Statistical modeling in molecular medicine: proteomics

Anna Gambin

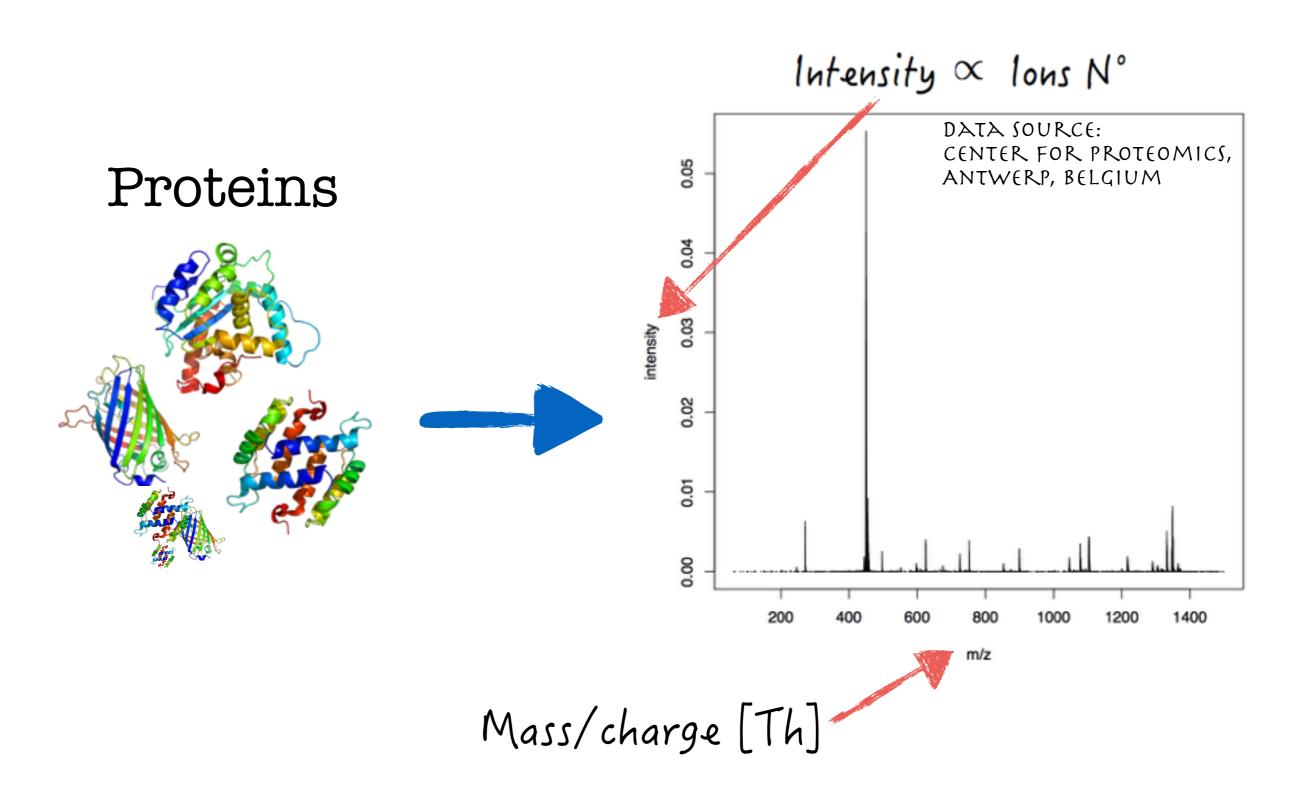
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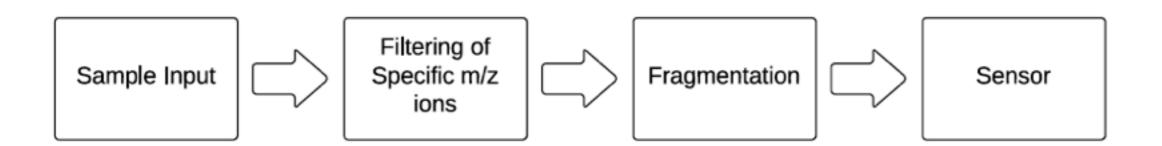
outline

- masSpec basics
- modeling isotopic distribution
- modeling exopeptidase activity
- incorporating MEROPS data
- peptidase activity in time
- modeling electron transfer dissociation
- deconvolution of spectra
- modeling fragmentation

Mass Spectrometry



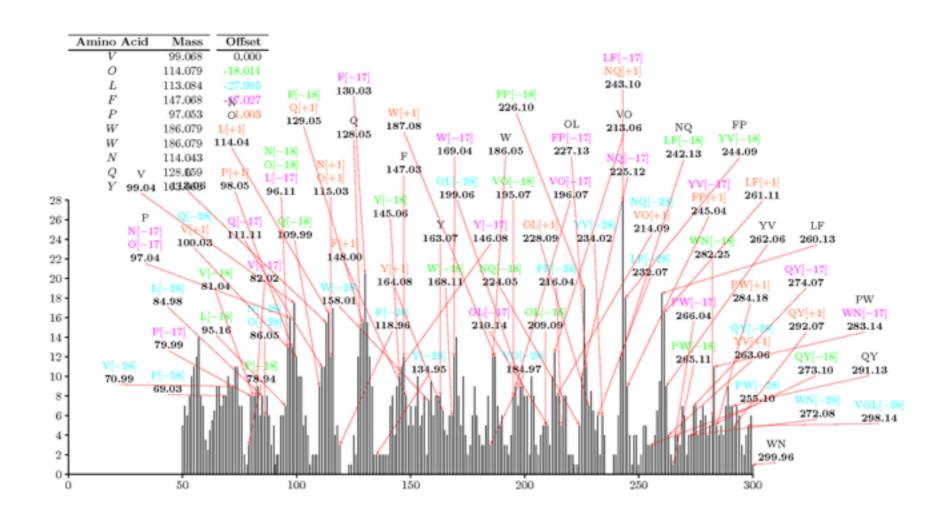
What is a Mass Spectrometer?



- A balance comprising
 - a dust-cleaner
 - a sieve
 - a knife
 - and a tracking system.

- The Mass Spectrometer
 - ionises the sample
 - manipulates the electrostatic field to move ions
 - fragments the ions
 - registers the ions

Identifying proteins is complicated



- there are plenty of proteins in a sample
- proteins are frequently fragmented
- even a single protein has a complicated signal

Chemical compounds are made of different isotopes

elements have different numbers of stable isotopes

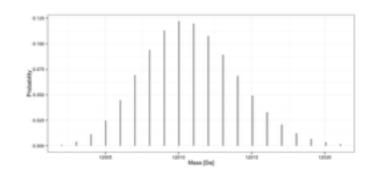
		The second second		
Element	Isotope	Extra Neutrons	Mass [Da]	Probability
Carbon	¹² C	0	12	0.9893
	$^{13}\mathrm{C}$		13.0033	0.0107
Hydrogen	^{1}H	0	1.0078	0.999885
	$^{2}\mathrm{H}$	1	2.0141	0.000115
Nitrogen	¹⁴ N	0	14.0031	0.99632
	^{15}N	1	15.0001	0.00368
Oxygen	¹⁶ O	0	15.9949	0.99757
	¹⁷ O	1	16.9991	0.00038
	¹⁸ O	2	17.9992	0.00205
Sulfu	^{32}S	0	31.9721	0.9493
	^{33}S	1	32.9714	0.0076
	³⁴ S	2	33.9679	0.0429
	³⁶ S	4	35.9671	0.0002
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differences in frequencies of observation

isotopes of different elements differ in mass differences

32.9714 - 31.9721 = 0,9993 [Da]

isotopic envelope



huge number of isotopologues

A chemical formula

$$C_cH_hN_nO_oS_s$$

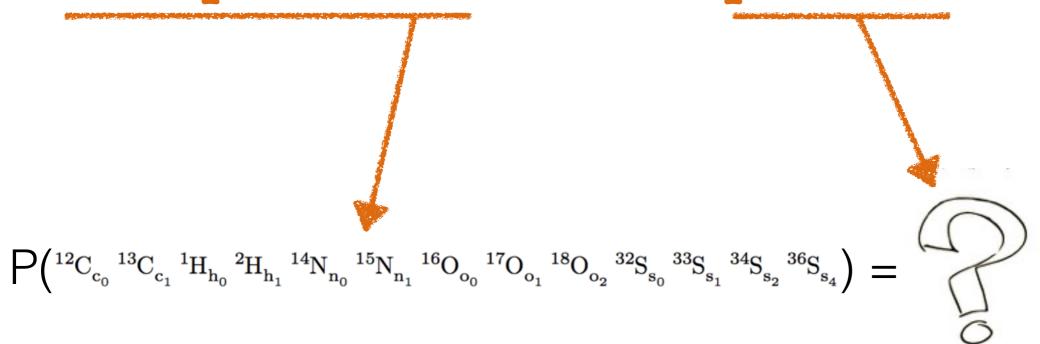
can be composed out of isotopes

$$\prod_{e \in \{\text{C,H,N,O,S}\}} \binom{n_e + i_e - 1}{n_e} \approx \prod_{e \in \{\text{C,H,N,O,S}\}} \frac{e^{ie - 1}}{\sqrt{2\pi(i_e - 1)}} \Big(\frac{n_e}{i_e - 1} + 1\Big)^{i_e - 1}$$

mays, where i_e - N° of atoms of element e i_e - N° of isotopes of element e

important observation

some isotopic variants are more probable than others



Assume

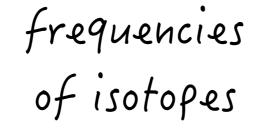
1) variants of isotopes of atoms are independent

2) elements vary in abundances of isotopes

$$P\left({}^{12}C_{c_0}{}^{13}C_{c_1}{}^{1}H_{h_0}{}^{2}H_{h_1}{}^{14}N_{n_0}{}^{15}N_{n_1}{}^{16}O_{o_0}{}^{17}O_{o_1}{}^{18}O_{o_2}{}^{32}S_{s_0}{}^{33}S_{s_1}{}^{34}S_{s_2}{}^{36}S_{s_4}\right) =$$

$$\binom{c}{c_0,\,c_1} \mathcal{P}(^{12}C)^{c_0} \mathcal{P}(^{13}C)^{c_1} \binom{h}{h_0,\,h_1} \mathcal{P}(^{1}H)^{h_0} \mathcal{P}(^{2}H)^{h_1} \binom{n}{n_0,\,n_1} \mathcal{P}(^{14}N)^{n_0} \mathcal{P}(^{15}N)^{n_1} \times \\$$

$$\binom{n}{o_0, o_1, o_2} \mathcal{P}(^{16}O)^{o_0} \mathcal{P}(^{17}O)^{o_1} \mathcal{P}(^{18}O)^{o_2} \binom{s}{s_0, s_1, s_2, s_4} \mathcal{P}(^{32}S)^{s_0} \mathcal{P}(^{33}S)^{s_1} \mathcal{P}(^{34}S)^{s_2} \mathcal{P}(^{36}S)^{s_4}$$







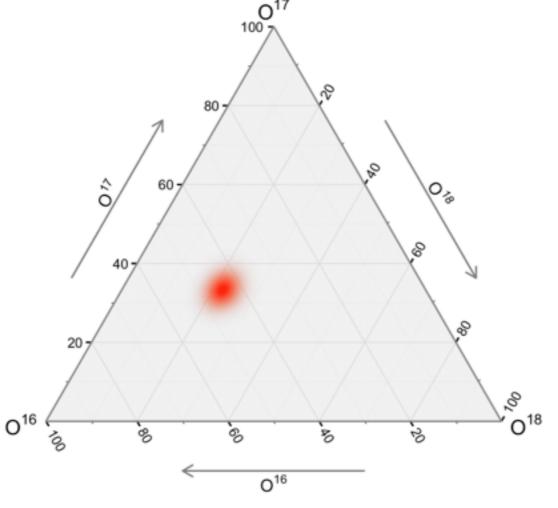
$$\mathcal{P}(^{16}\mathrm{O}) = \frac{4}{9} \quad \mathcal{P}(^{17}\mathrm{O}) = \frac{3}{9} \quad \mathcal{P}(^{18}\mathrm{O}) = \frac{2}{9} \quad \text{(not real world values!)}$$

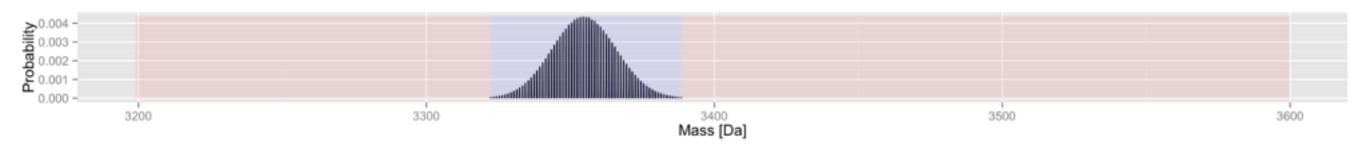
200 oxygen atoms

$$o_0 + o_1 + o_2 = 200$$

20301 variants

whereas 1043 bear 99% prob.

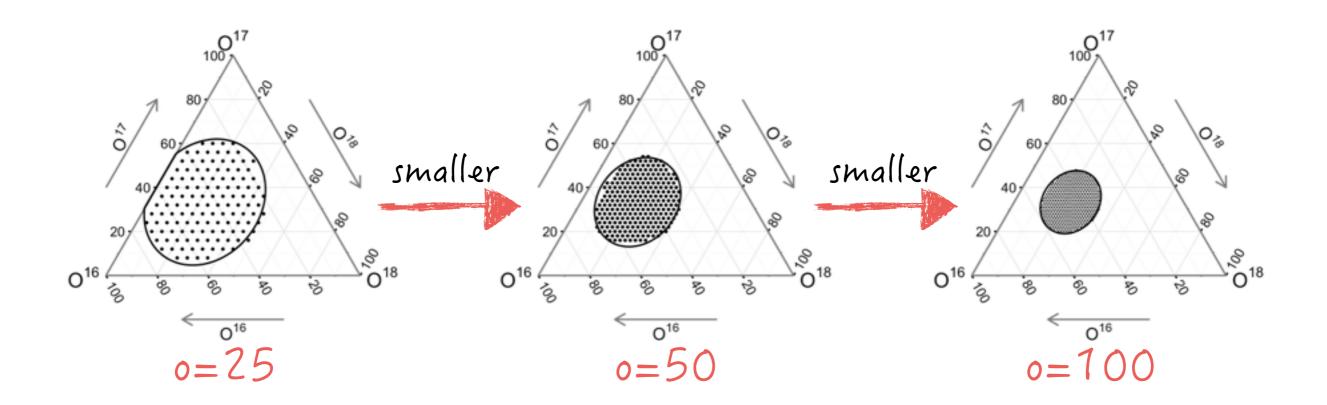


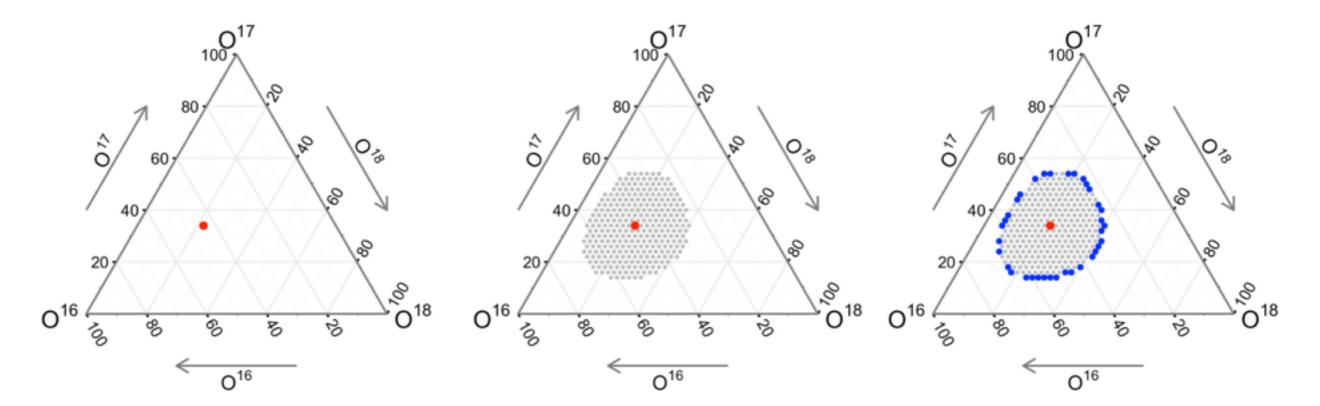


How much we gain by considering the smallest set with a fixed probability?

$$\#\Big(\underset{\text{VARIANTS}}{\text{PROBABLE}} \Big) \approx C_{\text{lattice}} \Big(\prod_{\text{Elements}} n_e^{\frac{i_e-1}{2}} \sqrt{\det \Delta_e} \Big) q_{\chi^2(k)}^k \frac{\pi^{k/2}}{\Gamma(k/2+1)} \propto$$

$$\prod_{\text{Elements}} n_e^{\frac{i_e-1}{2}} \quad \bigvee 5 \quad \prod_{\text{Elements}} n_e^{i_e-1}$$





To get the smallest set with probability P:

Find the most probable variant

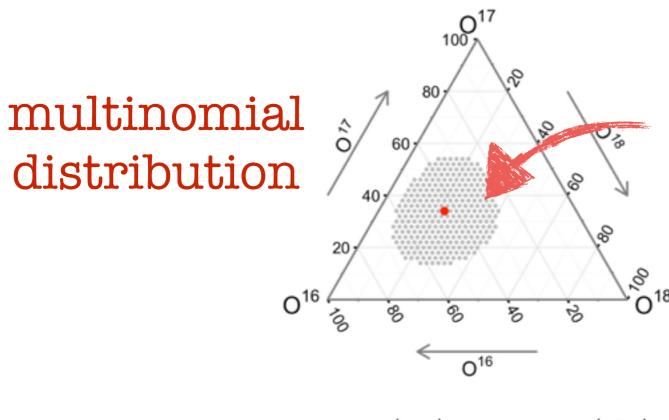
while Total Probability < P:

Get layer so that p > P(v) > = qp where $p = P(v_{min previous layer})$

Trim the **least probable variants** from the last layer so that **Total Probability** >= P

Monotonic Expansion Property:

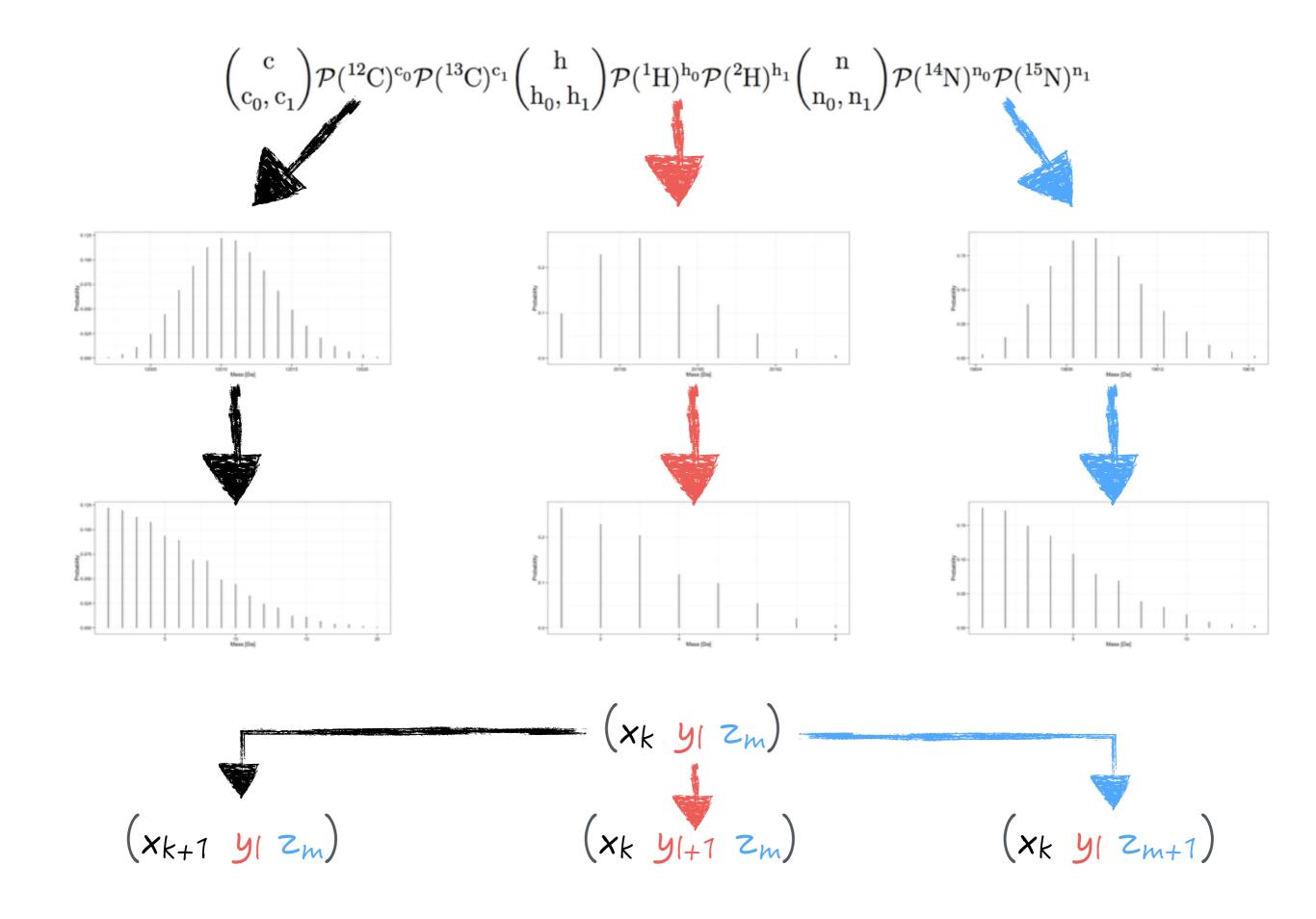
For each v set $\{W: P(W) >= P(v)\}$ is adjacent to v



Smallest set with current **Total Probability**

$$\begin{pmatrix} c \\ c_0, c_1 \end{pmatrix} \mathcal{P}(^{12}\mathrm{C})^{c_0} \mathcal{P}(^{13}\mathrm{C})^{c_1} \begin{pmatrix} h \\ h_0, h_1 \end{pmatrix} \mathcal{P}(^{1}\mathrm{H})^{h_0} \mathcal{P}(^{2}\mathrm{H})^{h_1} \begin{pmatrix} n \\ n_0, n_1 \end{pmatrix} \mathcal{P}(^{14}\mathrm{N})^{n_0} \mathcal{P}(^{15}\mathrm{N})^{n_1} \ ,$$

$$\begin{pmatrix} n \\ o_0, o_1, o_2 \end{pmatrix} \mathcal{P}(^{16}\mathrm{O})^{o_0} \mathcal{P}(^{17}\mathrm{O})^{o_1} \mathcal{P}(^{18}\mathrm{O})^{o_2} \begin{pmatrix} s \\ s_0, s_1, s_2, s_4 \end{pmatrix} \mathcal{P}(^{32}\mathrm{S})^{s_0} \mathcal{P}(^{33}\mathrm{S})^{s_1} \mathcal{P}(^{34}\mathrm{S})^{s_2} \mathcal{P}(^{36}\mathrm{S})^{s_4}$$



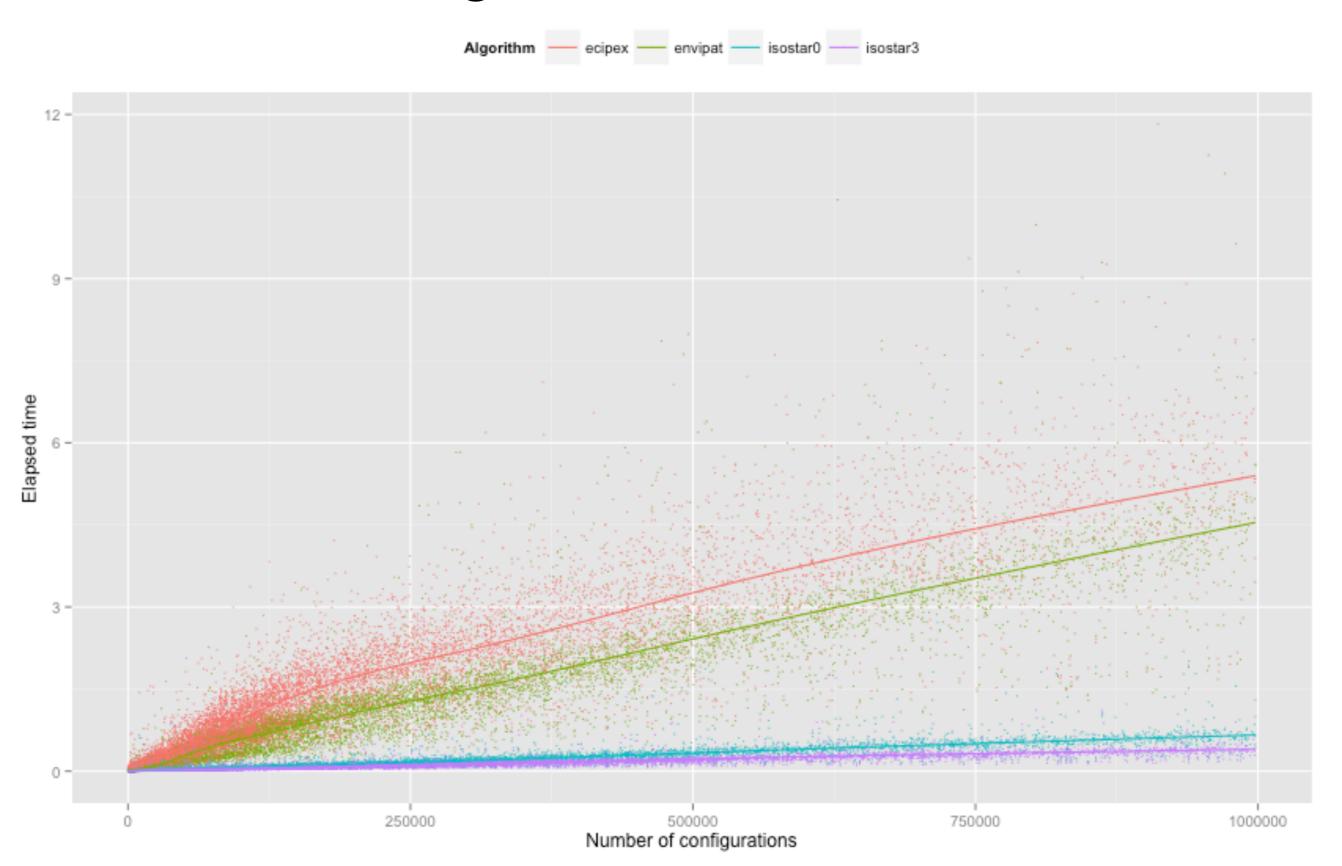
our OPTIMAL implementation uses

complexity

- queue for storing subsequent layers O(n)
- a version of quick select for trimming O(n)
- other tricks O(n)

O(n) in the total number of configurations

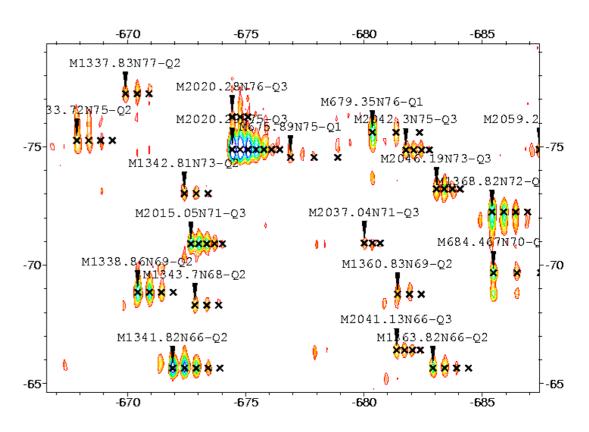
We provide theoretical background and get better run times

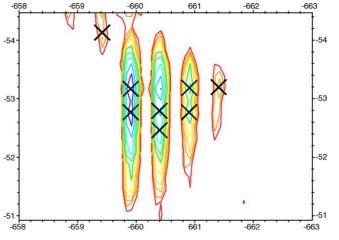


proteolytic fragmentation

LC-MS/MS

- data for colorectal cancer patients and healthy donors
- ca 1000 peptides
- preprocessing: spectra interpretation and retention time aligning









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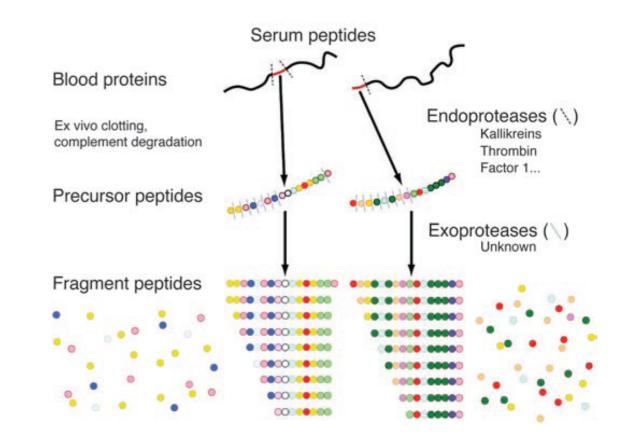


Automated reduction and interpretation of multidimensional mass spectra for analysis of complex peptide mixtures

Anna Gambin a*, Janusz Dutkowski a, Jakub Karczmarski b, Bogusław Kluge a, Krzysztof Kowalczyk a, Jerzy Ostrowski b, Jarosław Poznański c, Jerzy Tiuryn a, Magda Bakun c, Michał Dadlez c, d

Exopeptidase activity

- motivation: differential exoprotease activities contribute to cancer type—specific serum peptidome degradation
- our goal: first formal model estimated from LC-MS/MS data



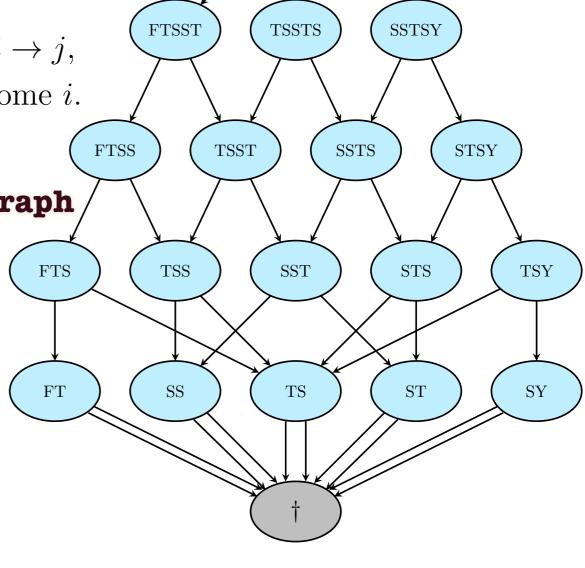
Villanueva, J., Nazarian, A., Lawlor, K., et al. 2008. A sequence-specific exopeptidase activity test (sseat) for "functional" biomarker discovery. *Mol. Cell. Proteomics* 7, 509–518.

Cleavage graph

$$Q(x, x') = \begin{cases} a_{\star i} & \text{if } x'_i = x_i + 1, \ x'_{-i} = x_{-i} \text{ for some } i, \\ a_{r(i,j)}x_i & \text{if } x'_j = x_j + 1, \ x'_i = x_i - 1, \\ & \text{and } x'_{-i-j} = x_{-i-j} \text{ for some } i \to j, \\ a_{i\dagger}x_i & \text{if } x'_i = x_i - 1, \ x'_{-i} = x_{-i} \text{ for some } i. \end{cases}$$

transition intensities for Markov process describing the flow of particles through the graph i.e. the process of peptidome degradation

$$Q(x,x') = egin{cases} a_{\star i} & ext{create} \ a_{r(i,j)}x_i & ext{move} \ \ a_{i\dagger}x_i & ext{annihilate/degrade} \end{cases}$$



FTSSTS

in equilibrium

Proposition 1 (Equilibrium distribution). The process (X(t)) has the equilibrium (stationary) distribution π given by:

$$\pi(x) = \prod_{i \in \mathcal{V}} e^{\lambda_i} \frac{\lambda_i^{x_i}}{x_i!},$$

where the configuration of intensities $(\lambda_i)_{i \in \mathcal{V}}$ is the unique solution to the following system of "balance" equations:

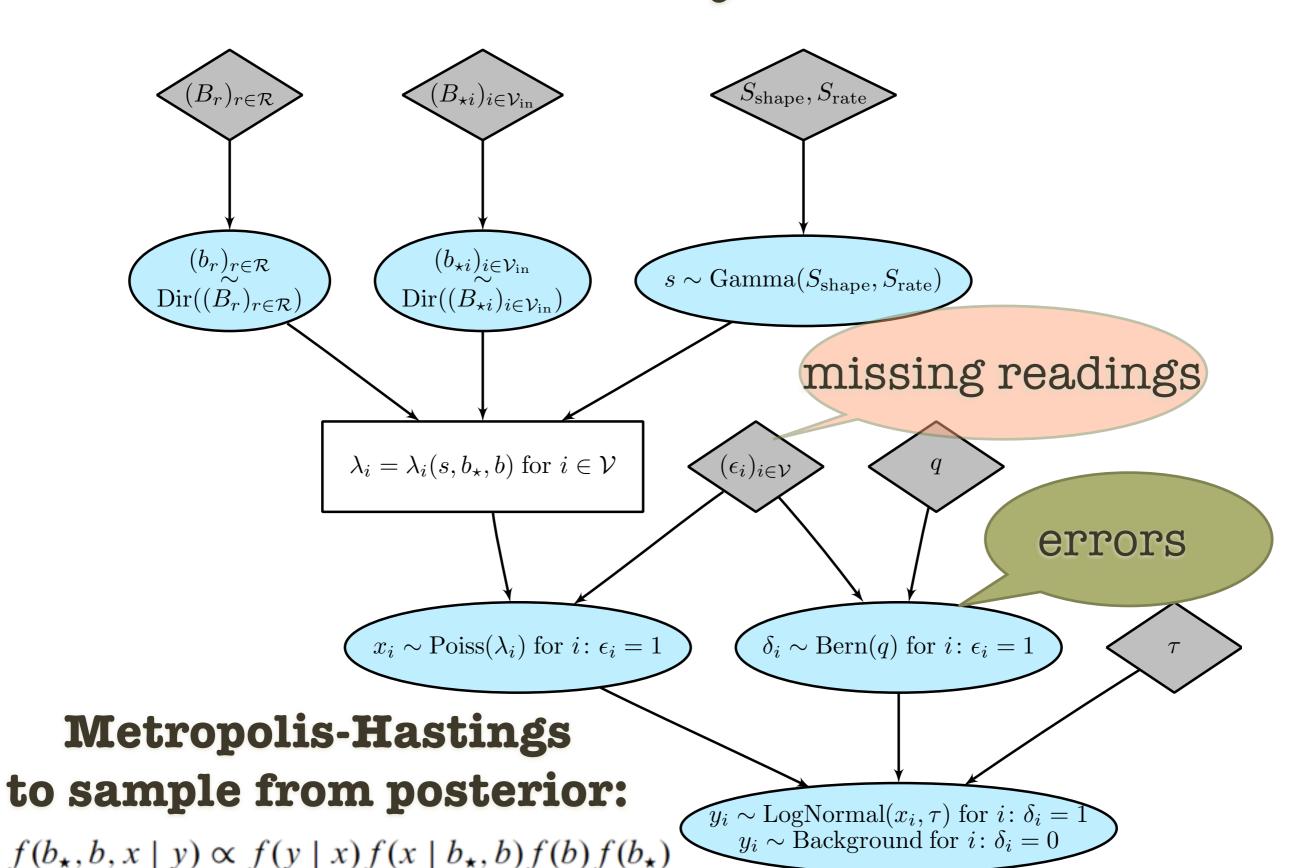
$$\sum_{k \to i} \lambda_k a_{r(k,i)} + a_{\star i} = \lambda_i \left(\sum_{i \to j} a_{r(i,j)} + a_{i\dagger} \right) \quad \text{for every } i \in \mathcal{V}.$$

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old as the hills, but...

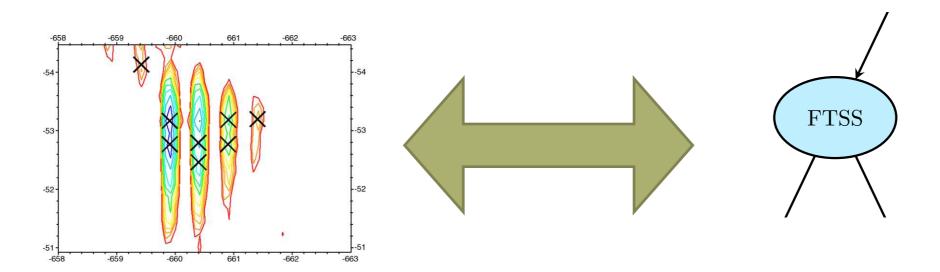
Modeling Exopeptidase Activity from LC-MS Data

hierarchical Bayesian model



NON TRIVIAL TASK: filling the cleavage graph with real data

- 1000 peptides: mass, charge, retention time
- 243 precursor peptides
- ca. 40 000 subsequences
- from aa sequence: calculate mass
- consider all charges
- predict retention time (random forests)



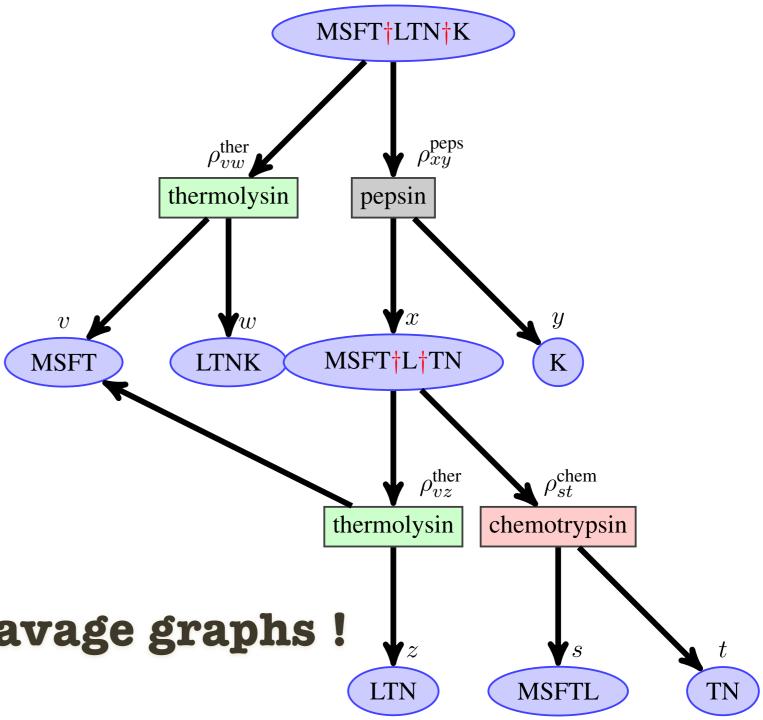
quite often: missing reads and errors!

Cleavage graph for real proteolytic events

 20 colorectal cancer patients and 20 healthy donors,

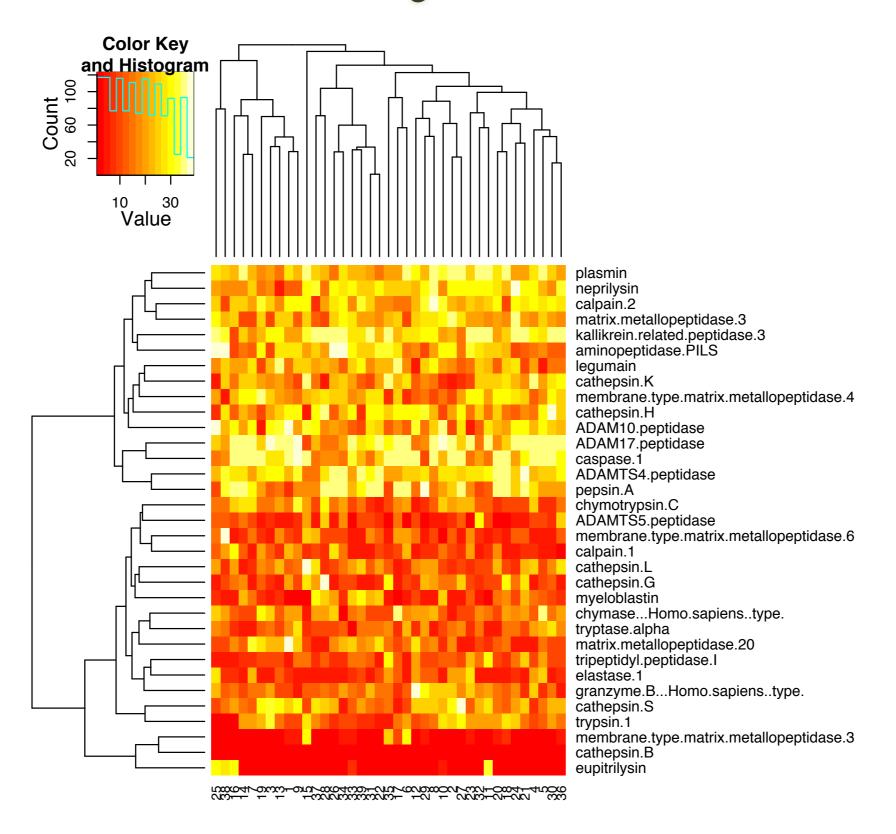
ca 1000 peptides,

preprocessing phase



MUCH SMALLER cleavage graphs!

identified enzymes make sense!



MSFT†LTN†K

pepsin

MSFT†L†TN

thermolysin

LTN

 $\rho_{st}^{\rm chem}$

chemotrypsin

MSFTL

stochastic dynamics in time



 ρ_{vw} the vector of all peptidase affinity coefficients for the cleavage $v \dagger w$

$$Q_{xx'} = \begin{cases} \mathbf{c^T} \rho_{vw} x_u & \text{if } x' = x - \epsilon_u + \epsilon_v + \epsilon_w \text{ and } u = v \dagger w ,\\ 0 & \text{otherwise.} \end{cases}$$

peptidase cutting intensities vector

to be estimated:

$$P(x,t) = \mathcal{P}(X(t) = x)$$
. calculated from

no more monomolecular system we have reactions:

thermolysin

LTNK

MSFT

 $\frac{\partial}{\partial t}P(x,t) = \sum (Q_{yx}P(y,t) - Q_{xy}P(x,t))$ CME

$$= \sum_{v} c^{\mathrm{T}} \rho_{vw} \left[(x_u + 1) P(x + \epsilon_u - \epsilon_v - \epsilon_w, t) - x_u P(x, t) \right]$$

A -> B and A-> B+C (endopeptidases) $u=v\dagger w$

$$= \sum_{u=v \dagger w} c^{\mathrm{T}} \rho_{vw} [x_u' P(x',t) - x_u P(x,t)],$$

$$\frac{\partial}{\partial t}P(x,t) = \sum_{y \neq x} (Q_{yx}P(y,t) - Q_{xy}P(x,t))$$

$$= \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \left[(x_u + 1)P(x + \epsilon_u - \epsilon_v - \epsilon_w, t) - x_u P(x,t) \right]$$

$$= \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \left[x_u' P(x',t) - x_u P(x,t) \right],$$

where $x' = x + \epsilon_u - \epsilon_v - \epsilon_w$, i.e. x' denotes a configuration before the cleavage $v \dagger w$.

$$\begin{split} \mathbf{E}_{q}\left(t\right) &= \sum_{x} x_{q} P(x,t), \\ \frac{d}{dt} \, \mathbf{E}_{q}\left(t\right) &= \sum_{x} x_{q} \frac{\partial}{\partial t} P(x,t) \\ &= \sum_{x} x_{q} \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \left[(x_{u}+1) P(x+\epsilon_{u}-\epsilon_{v}-\epsilon_{w},t) - x_{u} P(x,t) \right] \\ &= \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \left[\sum_{x} x_{q}(x_{u}+1) P(x+\epsilon_{u}-\epsilon_{v}-\epsilon_{w},t) - \sum_{x} x_{q} x_{u} P(x,t) \right] \\ &= \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \left[\sum_{x} (x-\epsilon_{u}+\epsilon_{v}+\epsilon_{w})_{q} x_{u} P(x,t) - \sum_{x} x_{q} x_{u} P(x,t) \right] \\ &= \sum_{u=v \uparrow w} c^{\mathrm{T}} \rho_{vw} \sum_{x} (-\epsilon_{u}+\epsilon_{v}+\epsilon_{w})_{q} x_{u} P(x,t). \end{split}$$

$$\frac{d}{t} E_{q}(t) = \sum_{u=q\dagger w} c^{T} \rho_{qw} E_{u}(t) + \sum_{u=v\dagger q} c^{T} \rho_{vq} E_{u}(t) - \sum_{q=v\dagger w} c^{T} \rho_{vw} E_{q}(t)$$

Denote by λ_{uq} the intensity of creating q from u by a single cleavage of the form $u = q \dagger w$ or $u = v \dagger q$, i.e. $\lambda_{uq} = c^{\mathrm{T}}(\rho_{qw} + \rho_{vq})$. Let $\lambda_{qq} = -\sum_{q=v\dagger w} c^{\mathrm{T}}\rho_{vw}$, i.e. minus the intensity of consuming q in all cleavages involving this peptide. Note that the following equality holds:

$$\lambda_{qq} = -\frac{1}{2} \left[\sum_{q=v \dagger w} \lambda_{qv} + \sum_{q=z \dagger v} \lambda_{qv} - \sum_{\substack{q=v \dagger w \\ q=z \dagger v}} \lambda_{qv} \right] = -\frac{1}{2} \sum_{q \to v} \lambda_{qv}.$$

Now the equations (4.2) have the following form:

$$\left[\frac{d}{dt} \operatorname{E}_{q}(t) = \sum_{u \to q} \lambda_{uq} \operatorname{E}_{u}(t) + \lambda_{qq} \operatorname{E}_{q}(t)\right]_{q \in \mathcal{V}}.$$
(4.3)

The solution of the system of linear constant coefficient ordinary differential equations like (4.3) is given by:

$$\mathbf{E}(t) = \mathbf{E}(0)^{\mathrm{T}} \exp(\Lambda t), \tag{4.4}$$

interesting moments...

 $E_q(t)$ the expected number of instances of peptide q at time t.

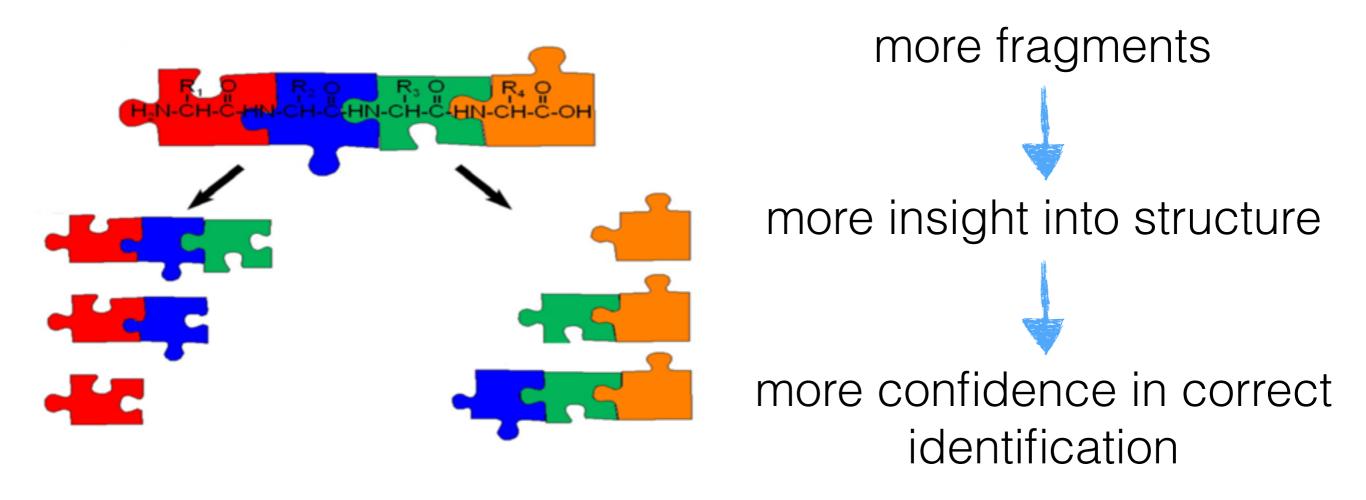
$$\mathbf{E}_{q}(t) = \sum_{x} x_{q} P(x, t),$$

$$\begin{bmatrix} \frac{\partial}{\partial t} \mathbf{E}_{q}(t) = \sum_{u \to q} \lambda_{uq} \mathbf{E}_{u}(t) + \lambda_{qq} \mathbf{E}_{q}(t) \end{bmatrix}_{q \in \mathbf{V}}$$

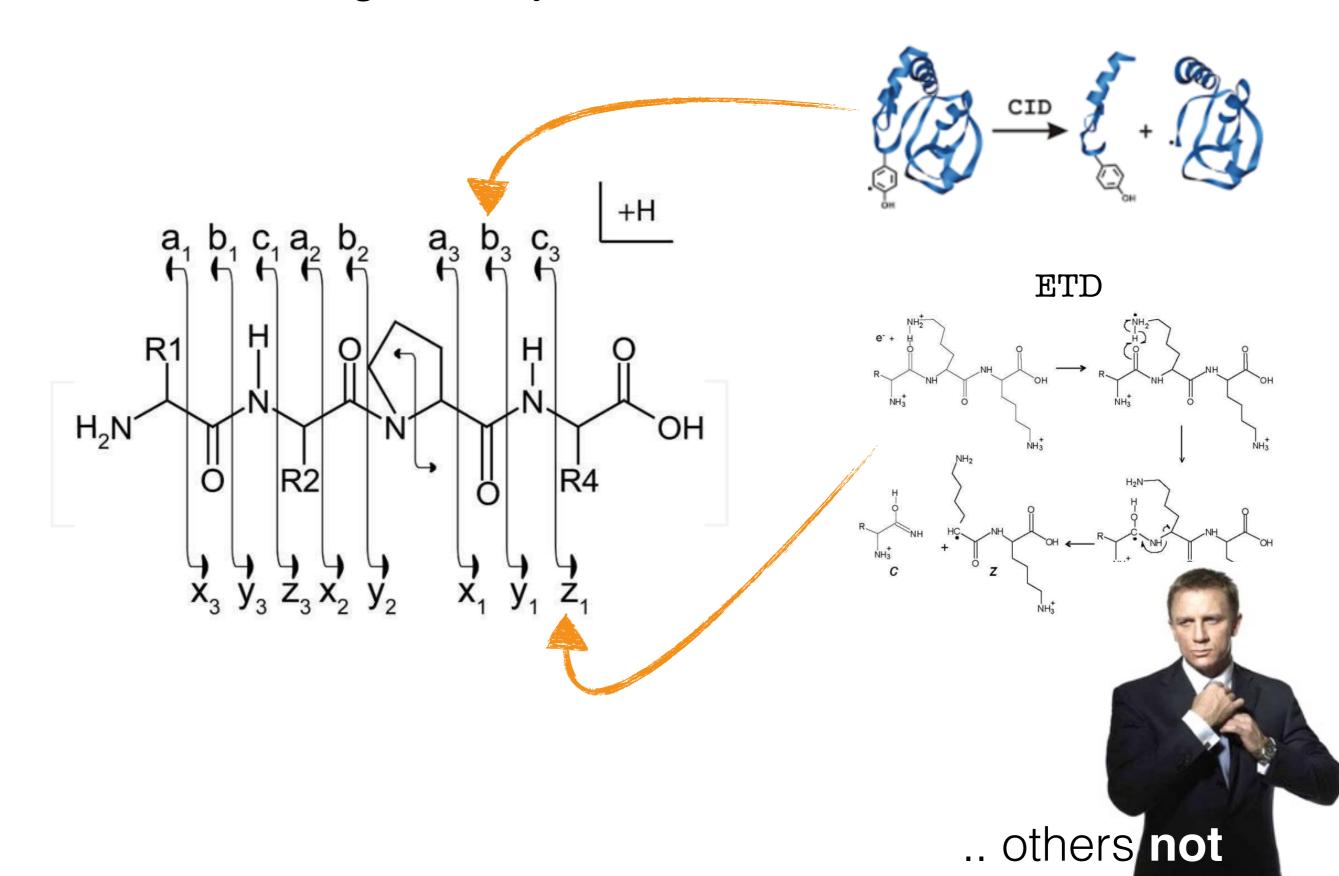
$$\mathbf{E}(t) = \mathbf{E}(0)^{\mathrm{T}} \exp(\Lambda t)$$

matrix $\Lambda = (\lambda_{vw})_{v,w \in \mathcal{V}}$ for peptide VAHRFKDLGEEN

ETD fragmentation

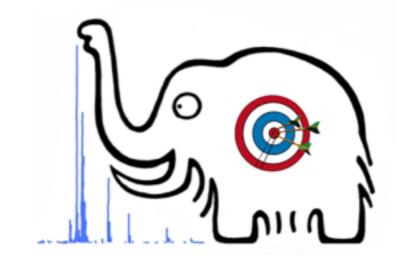


some bonds get easily broken



the goal of masstodon

understand fragmentation inside the instrument under different experimental conditions



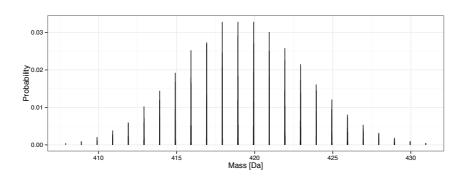
solution:

use purified chemical samples study fragmentation pathways locate fragments in data

- 1. deconvolute signals and
- 2. infer fragmentation reaction constants

using atomic compositions of the fragments we generate isotopic spectra with





we can aggregate masses to match data resolution

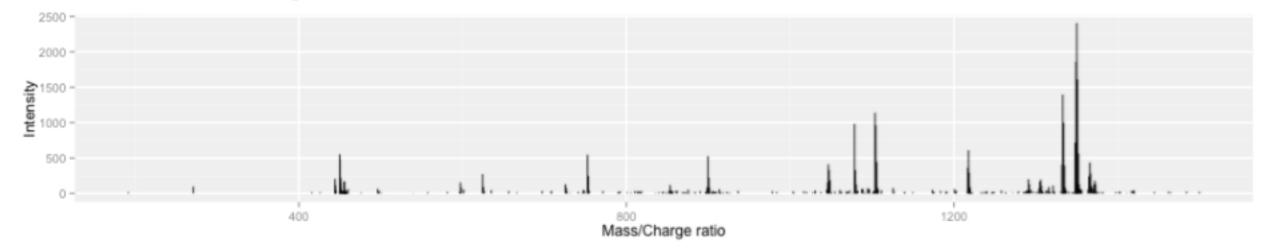
complications

we take into account charges

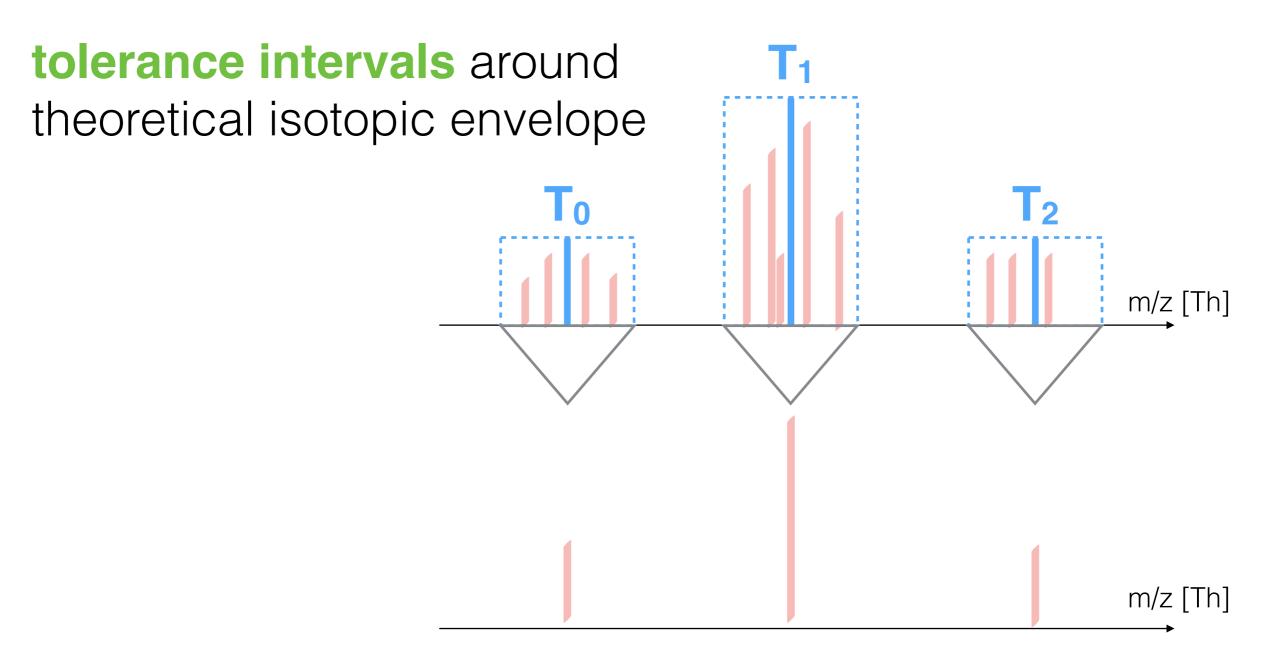
♣ ETD $[M+nH]^{n+} + A^{--} \longrightarrow [C+xH]^{x+} + [Z+(n-x)H]^{(n-x-1)-} + A$ ♦ PTR $[M+nH]^{n+} + A^{--} \longrightarrow [M+(n-1)H]^{(n-1)+} + AH$ ♥ ETnoD $[M+nH]^{n+} + A^{--} \longrightarrow [M+nH]^{(n-1)+-} + A$ ♠ HTR $[C+xH]^{x+} \longrightarrow [C+(x-1)H]^{x+-}$ $[Z+(n-x)H]^{(n-x-1)-} \longrightarrow [Z+(n-x+1)H]^{(n-x-1)}$

$$\begin{array}{c} \text{R} \\ \text{NH}_{2} \\ \text{R} \\ \text{NH}_{3} \\ \text{NH}_{3} \\ \text{NH}_{4} \\ \text{NH}_{3} \\ \text{NH}_{4} \\ \text{NH}_{5} \\ \text{NH}_{5}$$

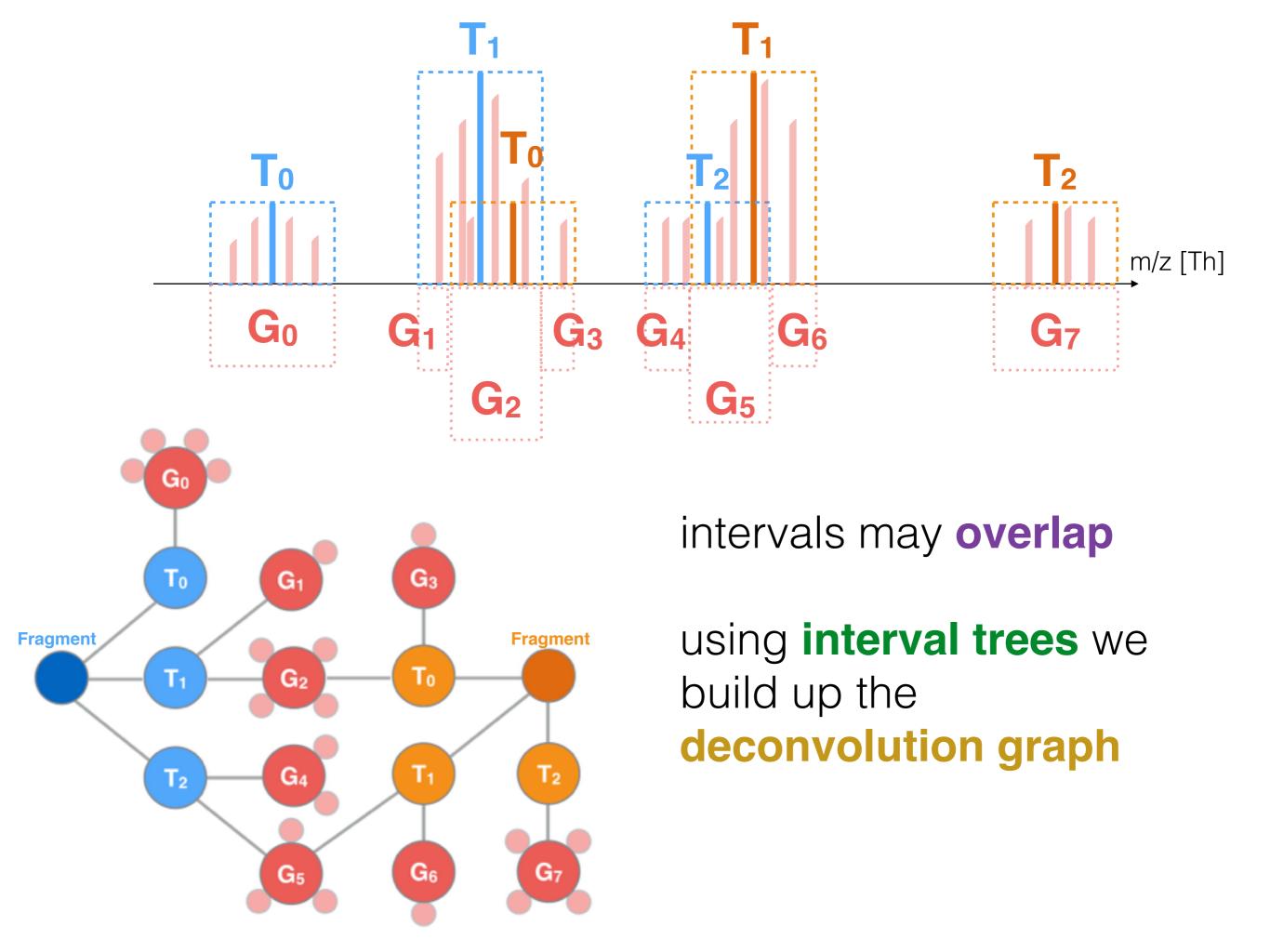
... and imprecisions in instrumental mass calibration

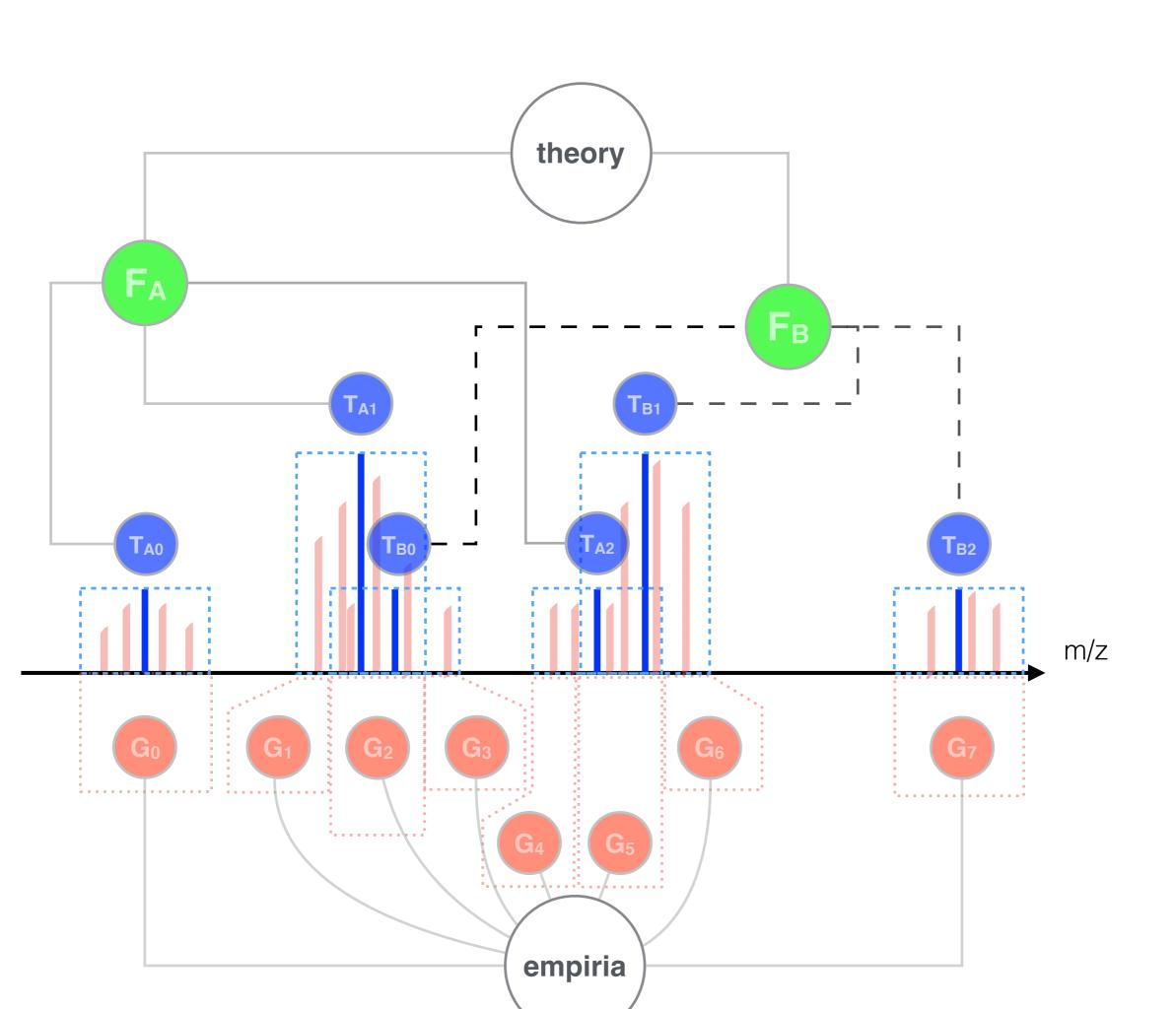


mass imprecisions

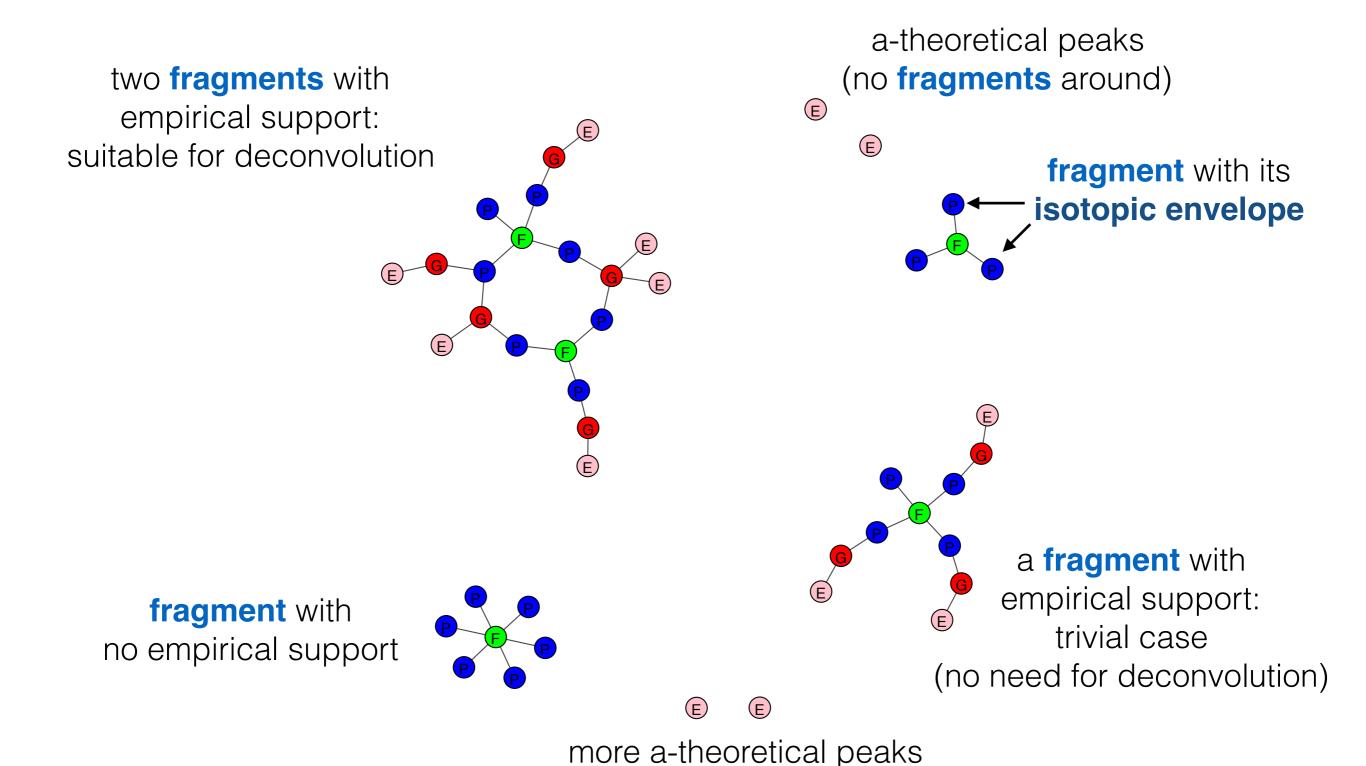


natural data centroiding

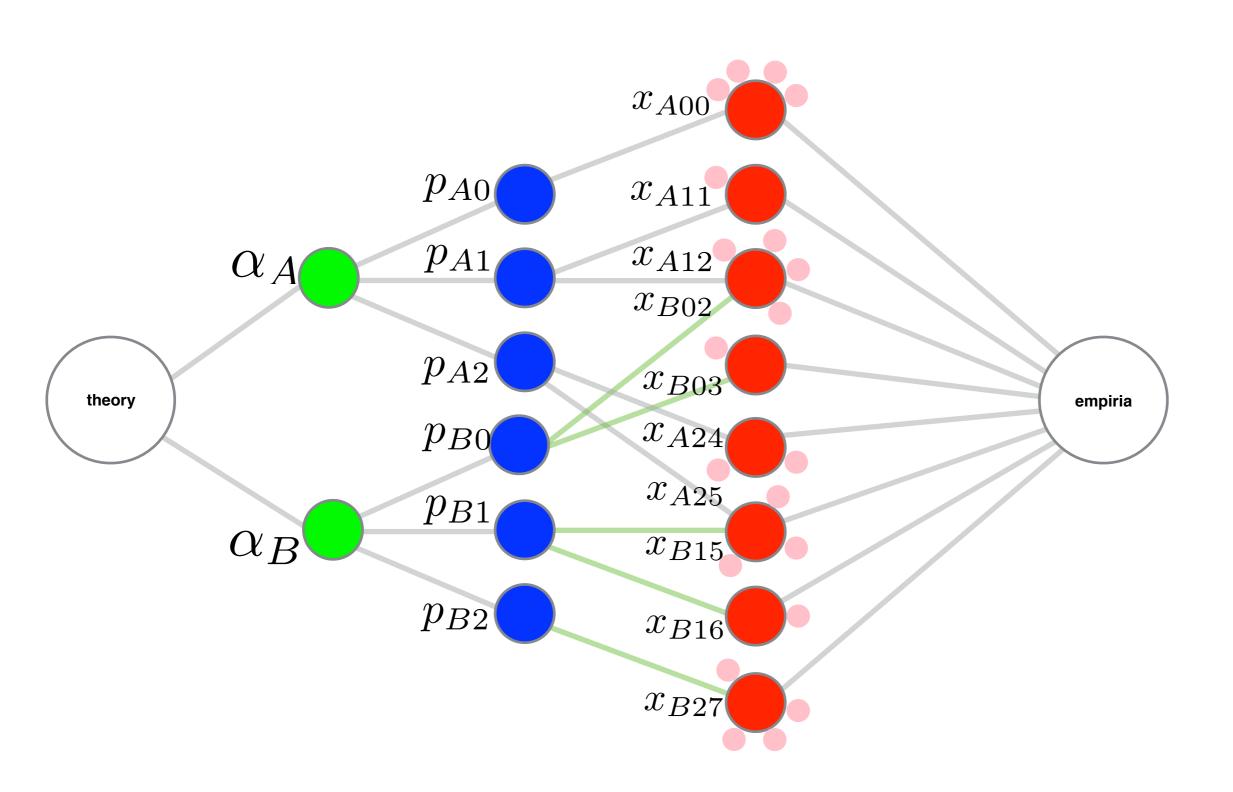




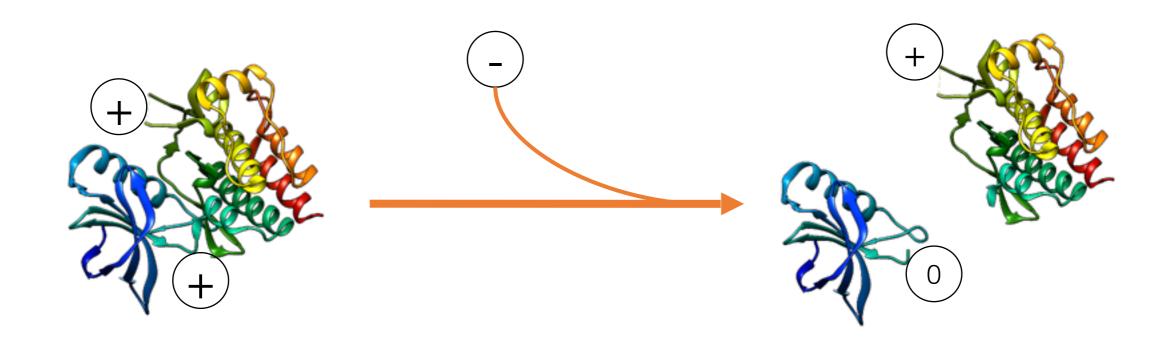
connected components of the deconvolution graph provide a wealth of insight into the spectrum



to perform deconvolution we present the problem as a linear programme similar to the max flow problem

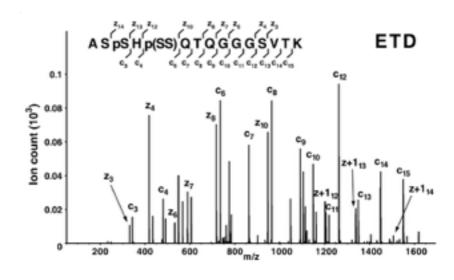


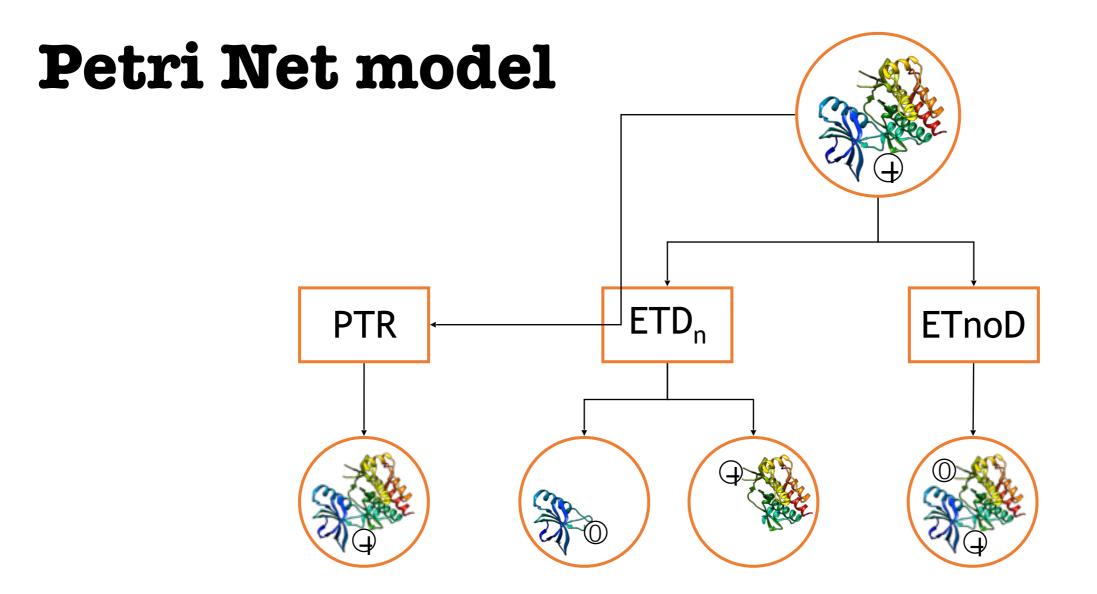
Electron Transfer Dissociation



Cleavage of protein backbone by a rapid neutralization of charge

- To identify proteins
- To sequence proteins de novo
- To identify post-translational modifications





• Electron Transfer Dissociation (ETD):

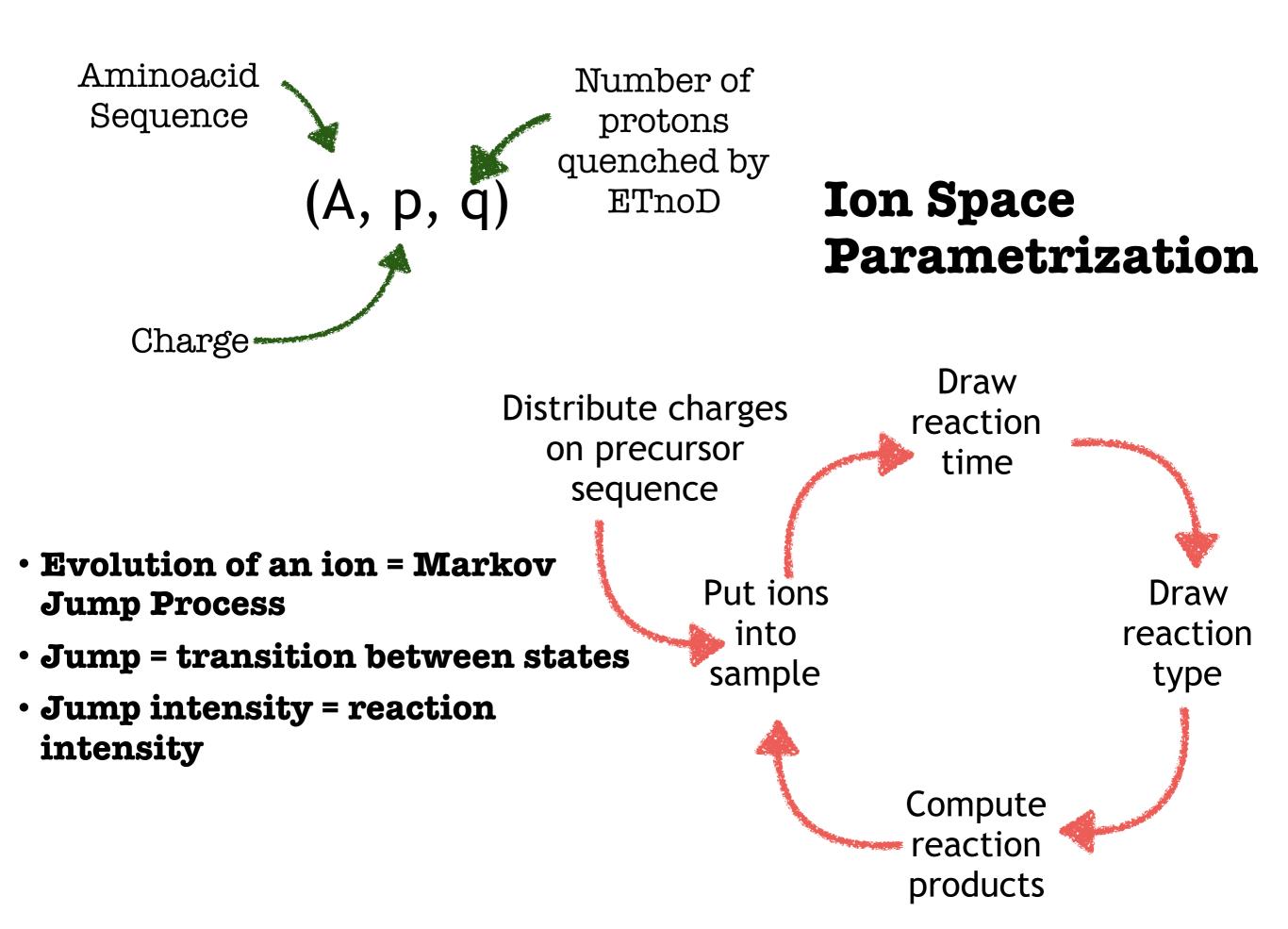
$$[M + nH]^{n+} \rightarrow [M_1 + n_1H]^{n1+} + [M2 + n_2H]^{n2+}$$

Proton Transfer Reaction (PTR):

$$[M + nH]^{n+} \rightarrow [M + (n-1)H]^{(n-1)+}$$

• Electron Transfer Without Dissociation (ETnoD):

$$[M + nH]^{n+} \rightarrow [M + nH]^{(n-1)+}$$



Population approach

Stochastic description of a single ion



ODE description of a big population of ions

- •• $x_v(t)$: average number of v molecules at time t
 - P: set of input (parent) transitions
 - *D*: set of output (daughter) transitions
 - v(r): substrate ion for reaction r
 - $I_r = Ip_{v(r)}^2 P_r$: intensity of reaction r

$$\dot{x}_v(t) = \sum_{p \in P} I_p x_{v(p)}(t) - \sum_{d \in D} I_d x_v(t)$$

Tree-like structure

- Each ion has a unique parent (substrate) ion
 - Observe that a parent has +1 charge
 - No parents for the root! Can be solved analytically

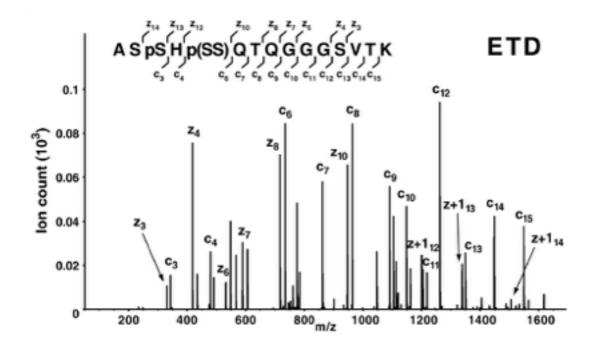
$$\dot{x}_R(t) = -Ip_R^2$$

$$x_R(t) = x_0 e^{-Ip_R^2 t}$$

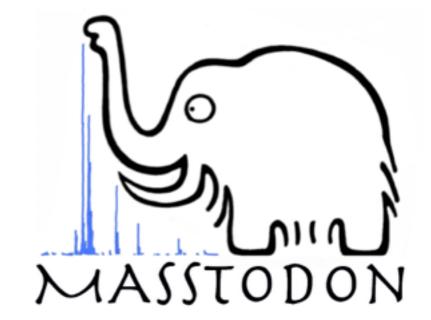
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$$x_v(t) = \sum_i A_i e^{-B_i t}$$

- A_i , B_i : coefficients dependent on parent transitions
- We have derived recursive formulas for them (also previously described by Gambin & Kluge)









Sequence	Charge	Electrons	Intensity
RPKPQQ	3	0	0.25
RPKP	1	1	0.01
PQQ	1	0	0.12
• • •	• • •	• • •	• • •

Intensity estimation

- Idea: find a set of intensities that best predicts the observed data
 - Solution: minimize the discrepancy with the BFGS algorithm

$$\min_{\theta} f(\theta) = d(P_{\theta}, 0) = \log \left(\sum_{(p,o) \in P_{\theta} \times 0} (p - o)^2 \right)$$

(θ : vector of intensities; P_{θ} : predicted ion proportions)

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