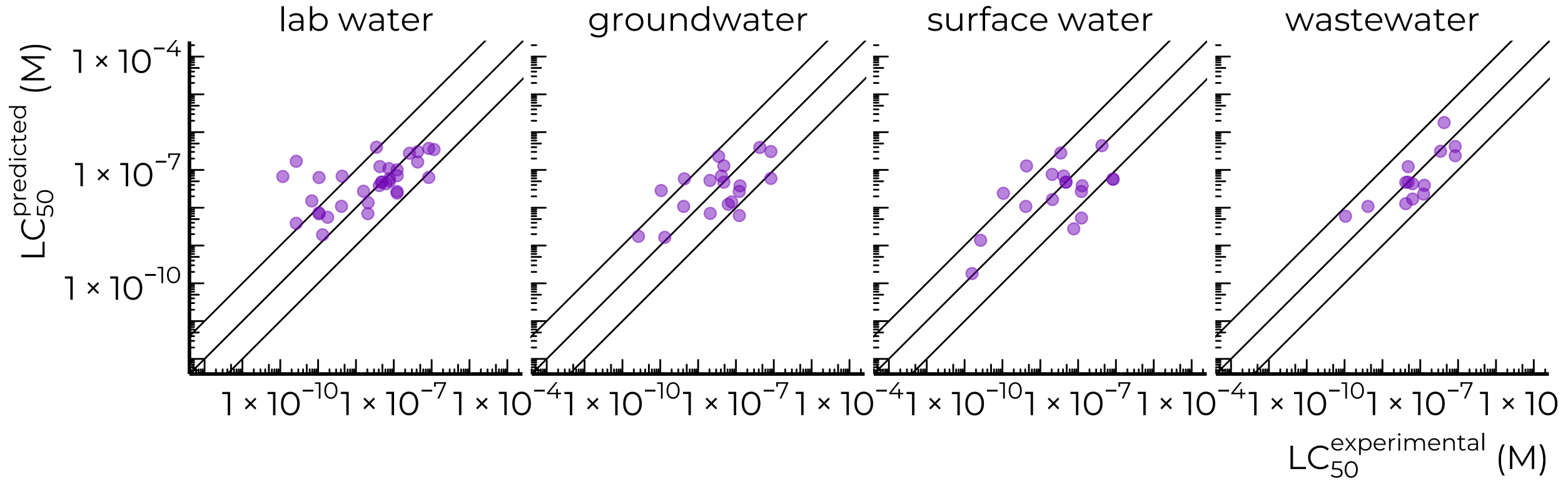


DIA and DDA MS² data



comparison with experimental LC₅₀

DDA



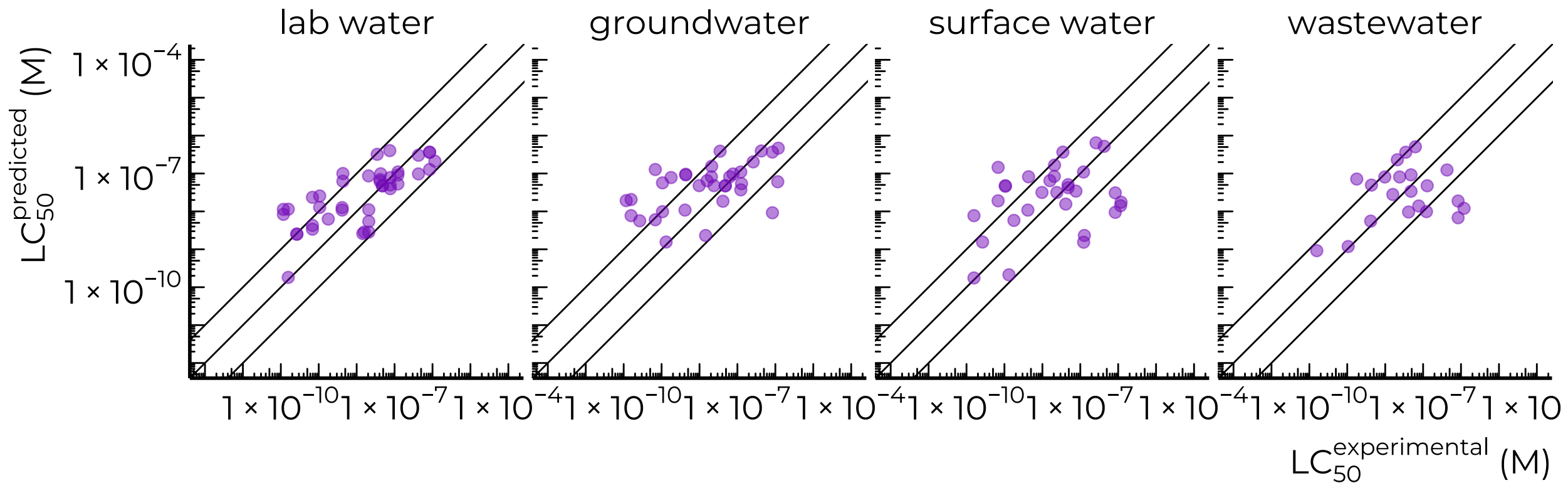
RMSE = 0.95 log-mM

0.74 log-mM

0.86 log-mM

0.47 log-mM

DIA



RMSE = 0.85 log-mM

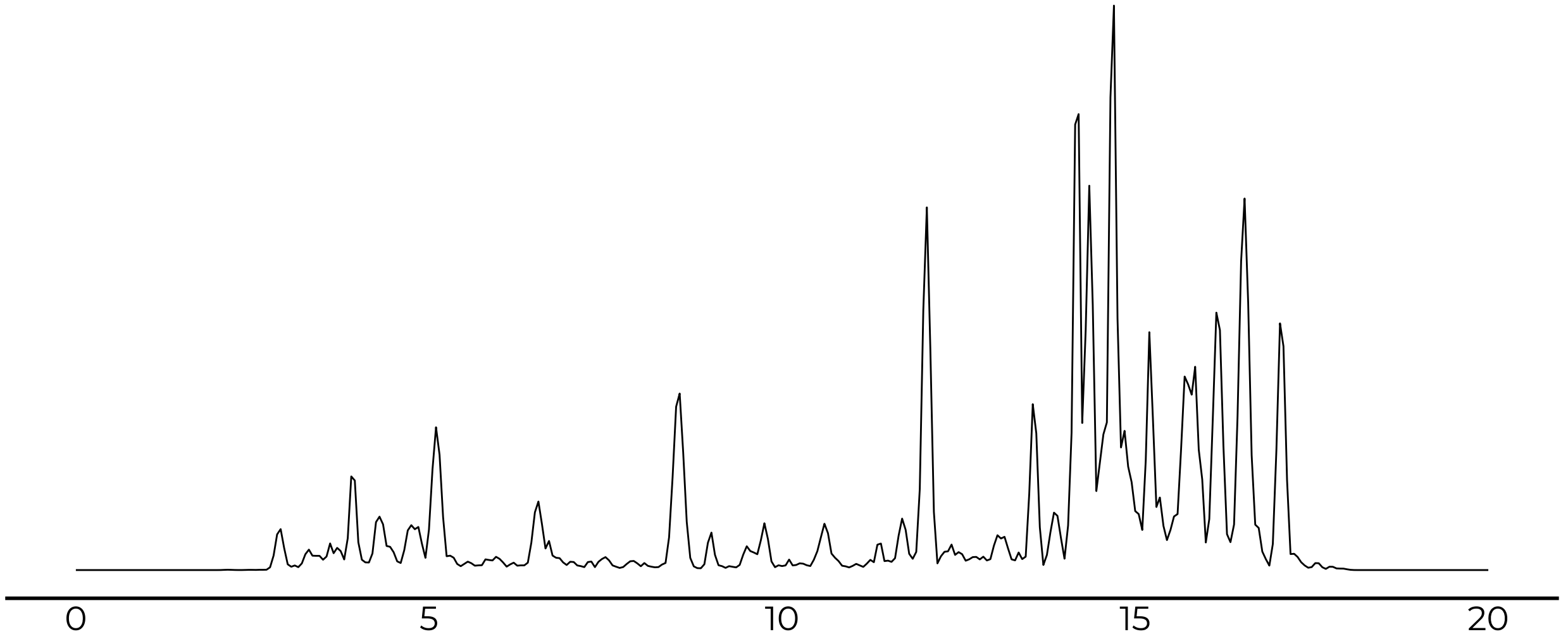
1.09 log-mM

1.18 log-mM

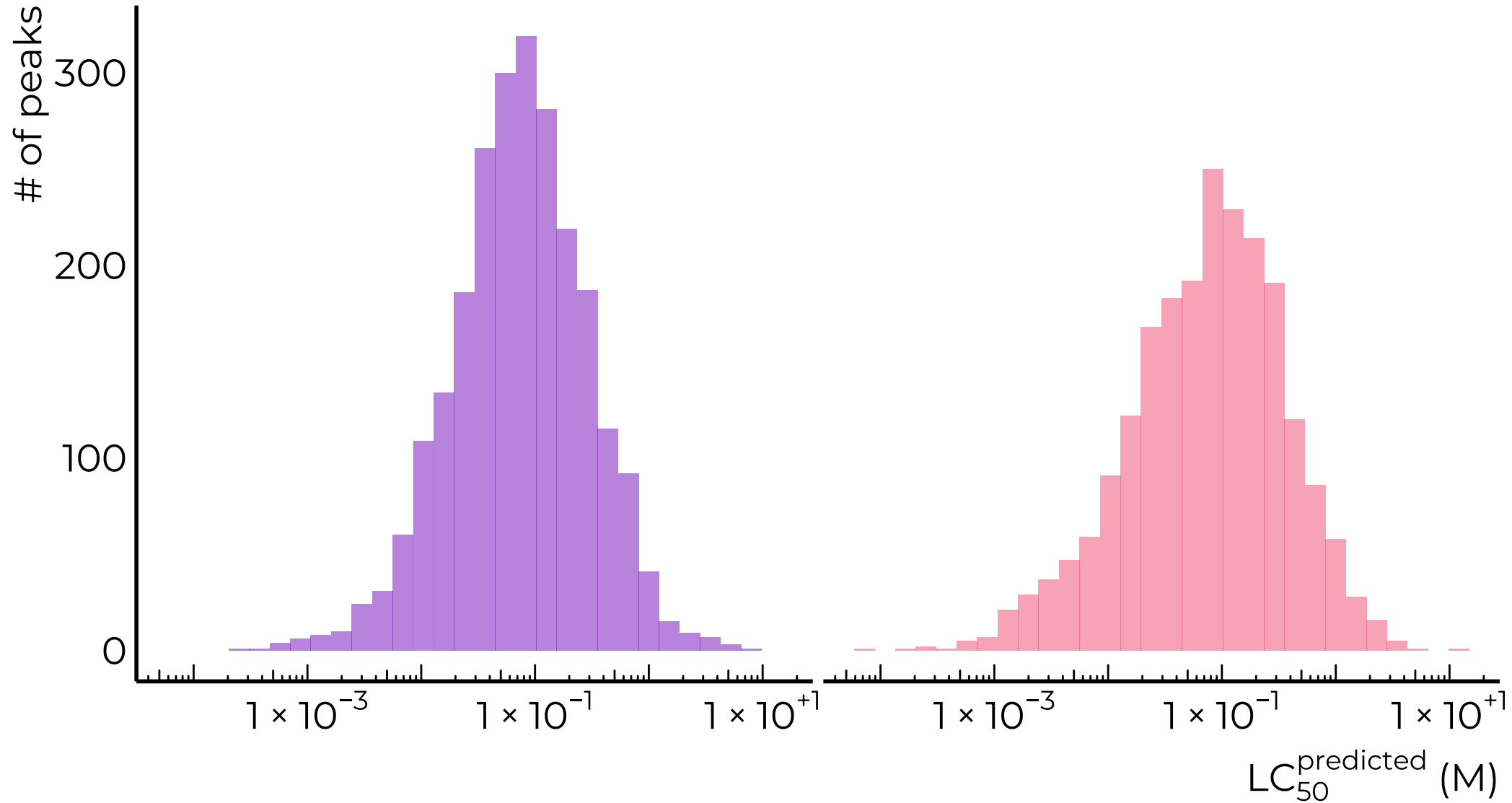
1.03 log-mM

pinpointing toxic chemicals

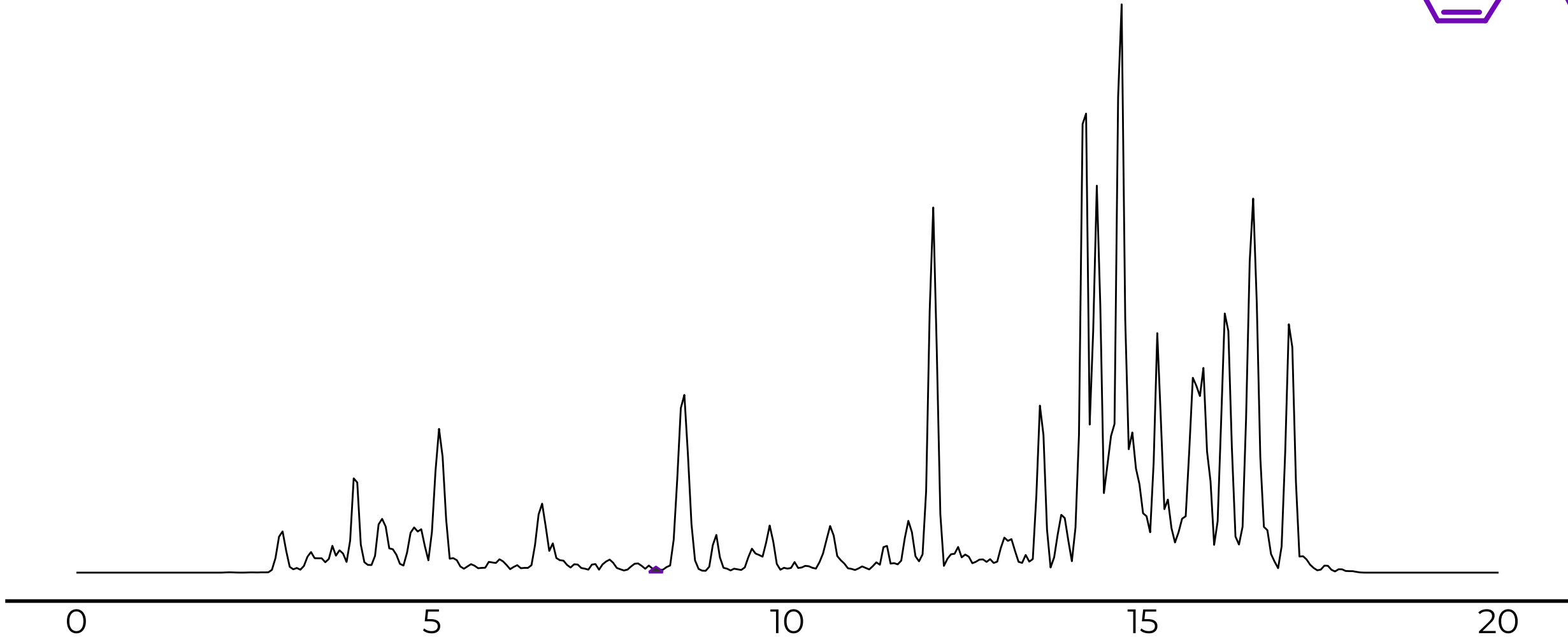
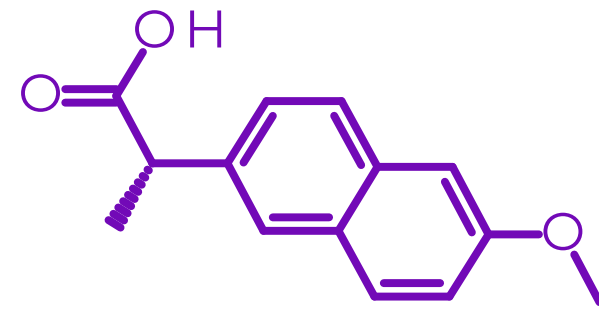
case study on wastewater



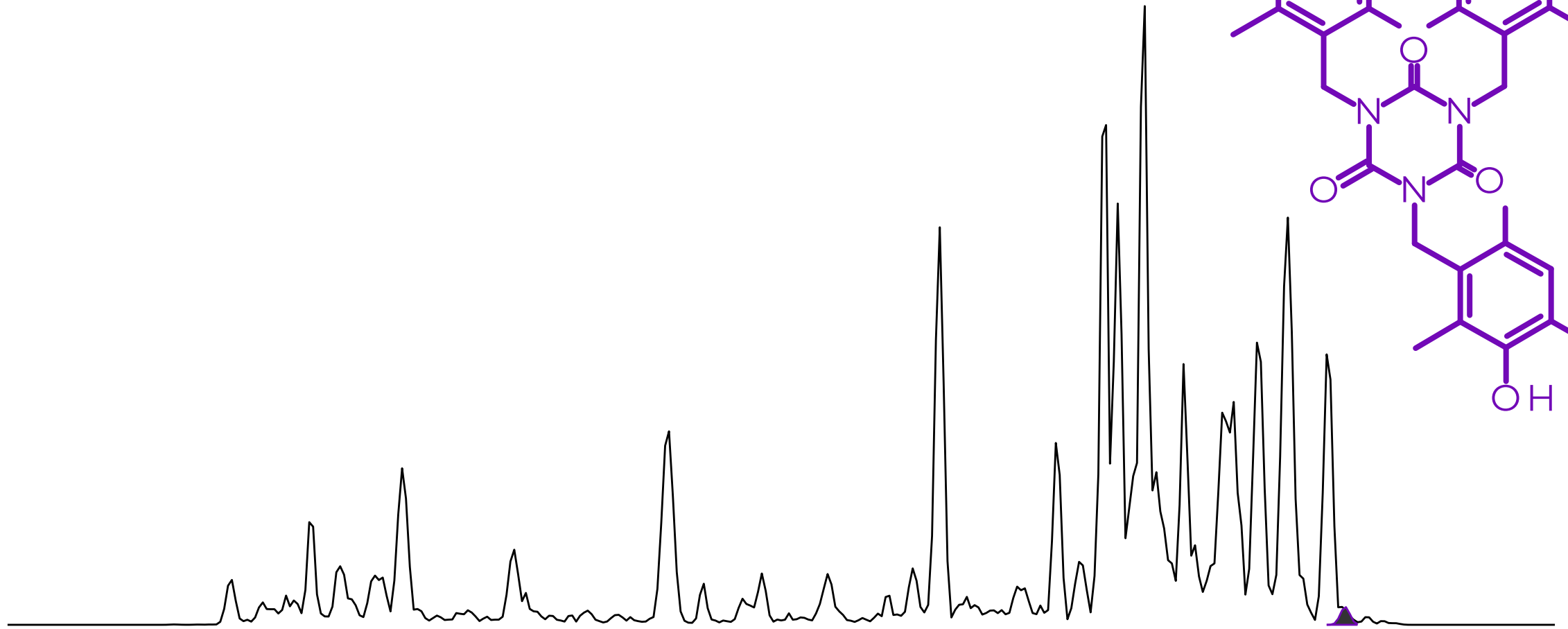
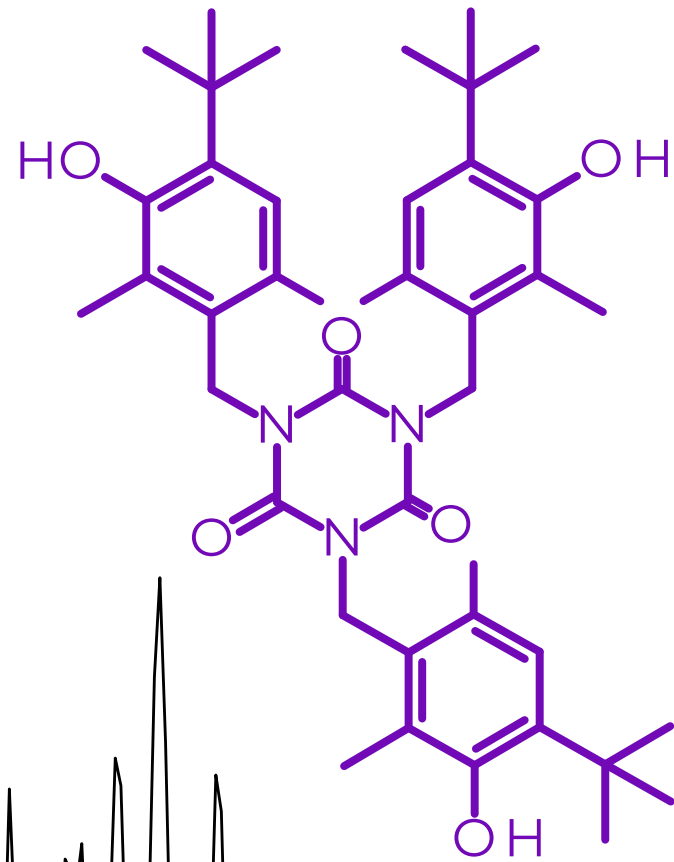
LC₅₀ distribution



naproxen



cyanox CY 1790



0

5

10

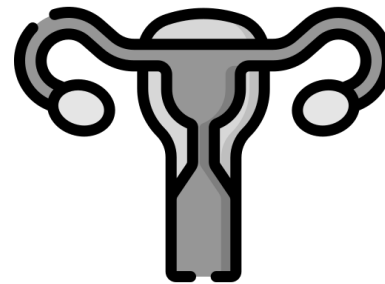
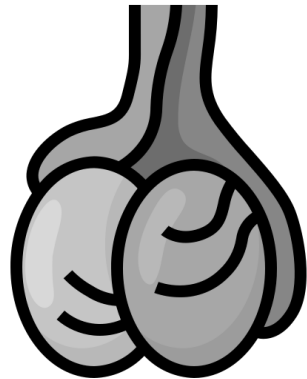
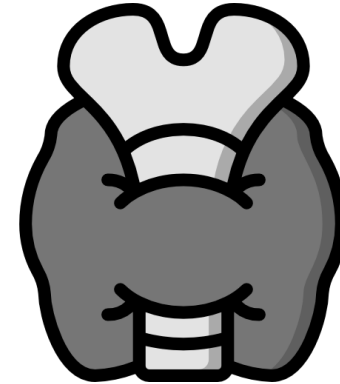
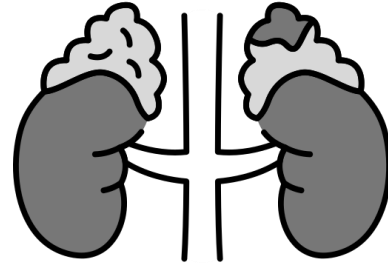
15

20

time

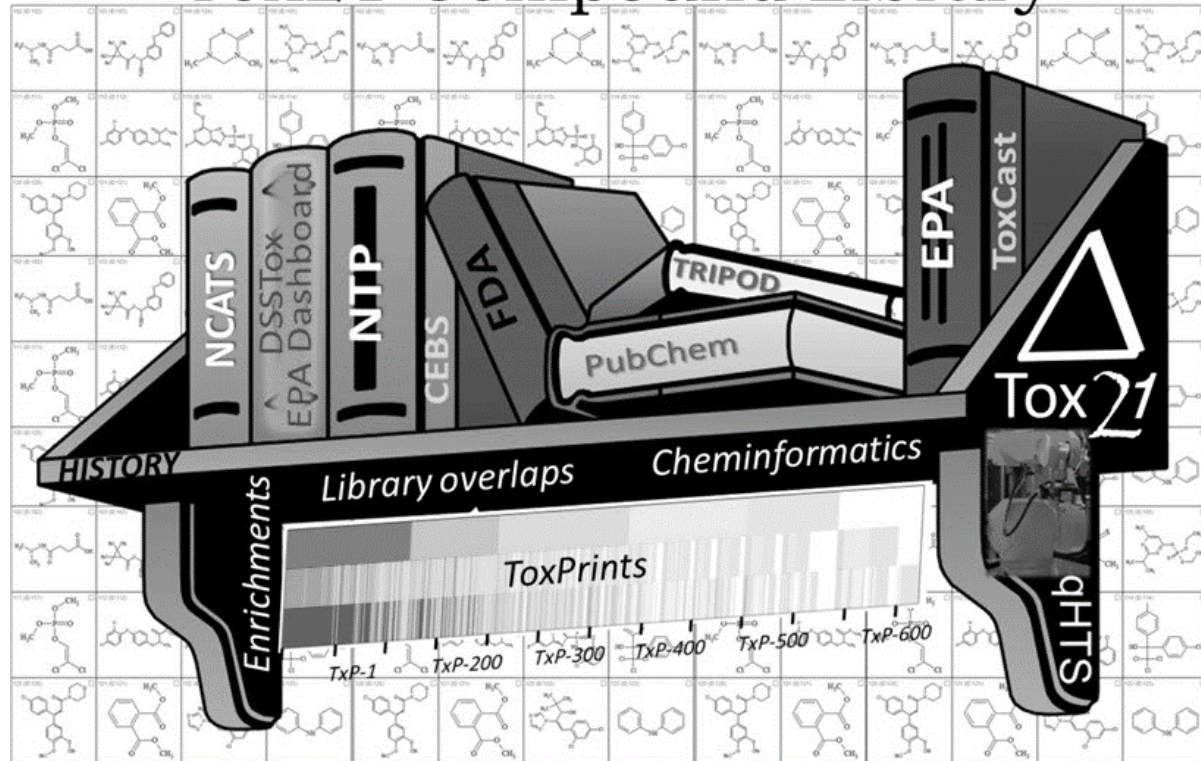
endocrine disrupting
chemicals

endocrine disruption



data

Tox21 Compound Library



nuclear receptor panel

nr.ahr

nr.ar.lbd

nr.ar

nr.aromatase

nr.er.lbd

nr.er

nr.ppar.gamma

stress response panel

sr.are

sr.atad5

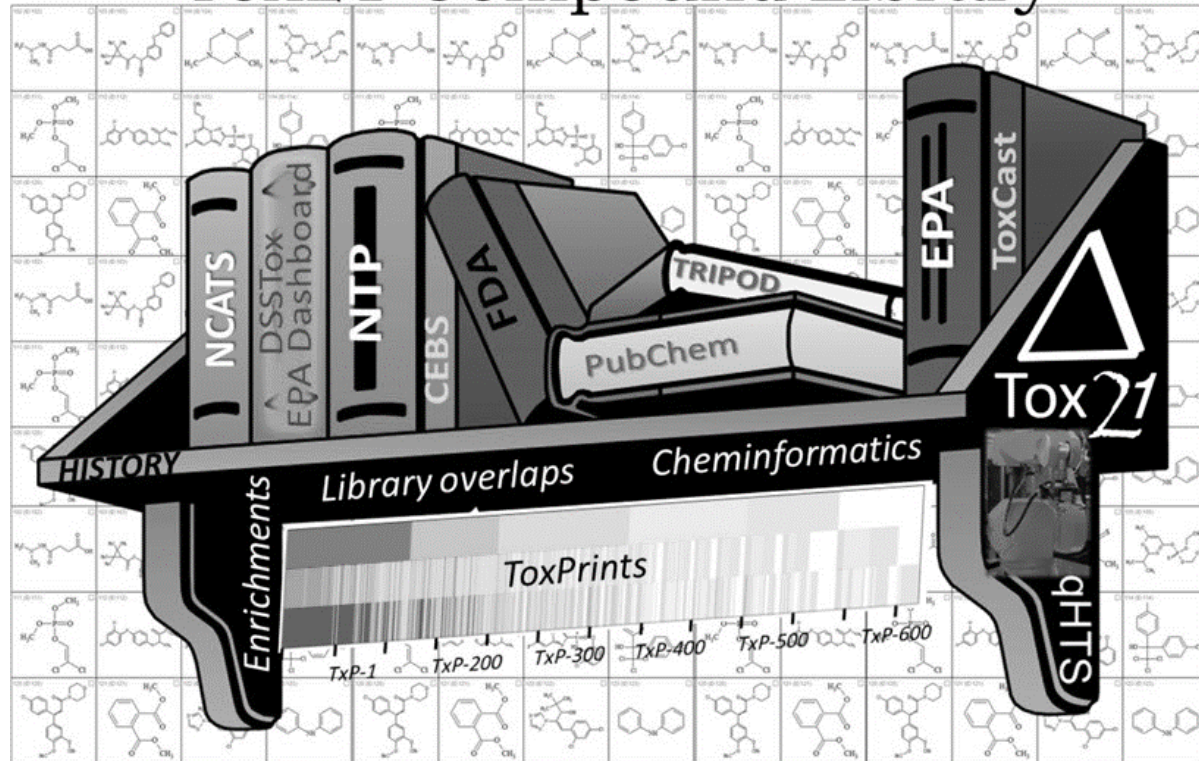
sr.hse

sr.mmp

sr.p53

data

Tox21 Compound Library



8,043 chemicals

5090 no replica

2953 with replica

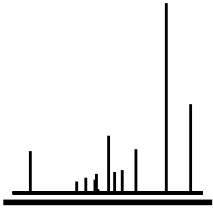
replica often inconsistent

precautionary principle

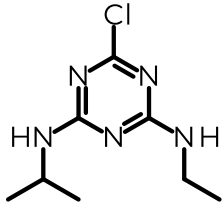
active chemicals

4% to 16%

workflow: training



MS² spectra



structure as SMILES



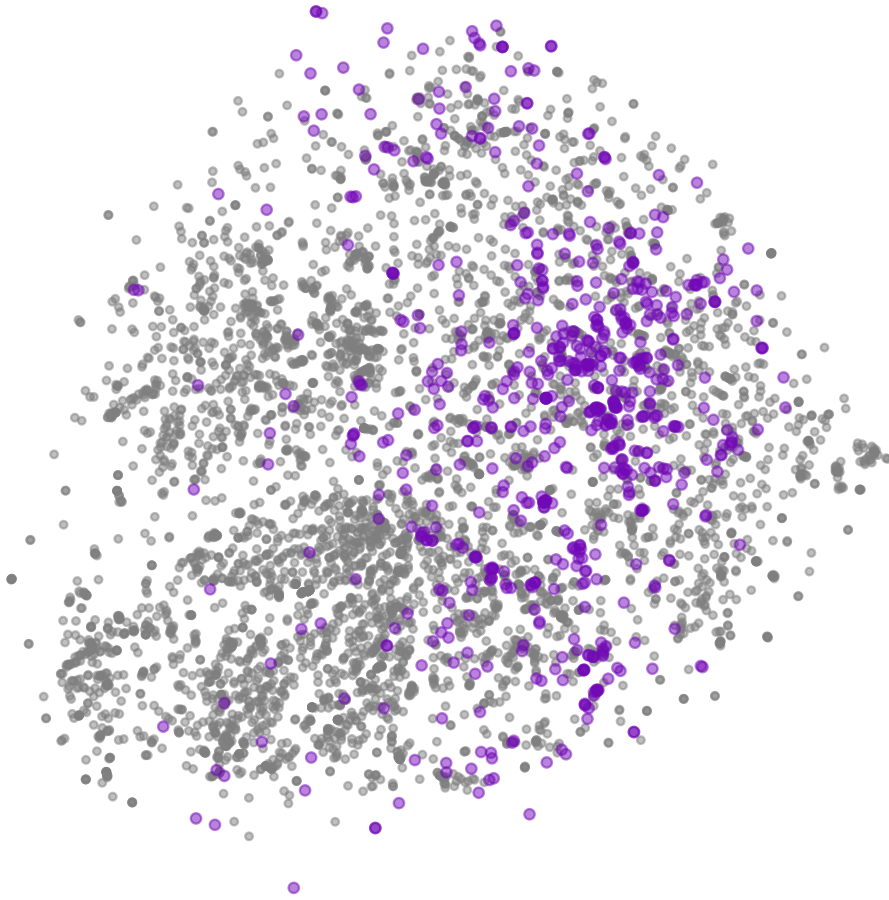
molecular descriptors



predict toxicity

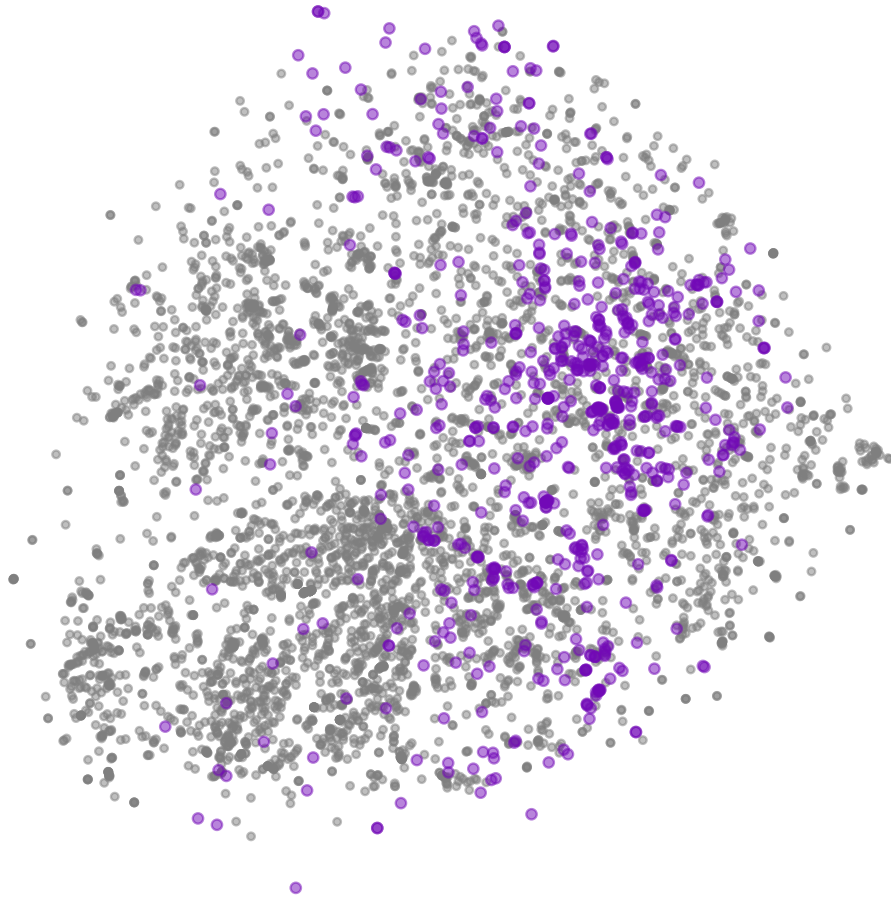
results: t-SNE

aryl hydrocarbon receptor

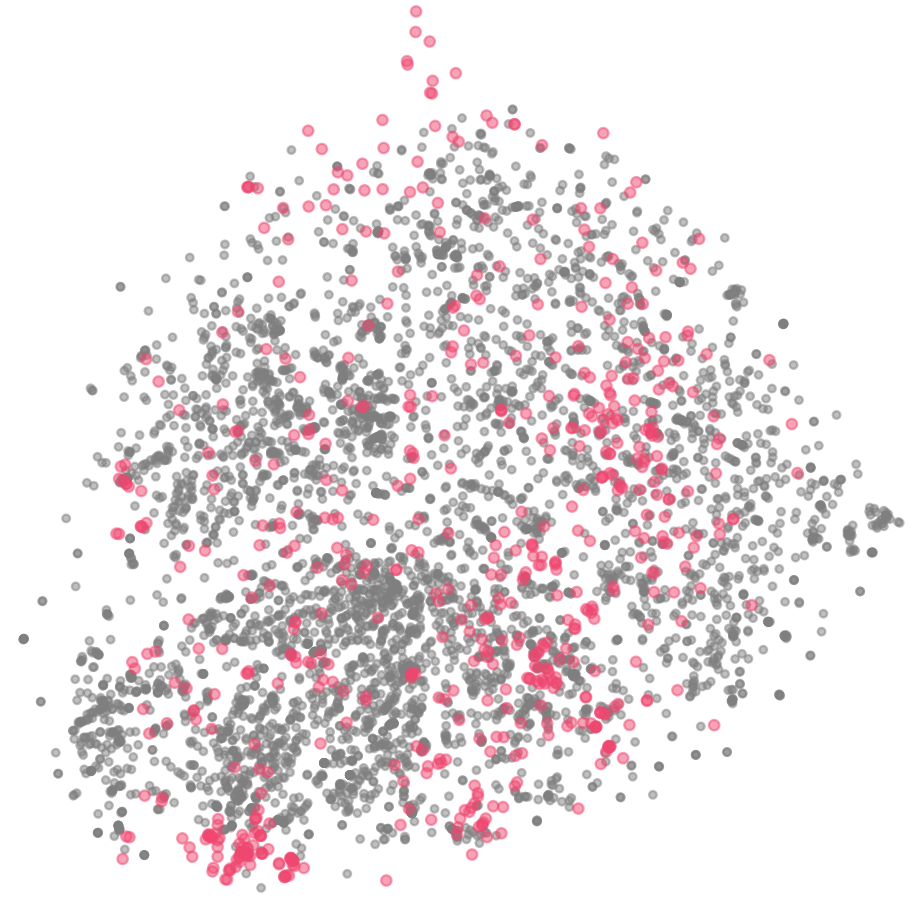


results: t-SNE

aryl hydrocarbon receptor activation



estrogen receptor activation



metrics

		true label	
		active	non-active
prediction	active	TP	FP
	non-active	FN	TN

which is more dramatic:

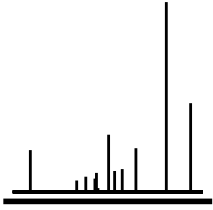
type I error

OR

type II error?

FPR @ TPR = 0.9

workflow: validation



MS² spectra



molecular fingerprints with SIRIUS+CSI:FingerID



predict LC₅₀ with pretrained gradient boosting

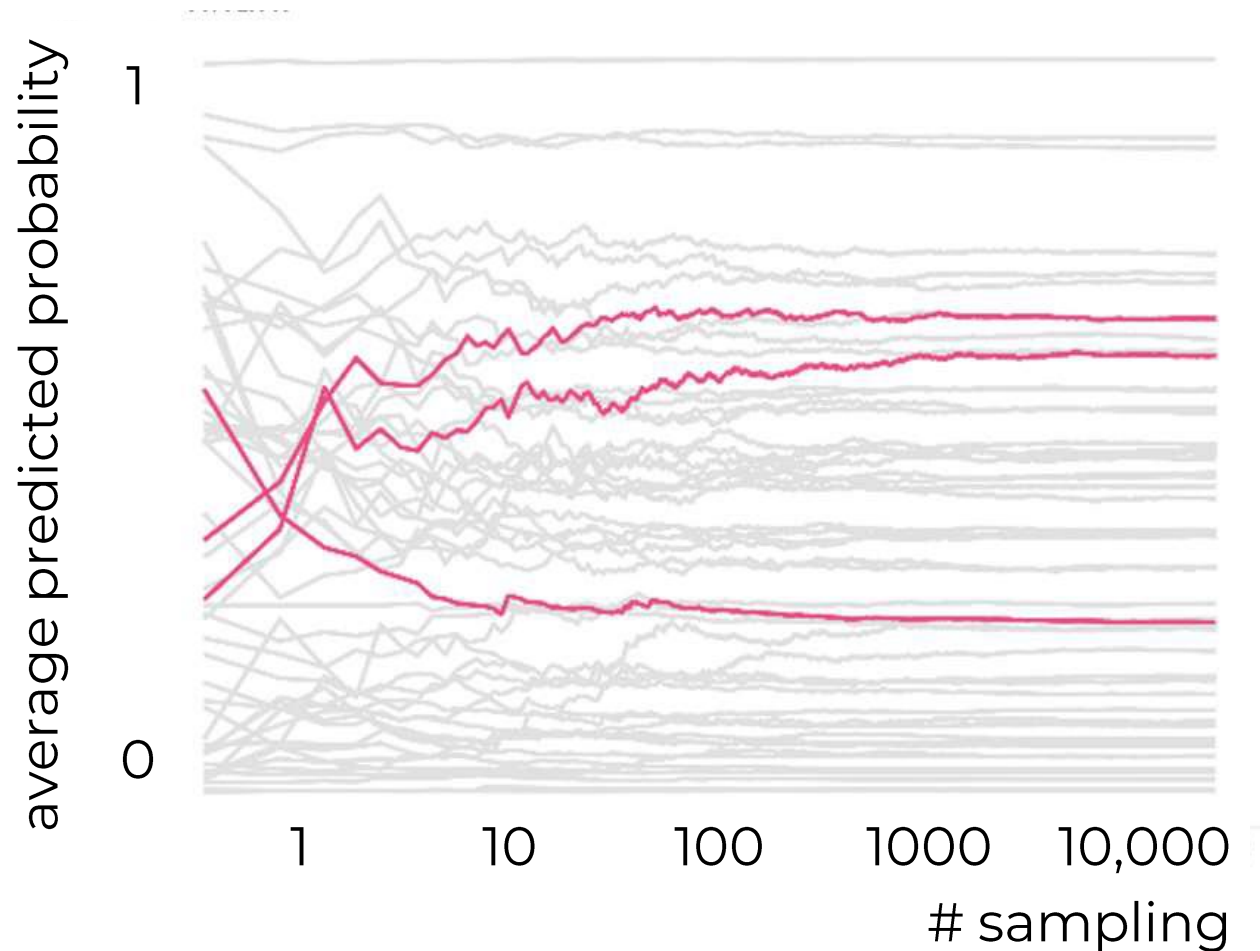
prediction accuracy

bioassay	FPR
sr.mmp	25.1%
sr.p53	25.4%
nr.ahr	41.8%
...	...
nr.ar	82.4%
nr.er	85.0%

MassBank & MoNA

748 compounds with MS² & tox

handling probabilistic fingerprints



Monte Carlo sampling
sampling each fingerprint

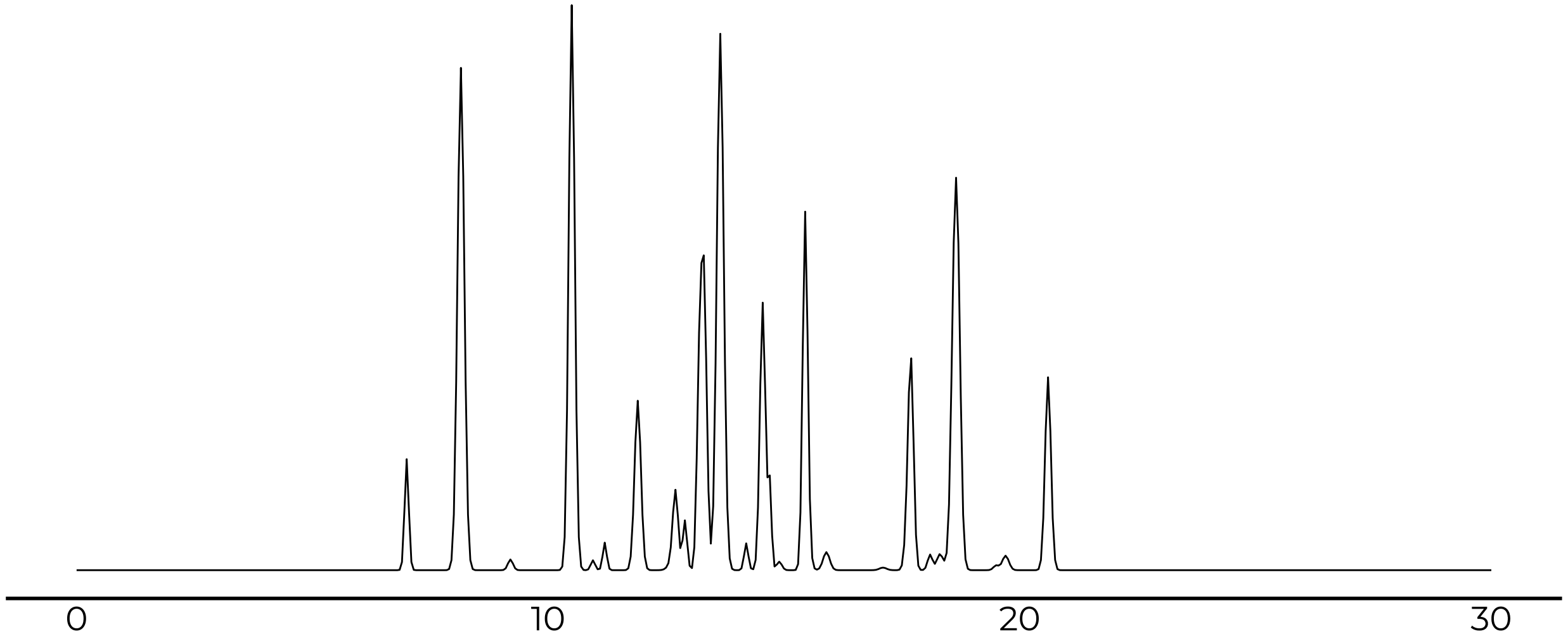
prediction changed with # of samples
2%...25%
more prone for multi-output

MS2Quant

quantification in ESI/HRMS

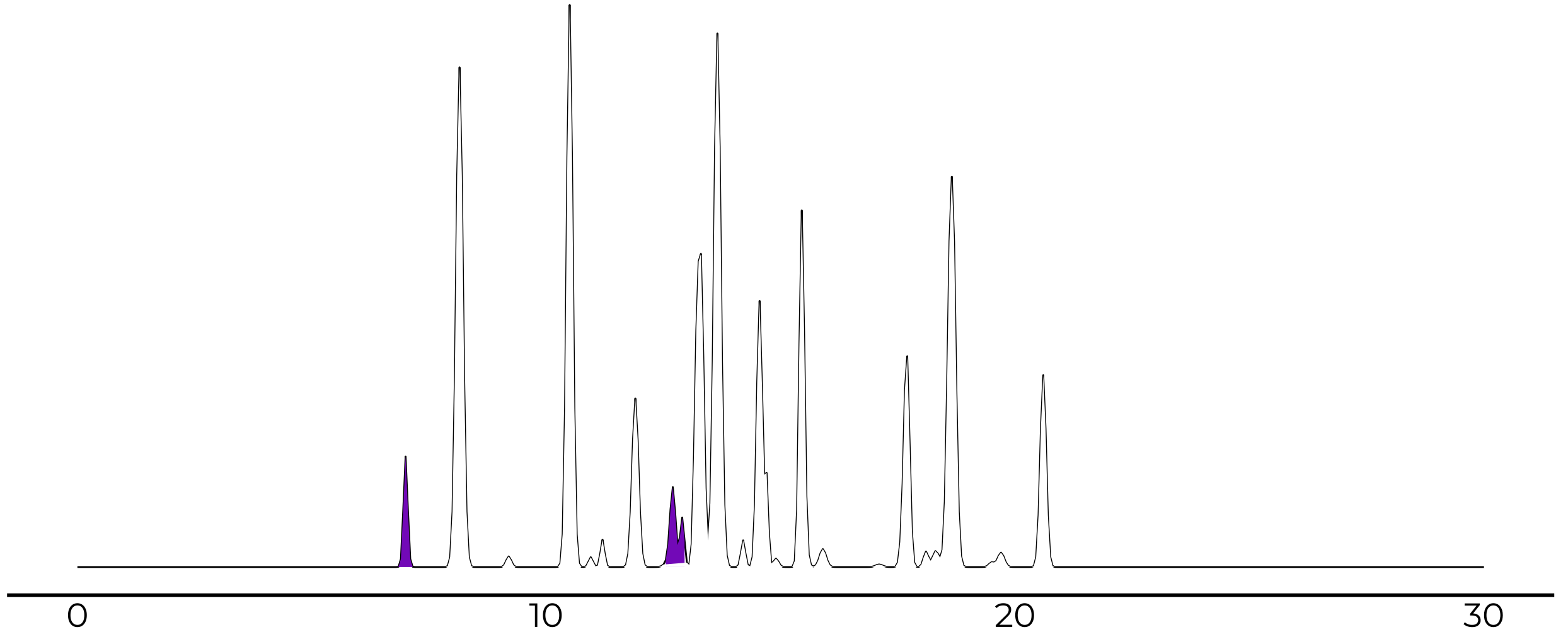
quantification in ESI/HRMS

Malm et al. Molecules 2021



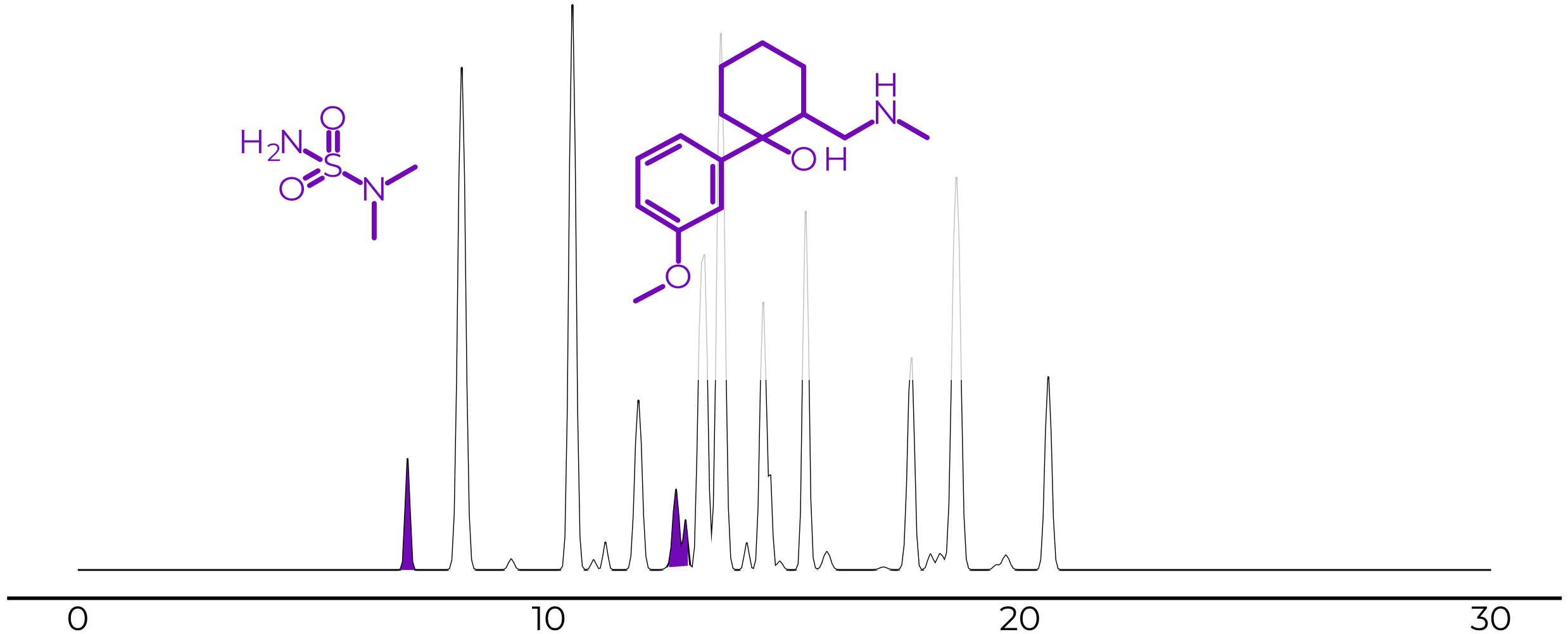
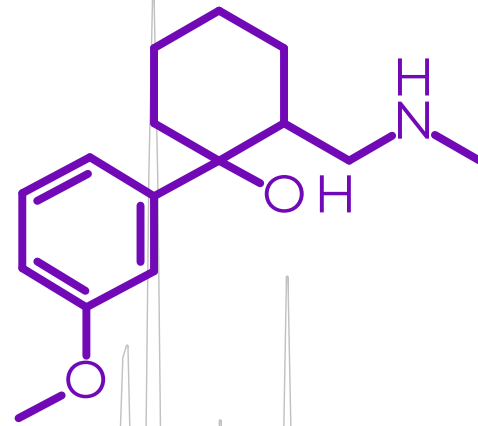
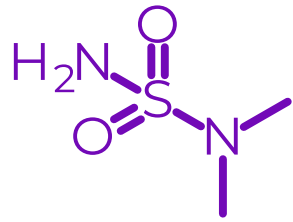
quantification in ESI/HRMS

Malm et al. Molecules 2021



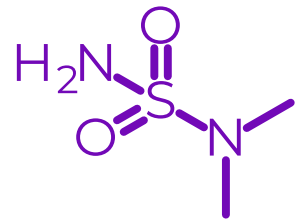
quantification in ESI/HRMS

Malm et al. Molecules 2021



quantification in ESI/HRMS

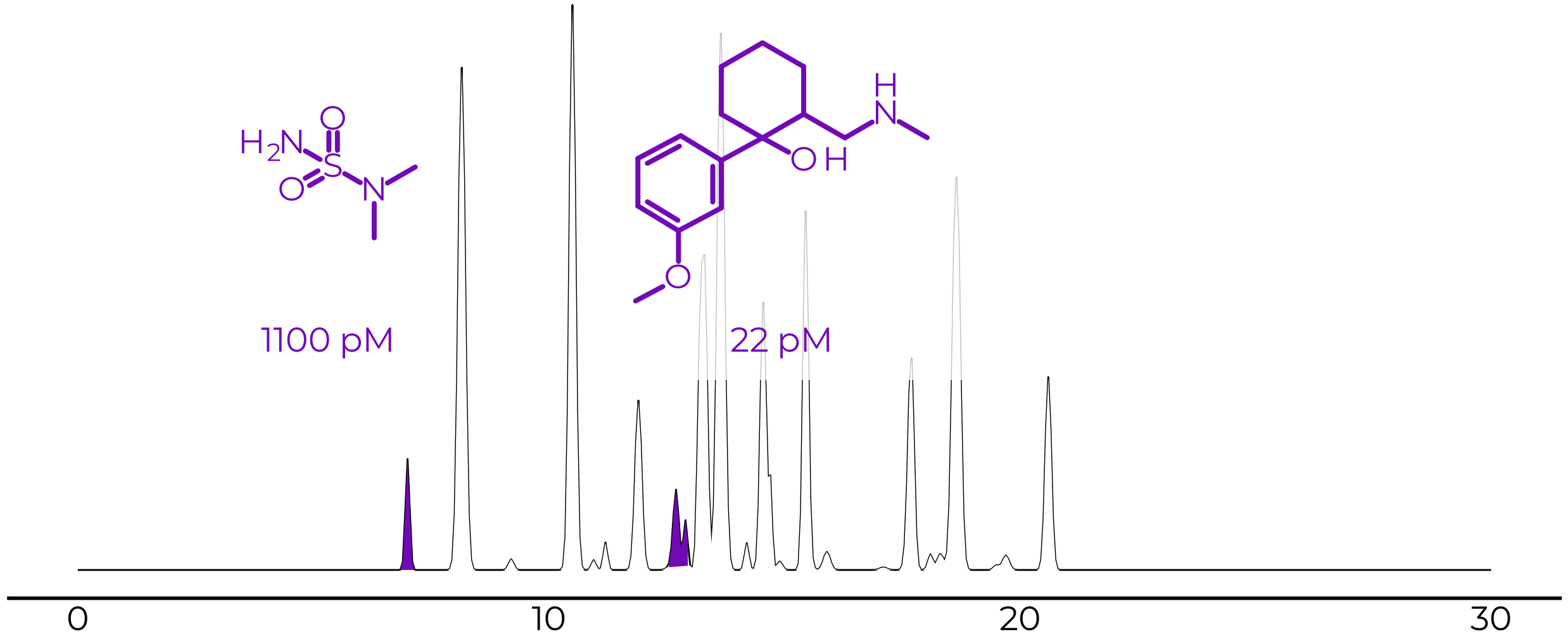
Malm et al. Molecules 2021



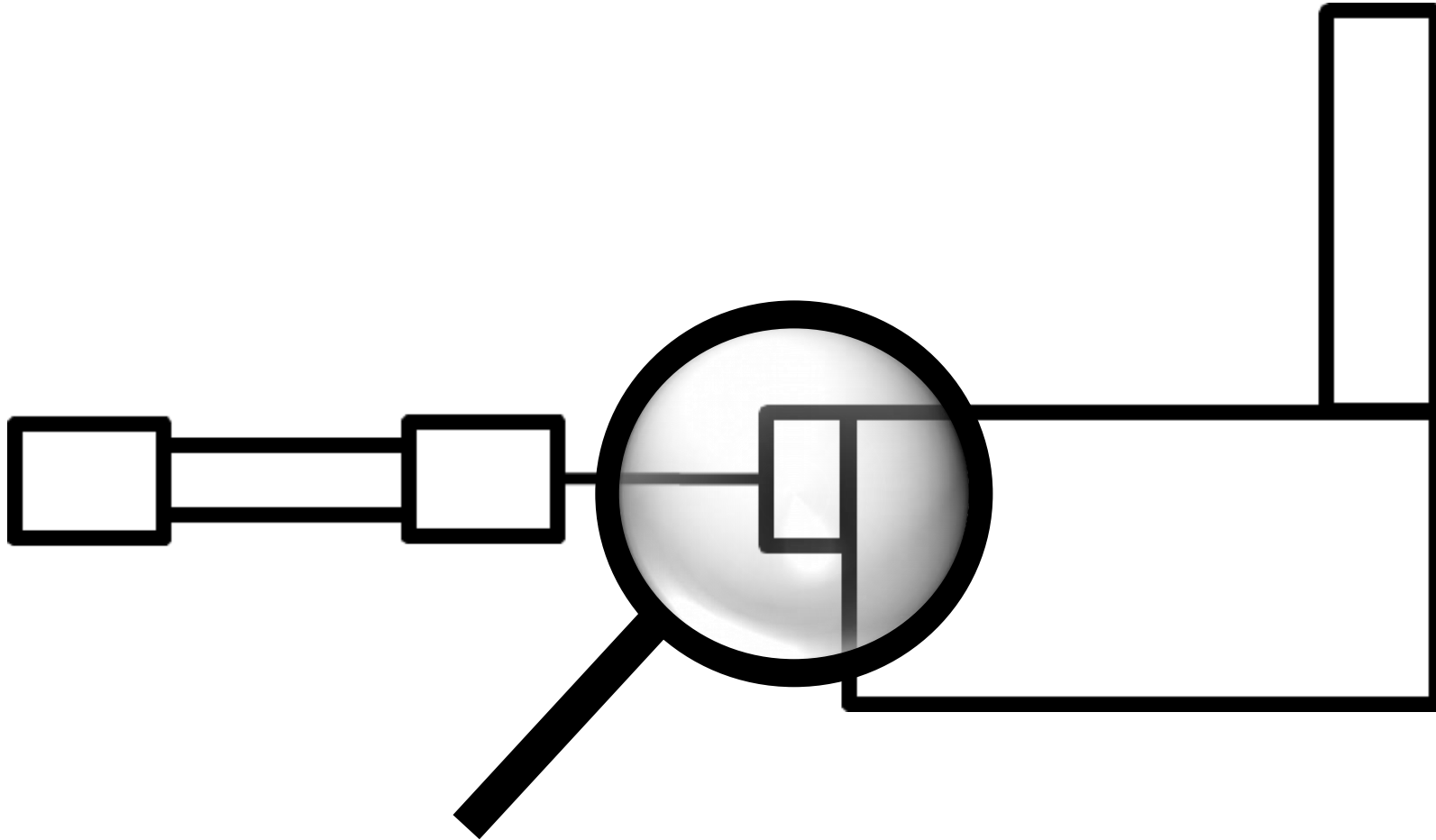
1100 pM



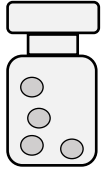
22 pM



electrospray

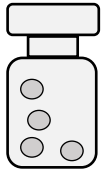


workflow

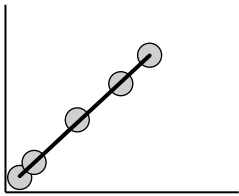


flow injections

workflow

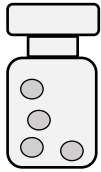


flow injections

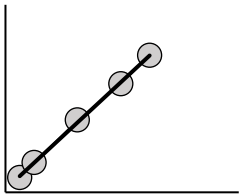


calibration graph

workflow



flow injections



calibration graph

$$\frac{\text{slope}_1}{\text{slope}_2} \rightarrow IE$$

relative measurements

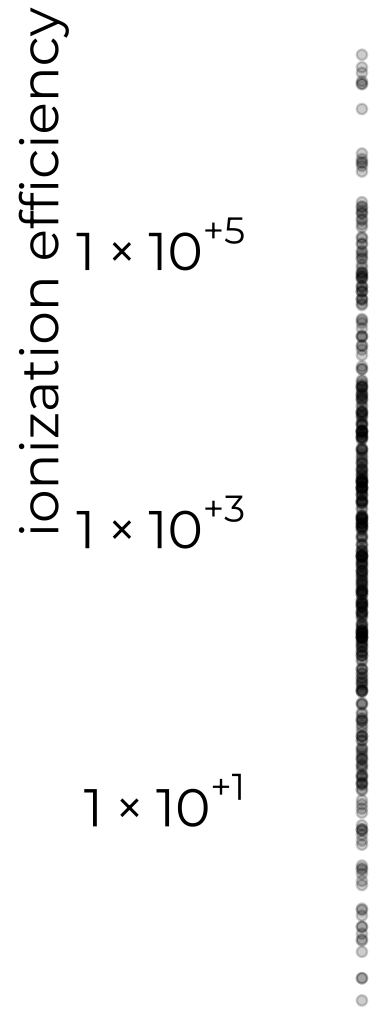
structure

structure

one solvent, purely analyte properties

377 chemicals

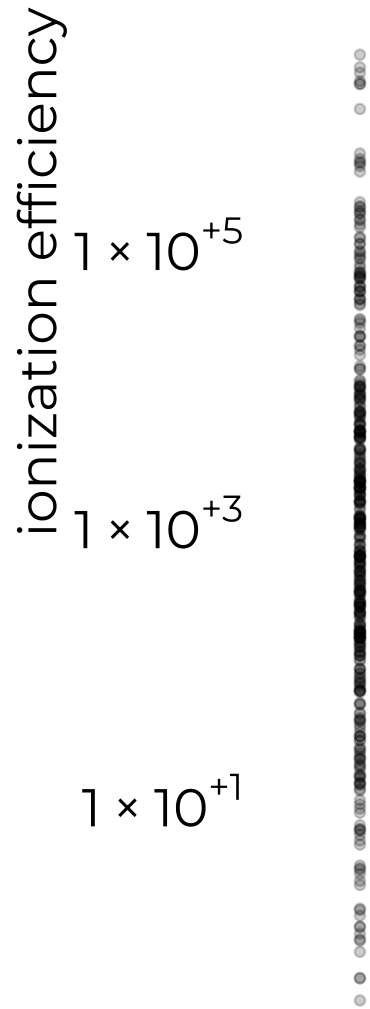
structure



one solvent, purely analyte properties

377 chemicals

structure



one solvent, purely analyte properties

377 chemicals

10,000,000x difference in ionization efficiency

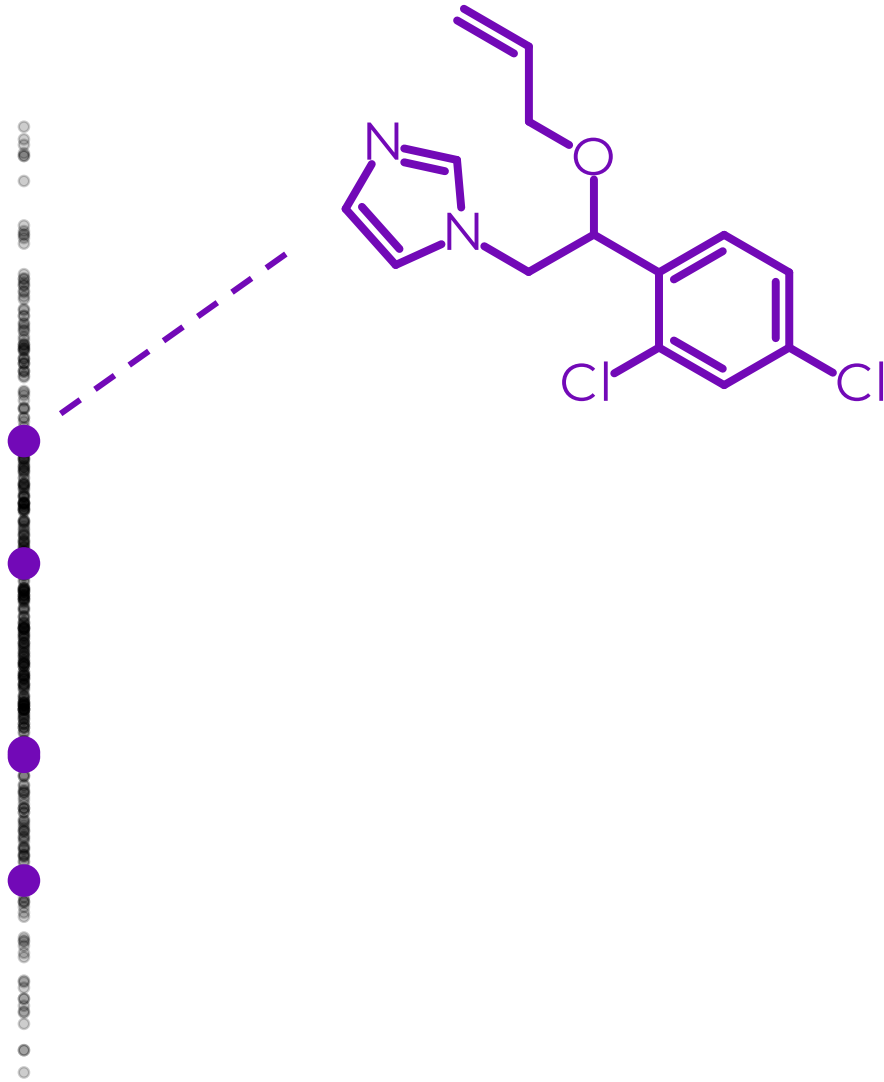
structure

ionization efficiency

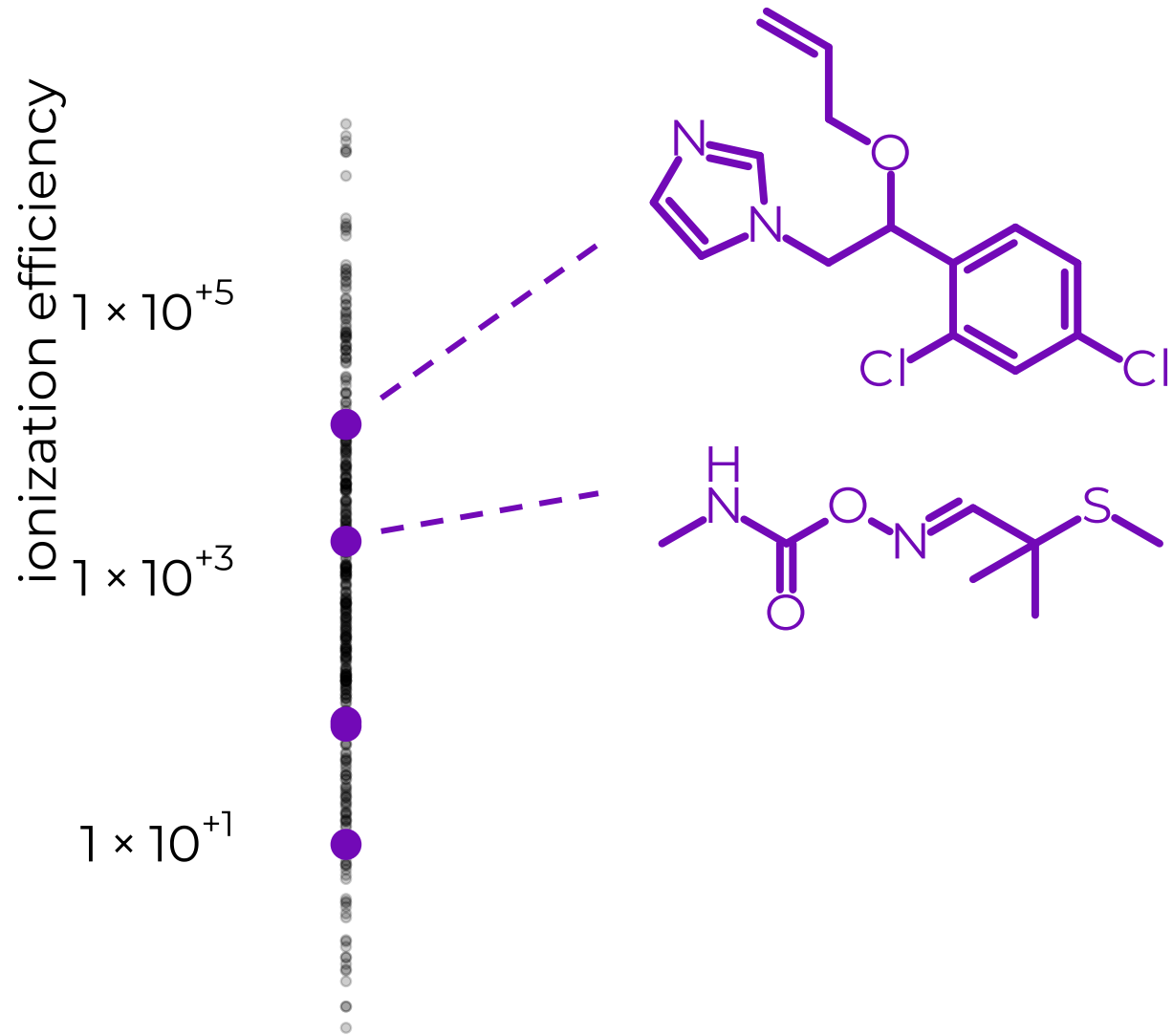
$1 \times 10^{+5}$

$1 \times 10^{+3}$

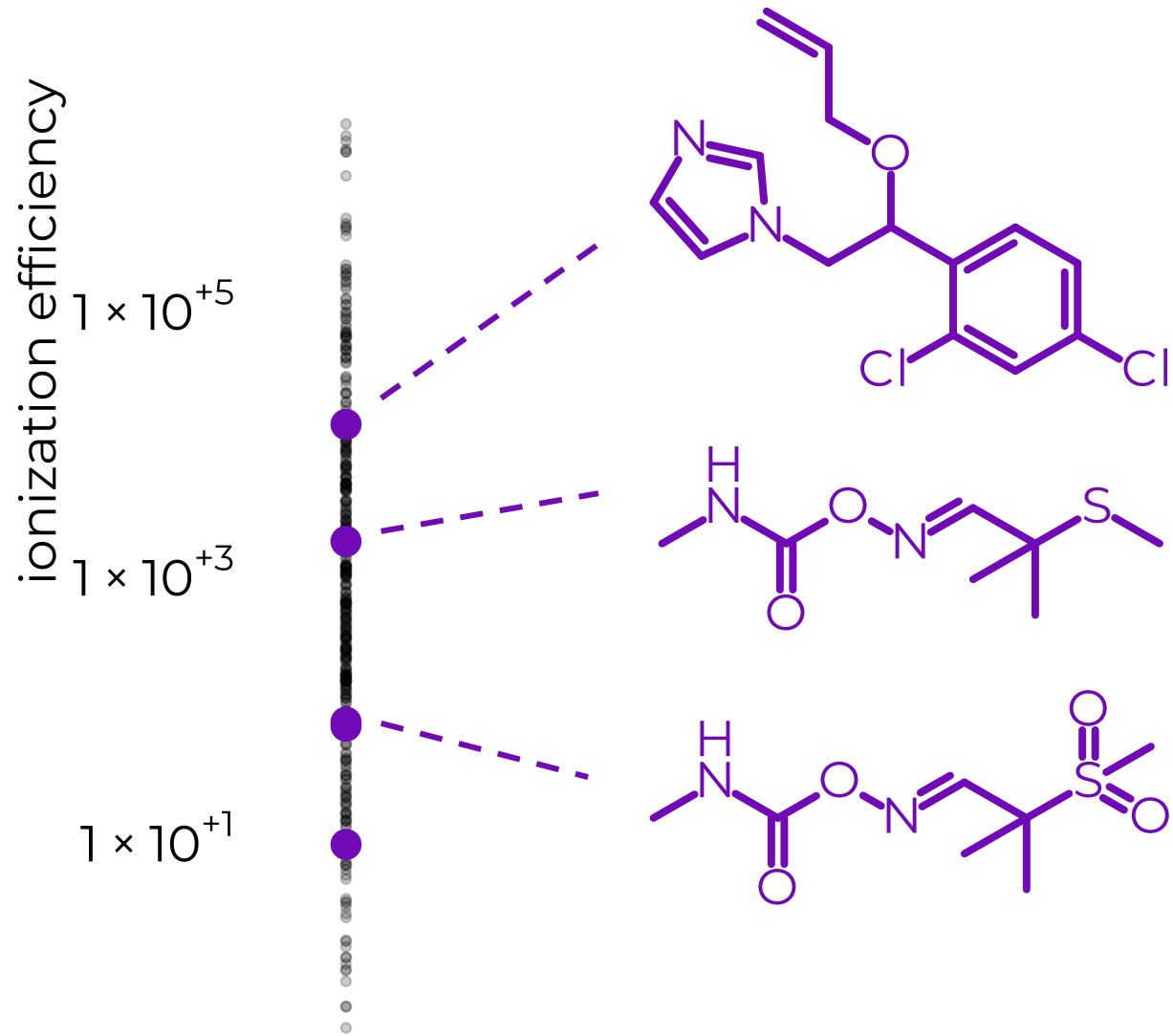
$1 \times 10^{+1}$



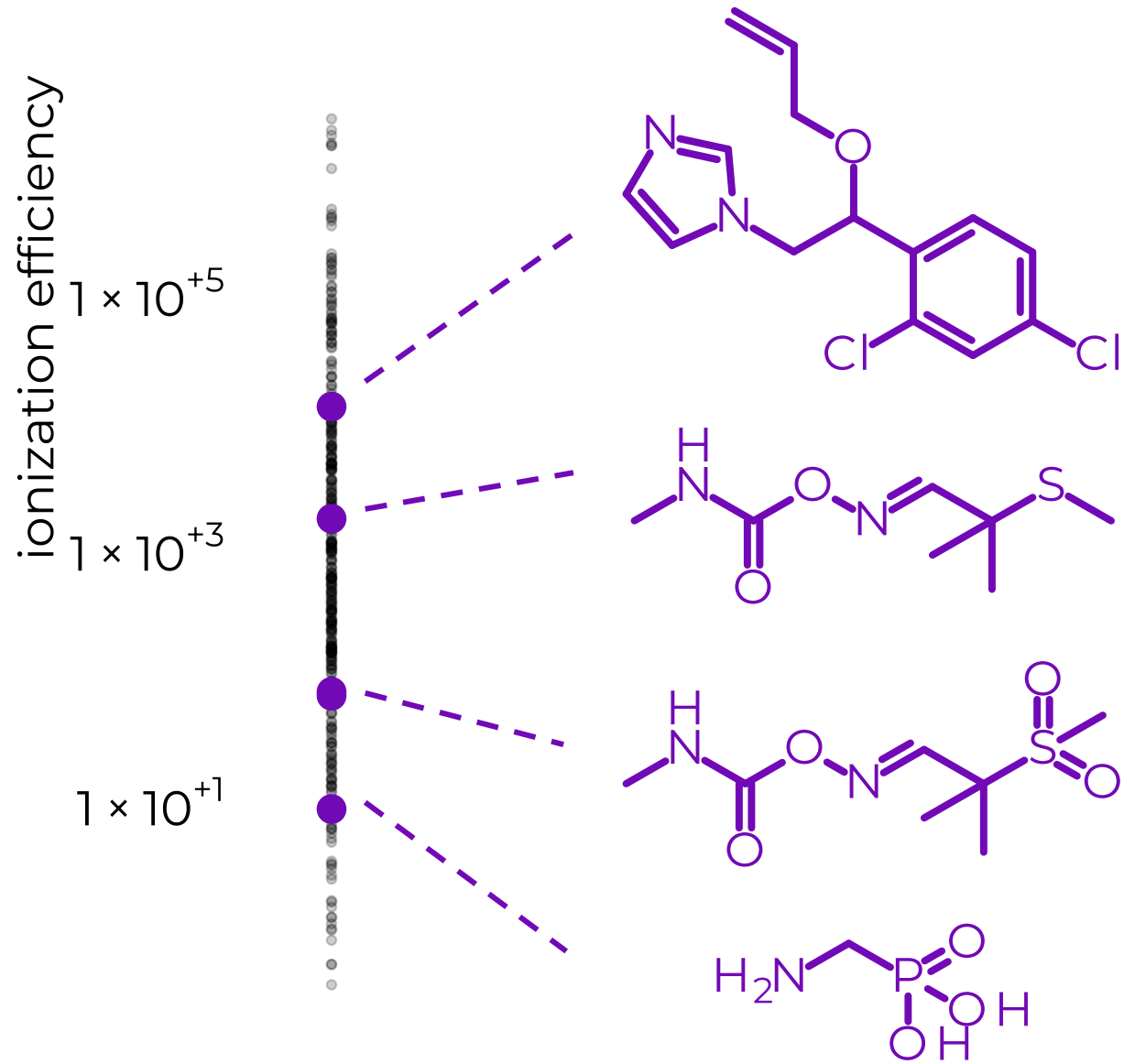
structure



structure



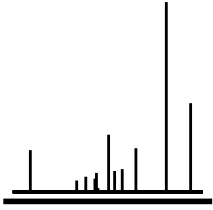
structure



quantification

with machine learning

workflow



MS² spectra



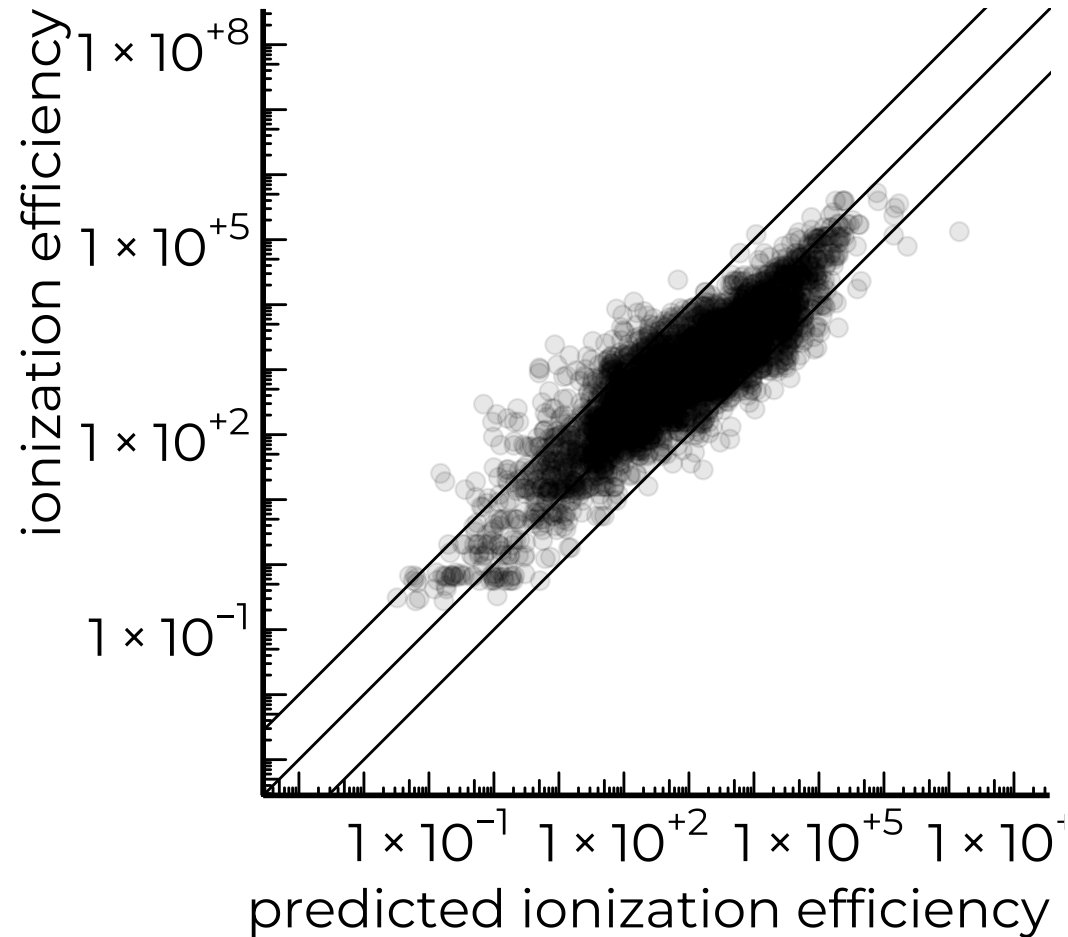
molecular fingerprints with SIRIUS



predict toxicity and ionization efficiency

performance

Sepman et al. Anal Chem 2023



IE range

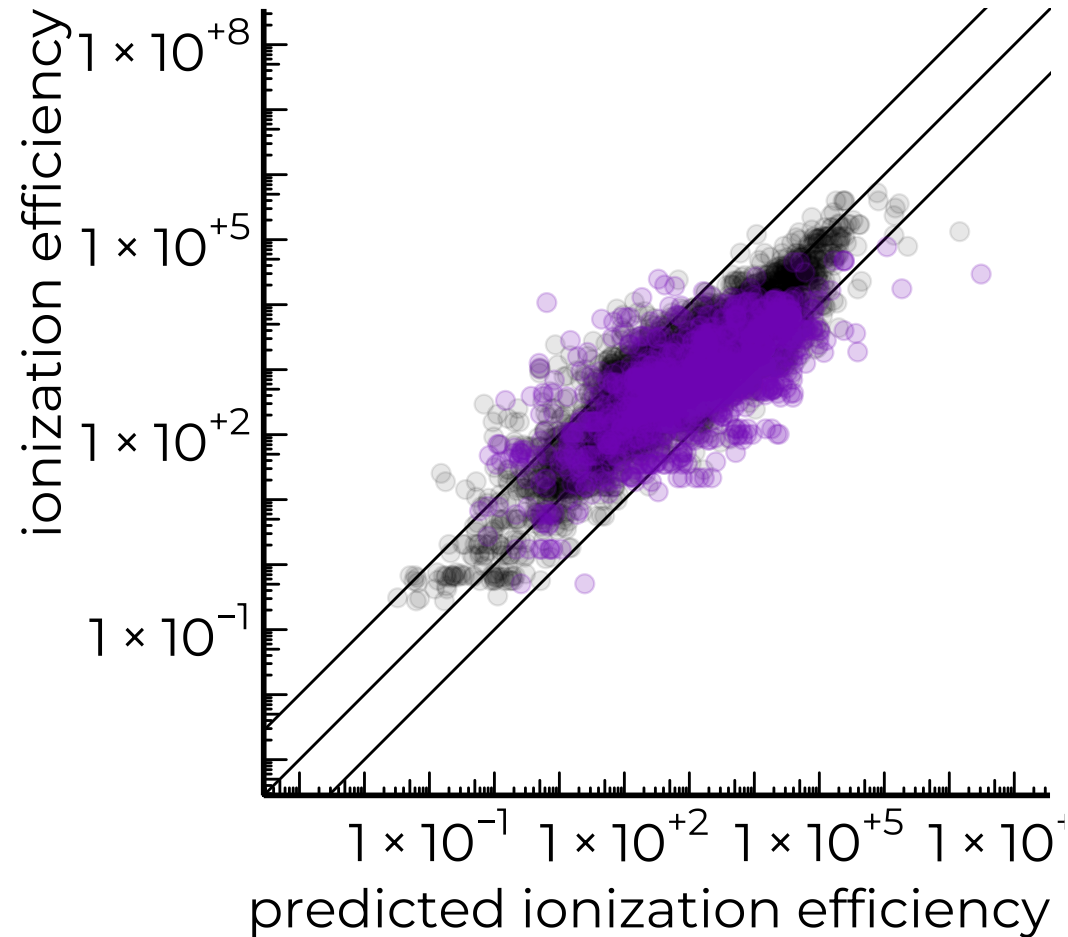
100,000,000

training set

RMSE 3.6x

performance

Sepman et al. Anal Chem 2023



IE range

100,000,000

training set

RMSE 3.6x

test set

RMSE 5.6x

application

compound	peak area
methiocarb sulfoxide	5,300
pyridaben	5,400
aldicarb-sulfone	70,800

application



predict ionization efficiency

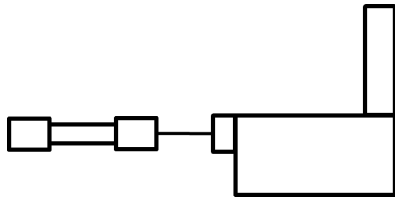
application

compound	peak area	log<i>E</i>_{pred}
methiocarb sulfoxide	5,300	2.57
pyridaben	5,400	3.78
aldicarb-sulfone	70,800	1.99

application



predict ionization efficiency



convert to instrument specific values

application

compound	peak area	log/E_{pred}	c (nM)
methiocarb sulfoxide	5,300	2.57	
pyridaben	5,400	3.78	
aldicarb-sulfone	70,800	1.99	
atrazine-D5			4.5
gabapentin-lactam			0.35
sitagliptin			0.23
5-methyl-1H-benzotriazole			0.94
neburon			3.4
caffeine			0.50

application

compound	peak area	logE_{pred}	c (nM)
methiocarb sulfoxide	5,300	2.57	
pyridaben	5,400	3.78	
aldicarb-sulfone	70,800	1.99	
atrazine-D5	450,000		4.5
gabapentin-lactam	10,400		0.35
sitagliptin	8,100		0.23
5-methyl-1H-benzotriazole	27,000		0.94
neburon	243,000		3.4
caffeine	5,600		0.50

application

$$RF_{\text{measured}} = \text{peak area} / c$$

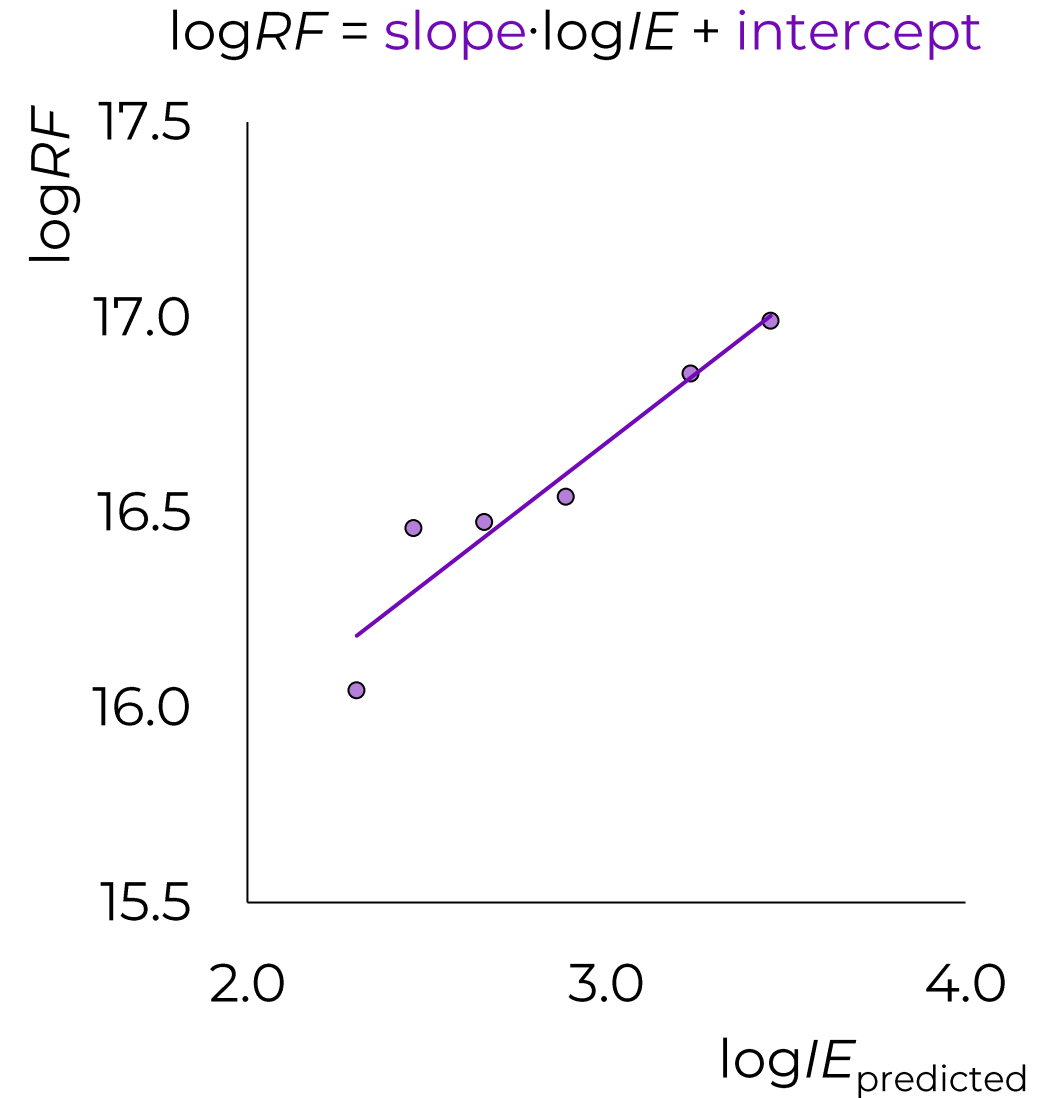
compound	peak area	\log/E_{pred}	c (nM)	$RF_{\text{meas}} \cdot 10^{16}$
methiocarb sulfoxide	5,300	2.57		
pyridaben	5,400	3.78		
aldicarb-sulfone	70,800	1.99		
atrazine-D5	450,000		4.5	9.8
gabapentin-lactam	10,400		0.35	3.0
sitagliptin	8,100		0.23	3.5
5-methyl-1H-benzotriazole	27,000		0.94	2.9
neburon	243,000		3.4	7.2
caffeine	5,600		0.50	1.1

application

compound	peak area	logI_{pred}	c (nM)	$RF_{\text{meas}} \cdot 10^{16}$
methiocarb sulfoxide	5,300	2.57		
pyridaben	5,400	3.78		
aldicarb-sulfone	70,800	1.99		
atrazine-D5	450,000	3.46	4.5	9.8
gabapentin-lactam	10,400	2.66	0.35	3.0
sitagliptin	8,100	2.89	0.23	3.5
5-methyl-1H-benzotriazole	27,000	2.46	0.94	2.9
neburon	243,000	3.23	3.4	7.2
caffeine	5,600	2.30	0.50	1.1

application

compound	peak area	$\log I/E_{\text{pred}}$
methiocarb sulfoxide	5,300	2.57
pyridaben	5,400	3.78
aldicarb-sulfone	70,800	1.99
atrazine-D5	450,000	3.46
gabapentin-lactam	10,400	2.66
sitagliptin	8,100	2.89
5-methyl-1H-benzotriazole	27,000	2.46
neburon	243,000	3.23
caffeine	5,600	2.30



application

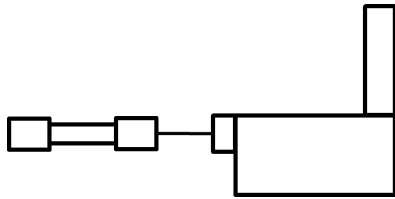
$$\log RF_{\text{predicted}} = \text{slope} \cdot \log I E_{\text{predicted}} + \text{intercept}$$

compound	peak area	log$I E_{\text{pred}}$	c (nM)	$RF_{\text{meas}} \cdot 10^{16}$	$RF_{\text{pred}} \cdot 10^{16}$
methiocarb sulfoxide	5,300	2.57			2.6
pyridaben	5,400	3.78			15.5
aldicarb-sulfone	70,800	1.99			1.1
atrazine-D5	450,000	3.46	4.5	9.8	
gabapentin-lactam	10,400	2.66	0.35	3.0	
sitagliptin	8,100	2.89	0.23	3.5	
5-methyl-1H-benzotriazole	27,000	2.46	0.94	2.9	
neburon	243,000	3.23	3.4	7.2	
caffeine	5,600	2.30	0.50	1.1	

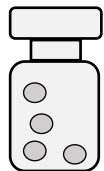
application



predict ionization efficiency



convert to instrument specific values



estimate concentration

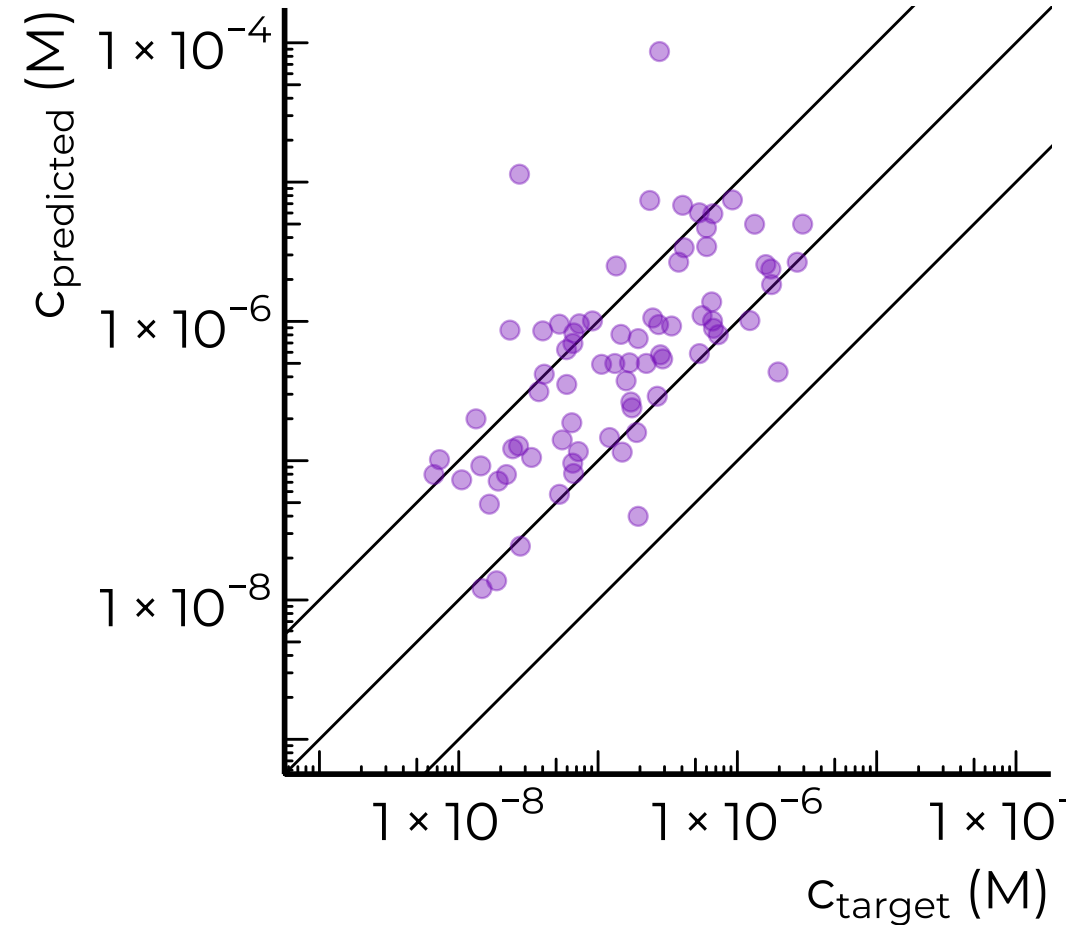
application

$$c = \text{peak area} / RF_{\text{predicted}}$$

compound	peak area	logI_{pred}	c (nM)	$RF_{\text{meas}} \cdot 10^{16}$	$RF_{\text{pred}} \cdot 10^{16}$	c_{pred} (nM)
methiocarb sulfoxide	5,300	2.57			2.6	0.20
pyridaben	5,400	3.78			15.5	0.035
aldicarb-sulfone	70,800	1.99			1.1	6.3
atrazine-D5	450,000	3.46	4.5	9.8		
gabapentin-lactam	10,400	2.66	0.35	3.0		
sitagliptin	8,100	2.89	0.23	3.5		
5-methyl-1H-benzotriazole	27,000	2.46	0.94	2.9		
neburon	243,000	3.23	3.4	7.2		
caffeine	5,600	2.30	0.50	1.1		

ionization efficiency

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mean prediction error

7.4x

geometric mean prediction error

4.5x

median prediction error

4.0x

summary

prioritization in NTS

toxicity



concentration



risk



prioritization in NTS

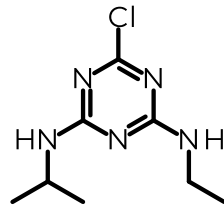
toxicity



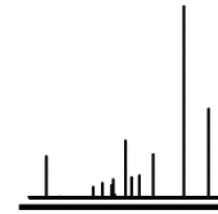
concentration



risk



structure



MS² spectrum

