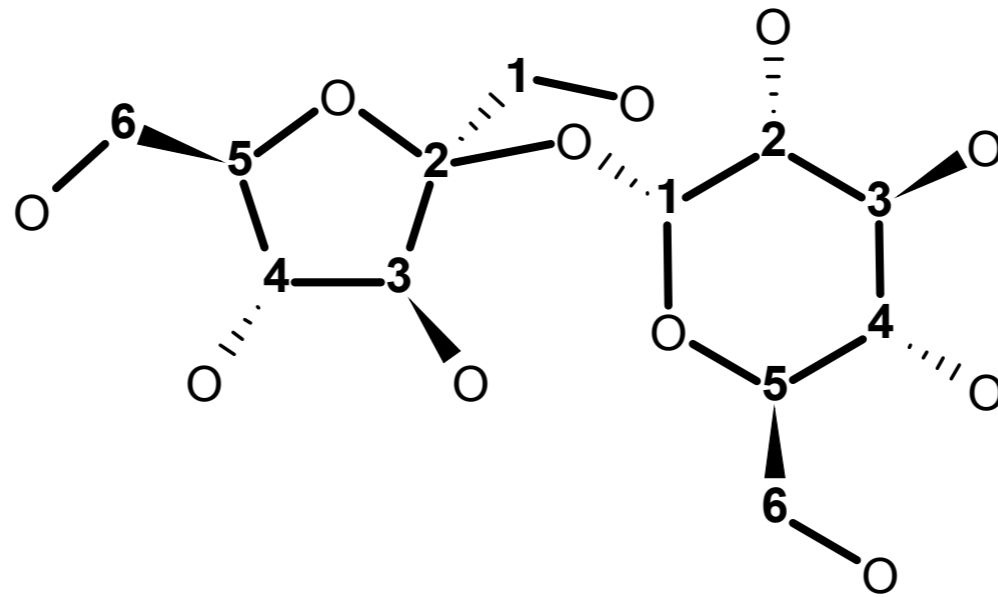


# INADEQUATE

Christopher Anand  
(with Alex Bain, Sean Watson, Anuroop Sharma)

# Small Molecules



- biological products
- possible medical applications
- want to know structure
- look at C-C bonds, double-quantum structure

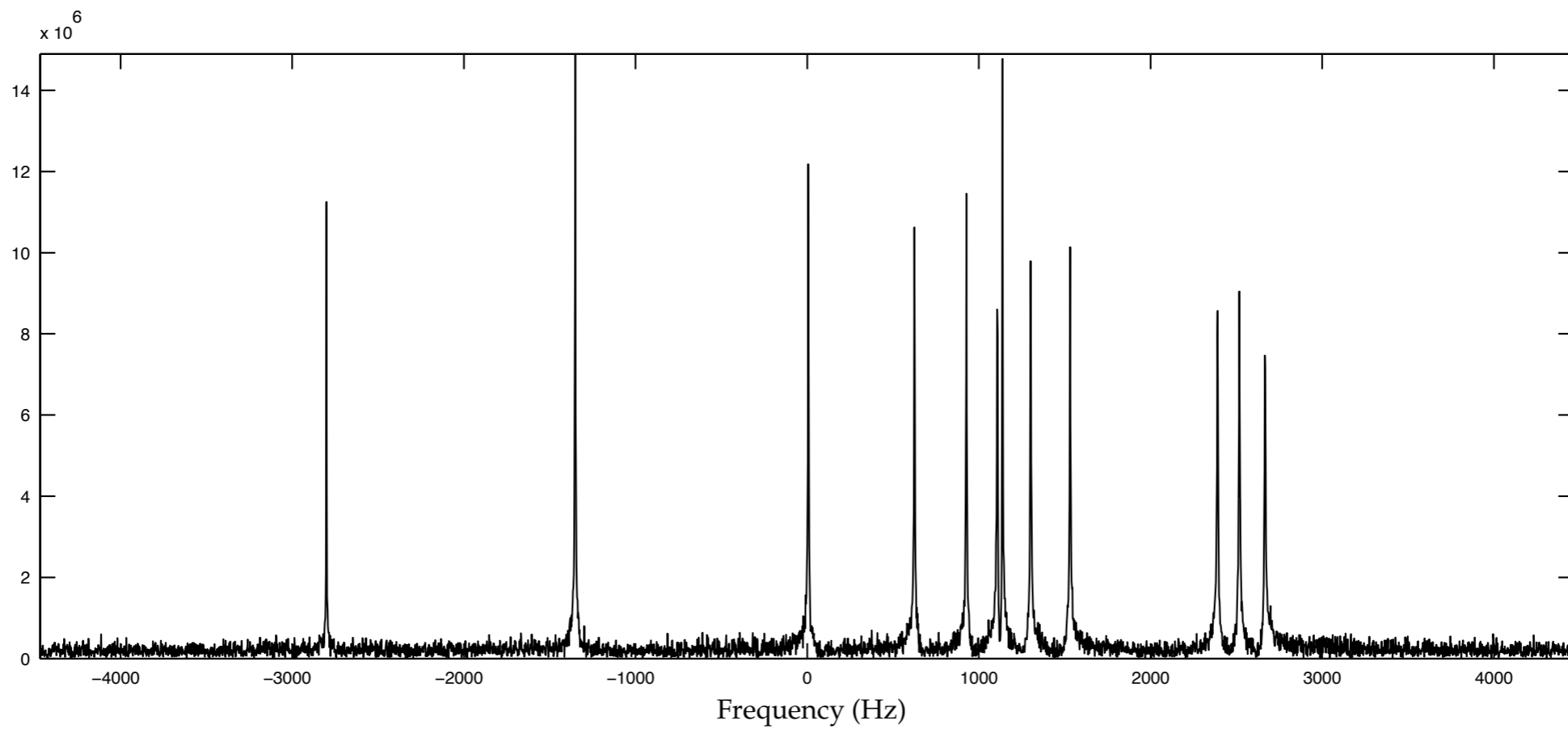
# Single Quantum

- Single Quantum = Bloch Equations
- Complex Form

$$\frac{d}{dt} \begin{pmatrix} \rho_{+1} \\ \rho_0 \\ \rho_{-1} \\ \rho_{eq} \end{pmatrix} = - \begin{pmatrix} i\omega + R_2 & i\frac{\gamma B_1}{\sqrt{2}} & 0 & 0 \\ i\frac{\gamma B_1}{\sqrt{2}} & R_1 & i\frac{\gamma B_1}{\sqrt{2}} & -R_1 \\ 0 & i\frac{\gamma B_1}{\sqrt{2}} & -i\omega + R_2 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \rho_{+1} \\ \rho_0 \\ \rho_{-1} \\ \rho_{eq} \end{pmatrix}$$

# Step I

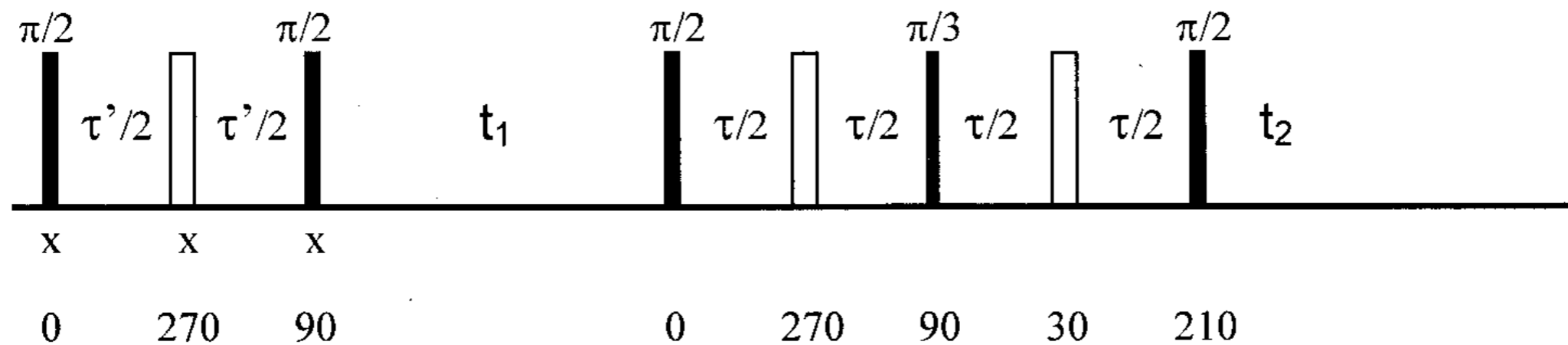
- measure C spectrum



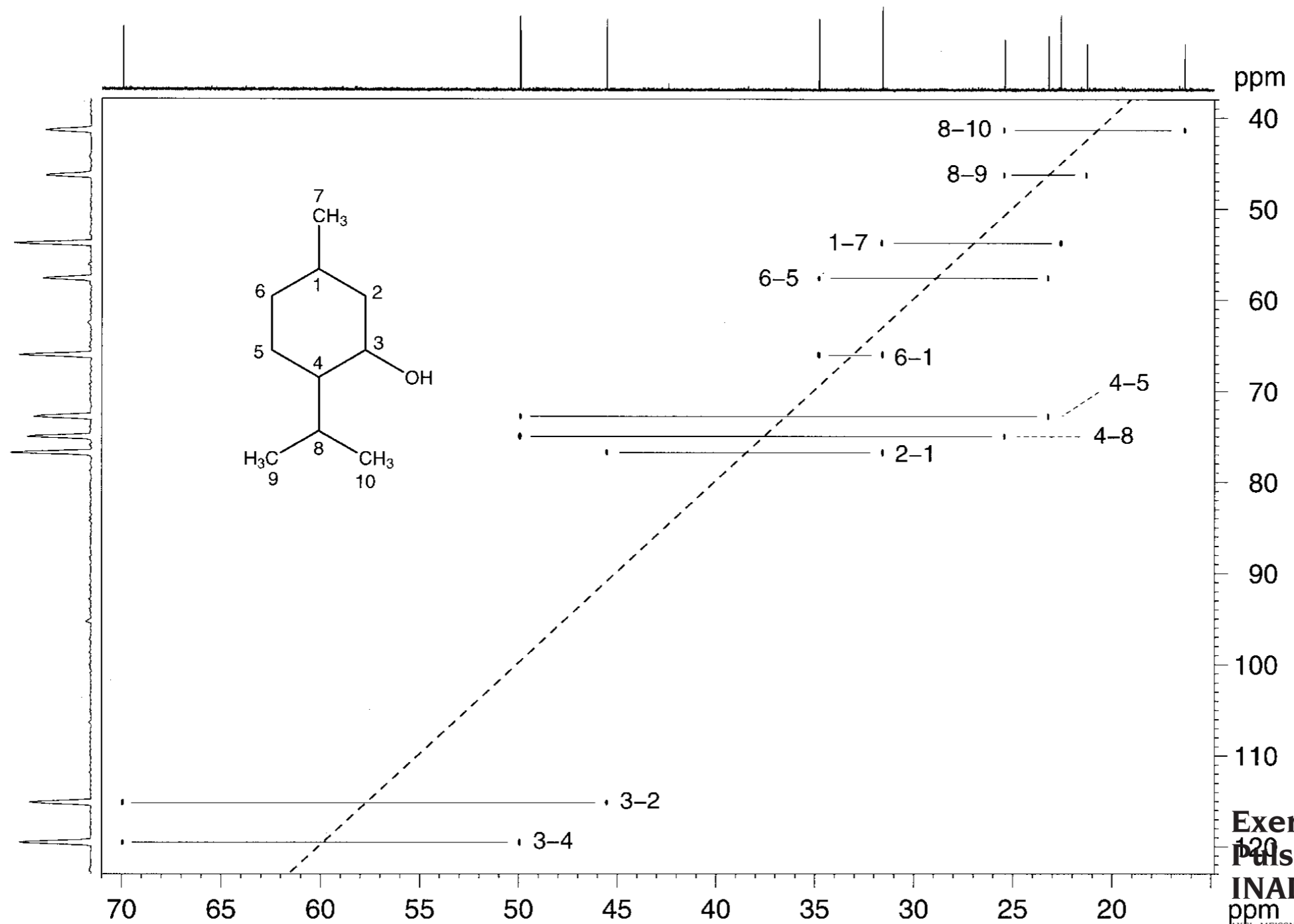


# Measure 2Q Quantum

- create 2Q spin
- let it evolve (delay 1)
- put it back into 1Q
- measure (readout 2)

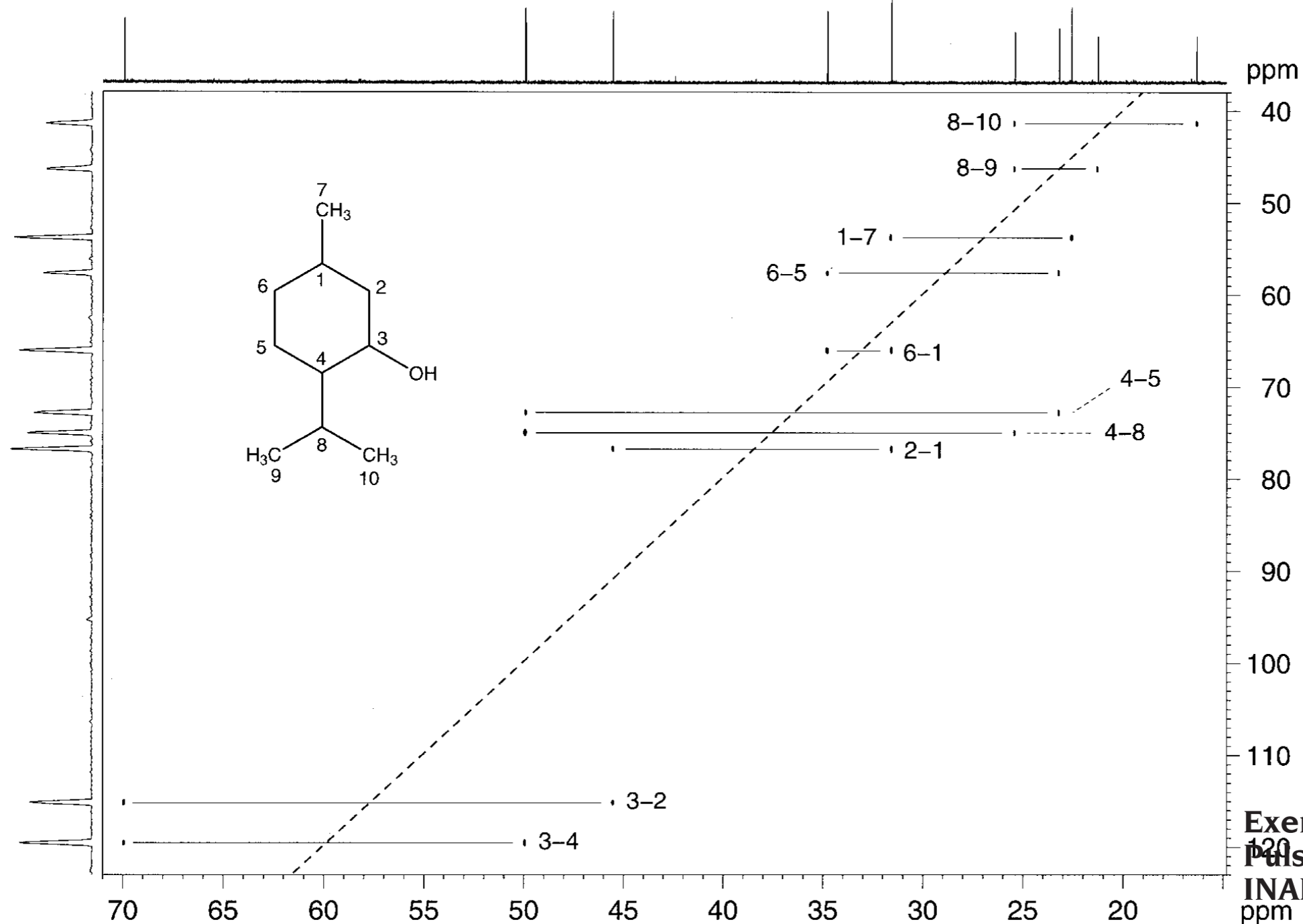


# Isolated Signal



# Isolated Signal

readout = directly acquired



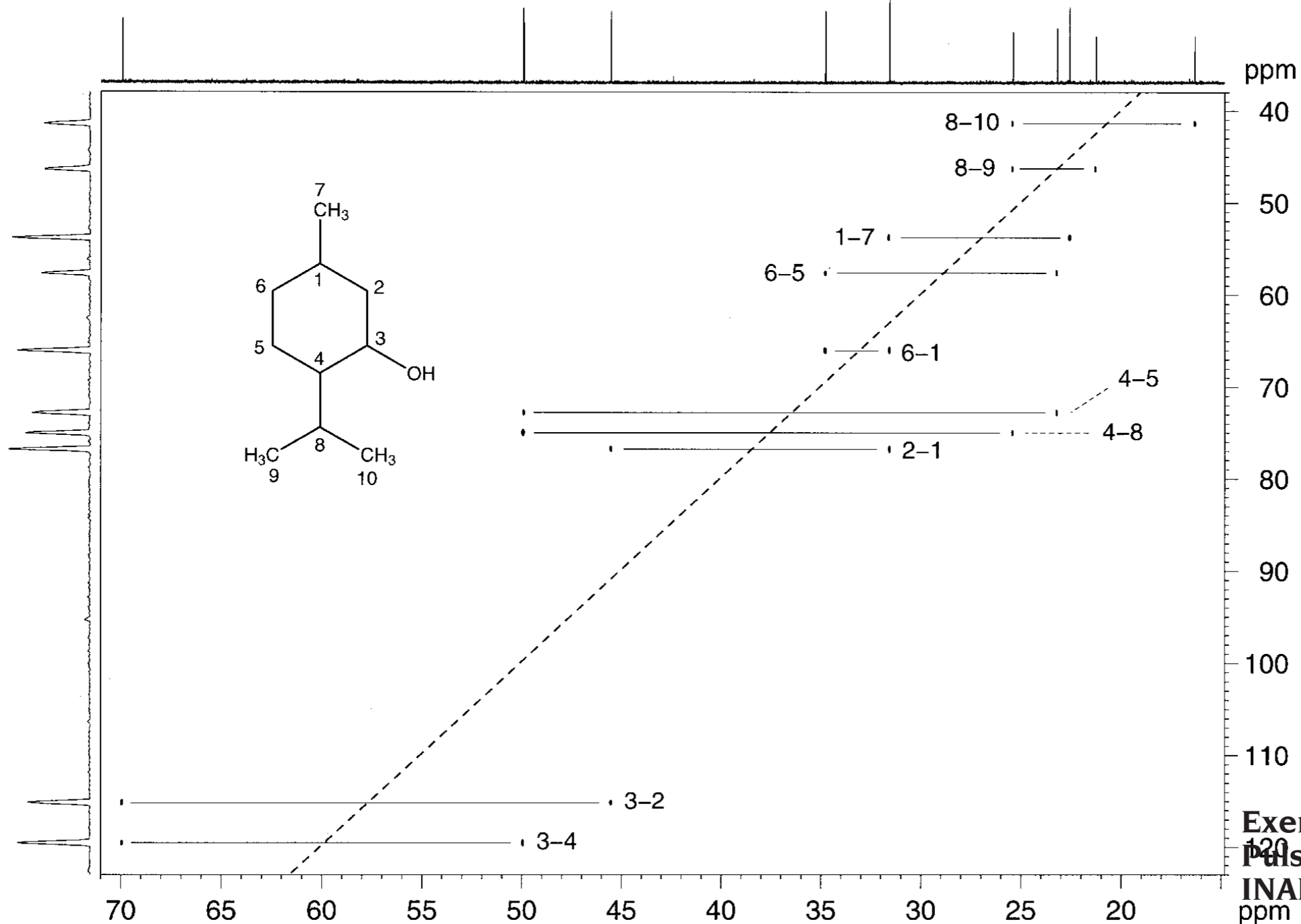
Exercise in Modern NMR  
Pulse Sequence Design:  
**INADEQUATE CR**  
ppm



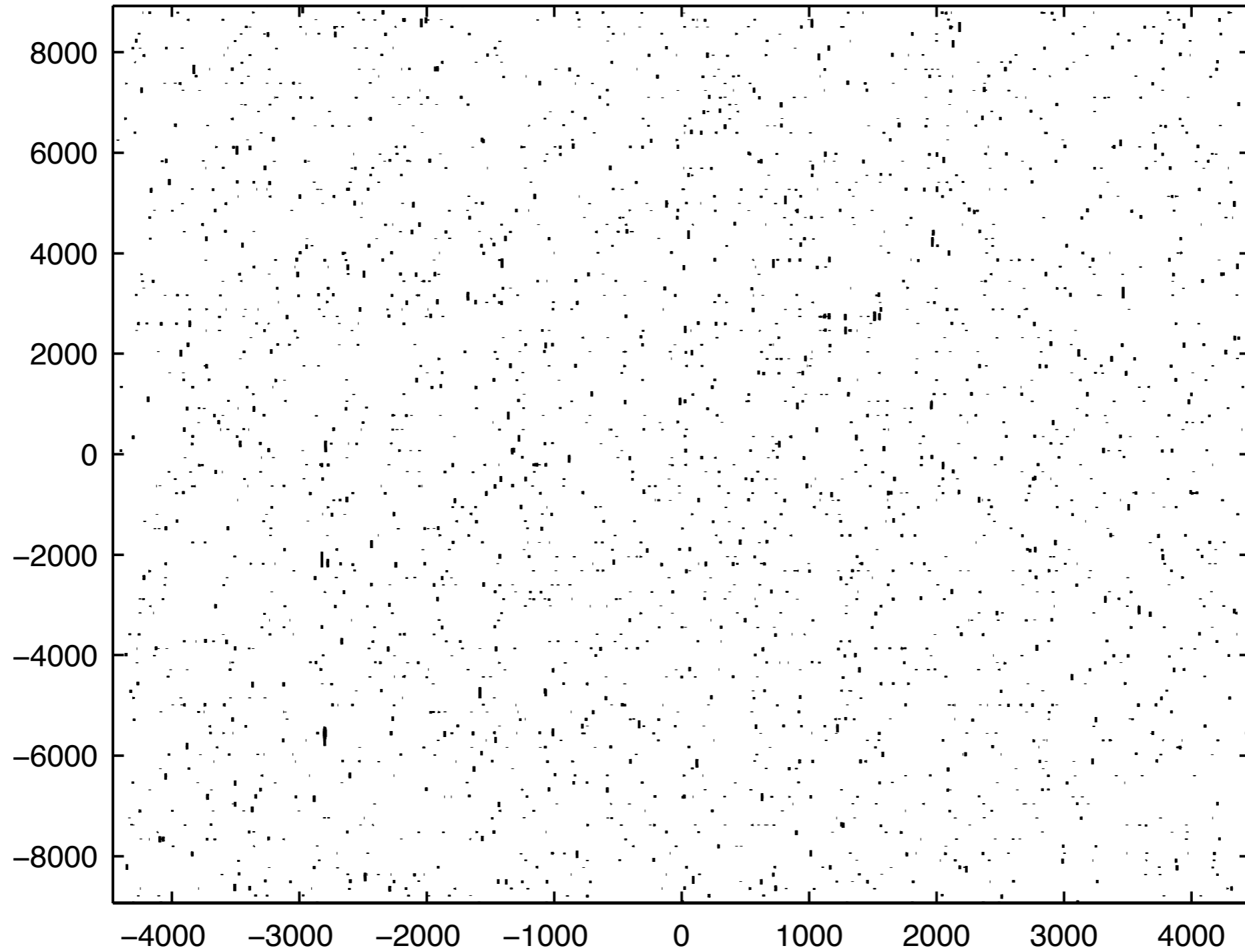
# Isolated Signal

readout = directly acquired

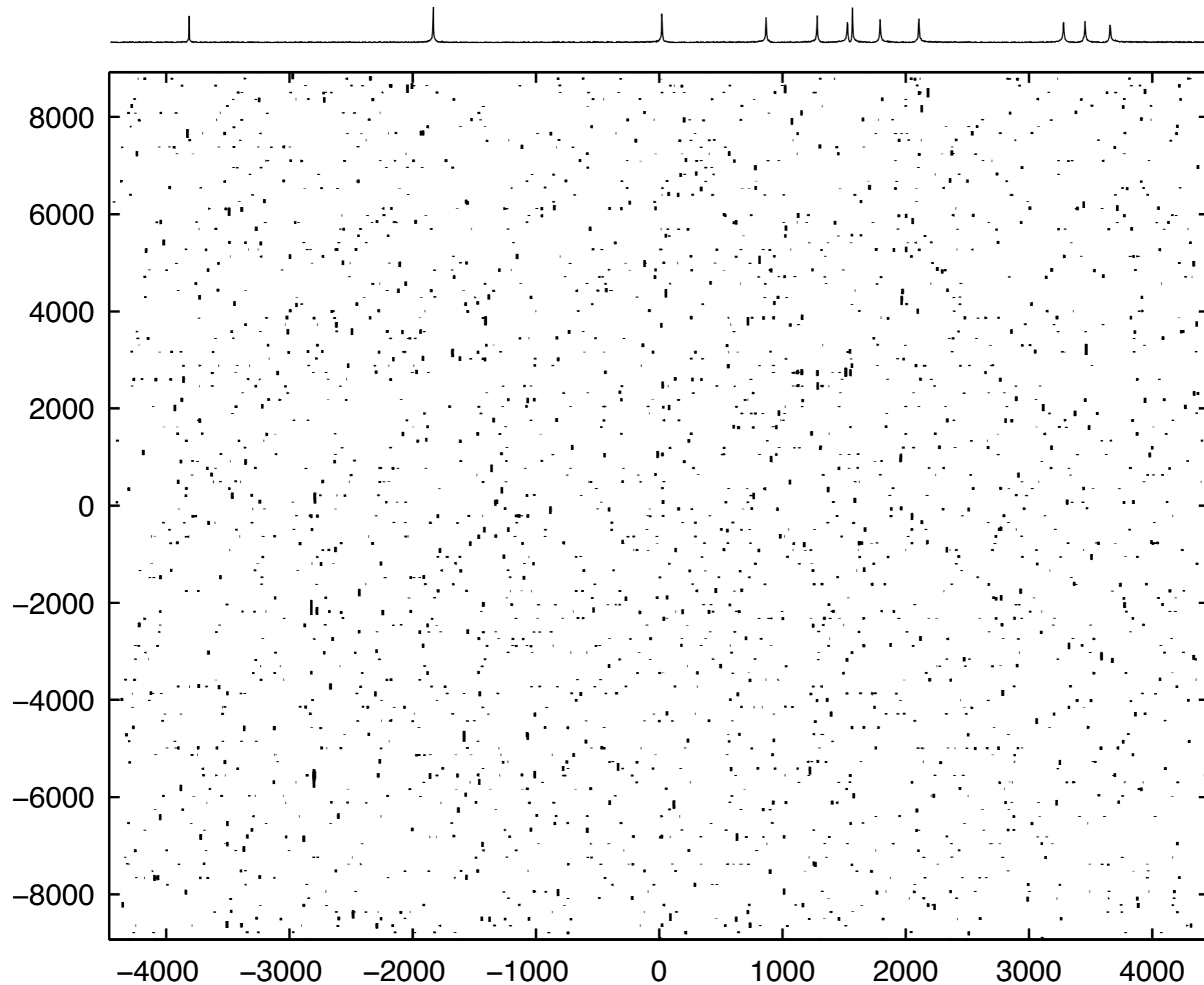
delay = indirectly acquired



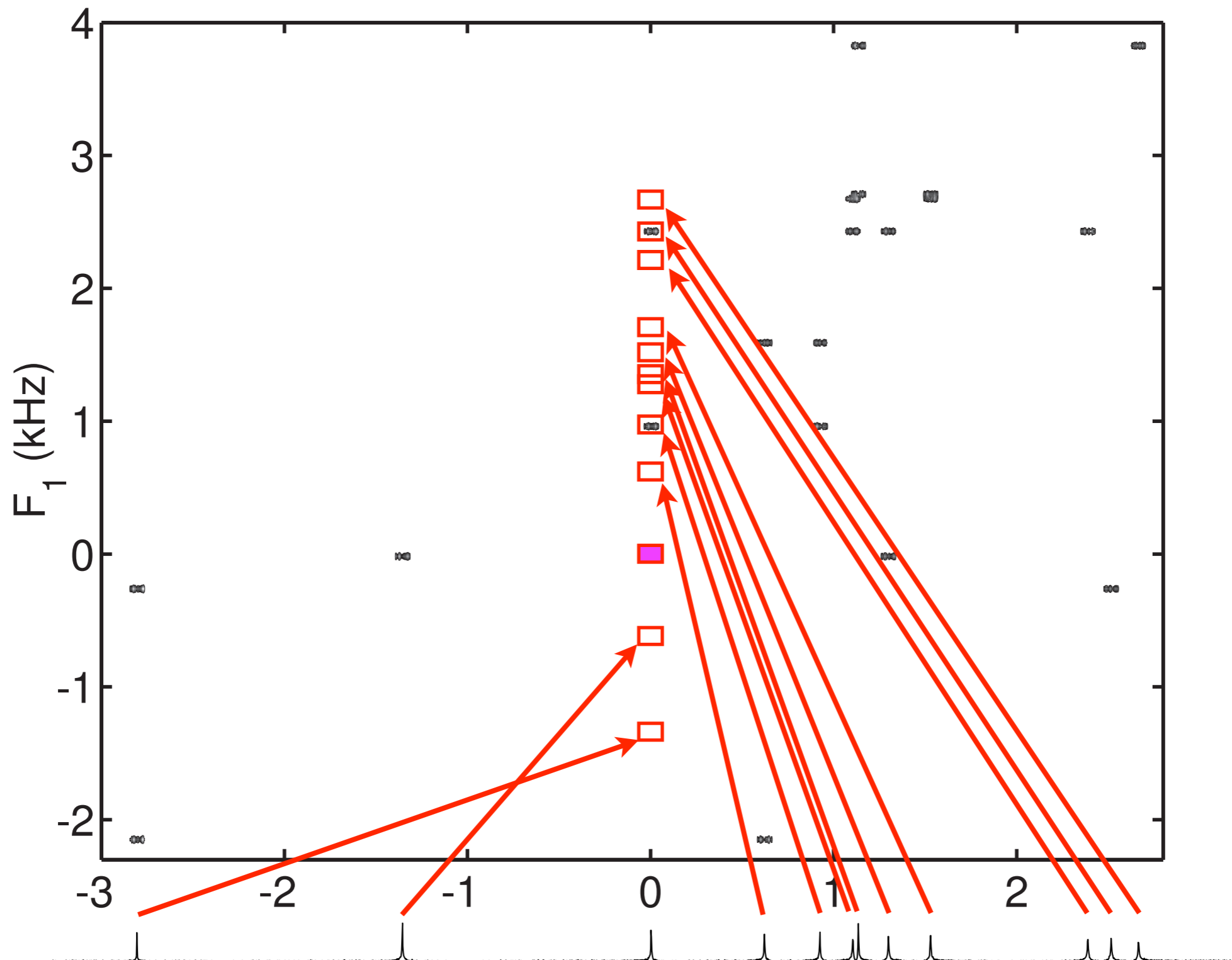
# Problem: Noise



# Problem: Noise



# Box the Signal $\mathcal{S}_{ij}$



$$\min \|m - \mathcal{S}\|^2 \quad (2)$$

$$+ \lambda_1 \|\delta_x \mathcal{S}\|^2 \quad (3)$$

$$+ \lambda_2 \sum_{ij} (1 - p_{ij})^2 \|\mathcal{S}_{ij} + \mathcal{S}_{ji}\|^2 \quad (4)$$

$$+ \lambda_3 \sum_{ij} (\|\mathcal{S}_{ij}\|^2 - \|\mathcal{S}_{ji}\|^2)^2 \quad (5)$$

$$+ \mu_1 \sum_i \left( 2 - \sum_{j \neq i} p_{ij} \right)^4 \quad (6)$$

$$+ \mu_2 \sum_{ij} p_{ij} \quad (7)$$

$$\text{s.t. } p_{ij} \geq 0 \quad (8)$$

$$p_{ij} \leq 1 \quad (9)$$

$$\|\delta_x \mathcal{S}\|^2 = \sum_i (s_i - s_{i+1})^2$$

s.t.  $s_i$  and  $s_{i+1}$  are horizontally adjacent in the same box

# Too Hard

- Non-quadratic + bi-quadratic terms
- takes too long to solve
- solve alternately for  $S$  and  $p$  (Gauss-Seidel)

# Solve for $\mathcal{S}$

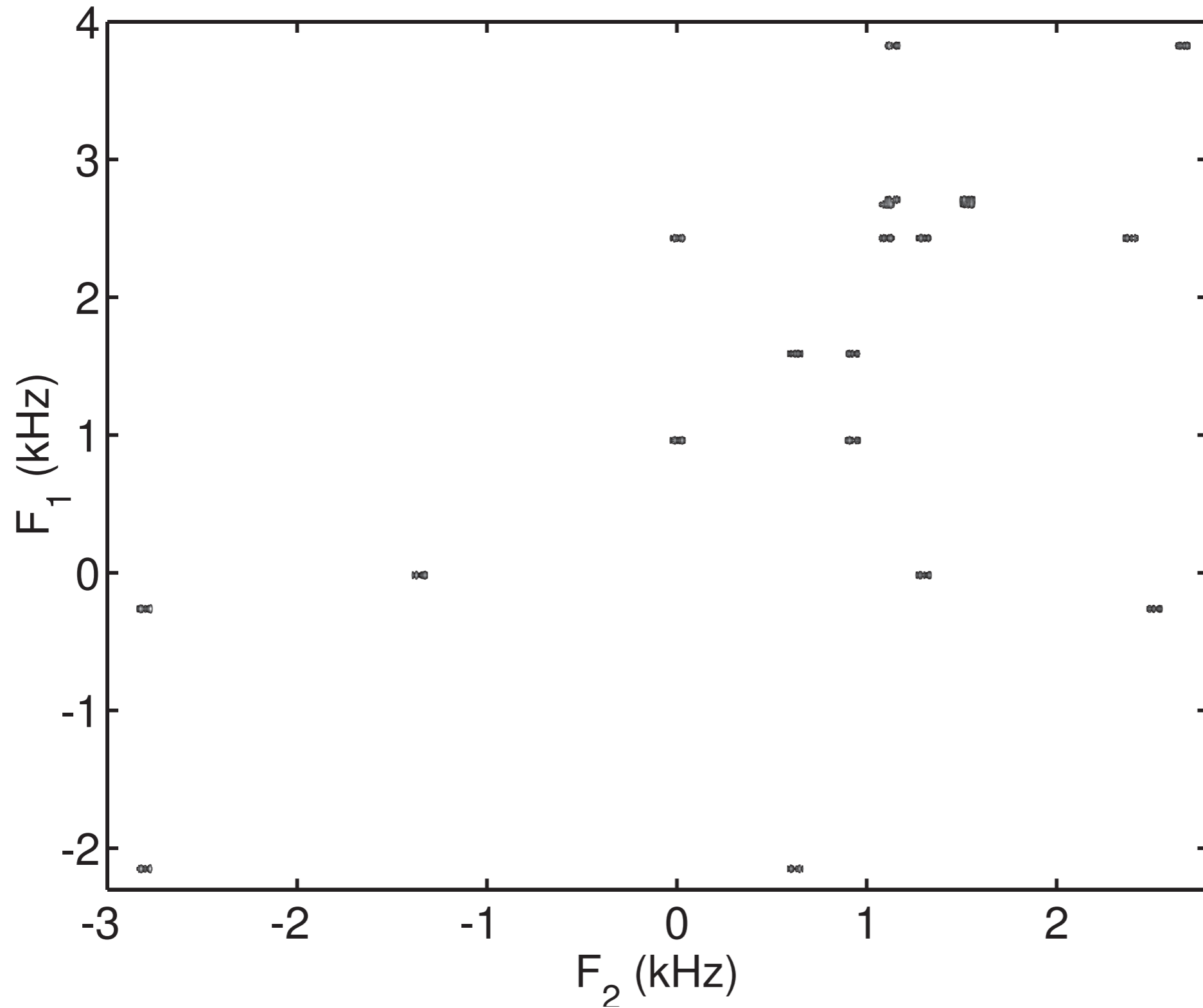
$$\begin{aligned} \min_{\mathcal{S}} \quad & \|\mathcal{m} - \mathcal{S}\|^2 + \lambda_1 \|\delta_x \mathcal{S}\|^2 + \lambda_2 \sum_{ij} (1 - p_{ij})^2 \|\mathcal{S}_{ij} + \mathcal{S}_{ji}\|^2 \\ & + \lambda_3 \sum_{ij} (\|\mathcal{S}_{ij}\|^2 - \|\mathcal{S}_{ji}\|^2)^2 \end{aligned}$$

# Solve for p

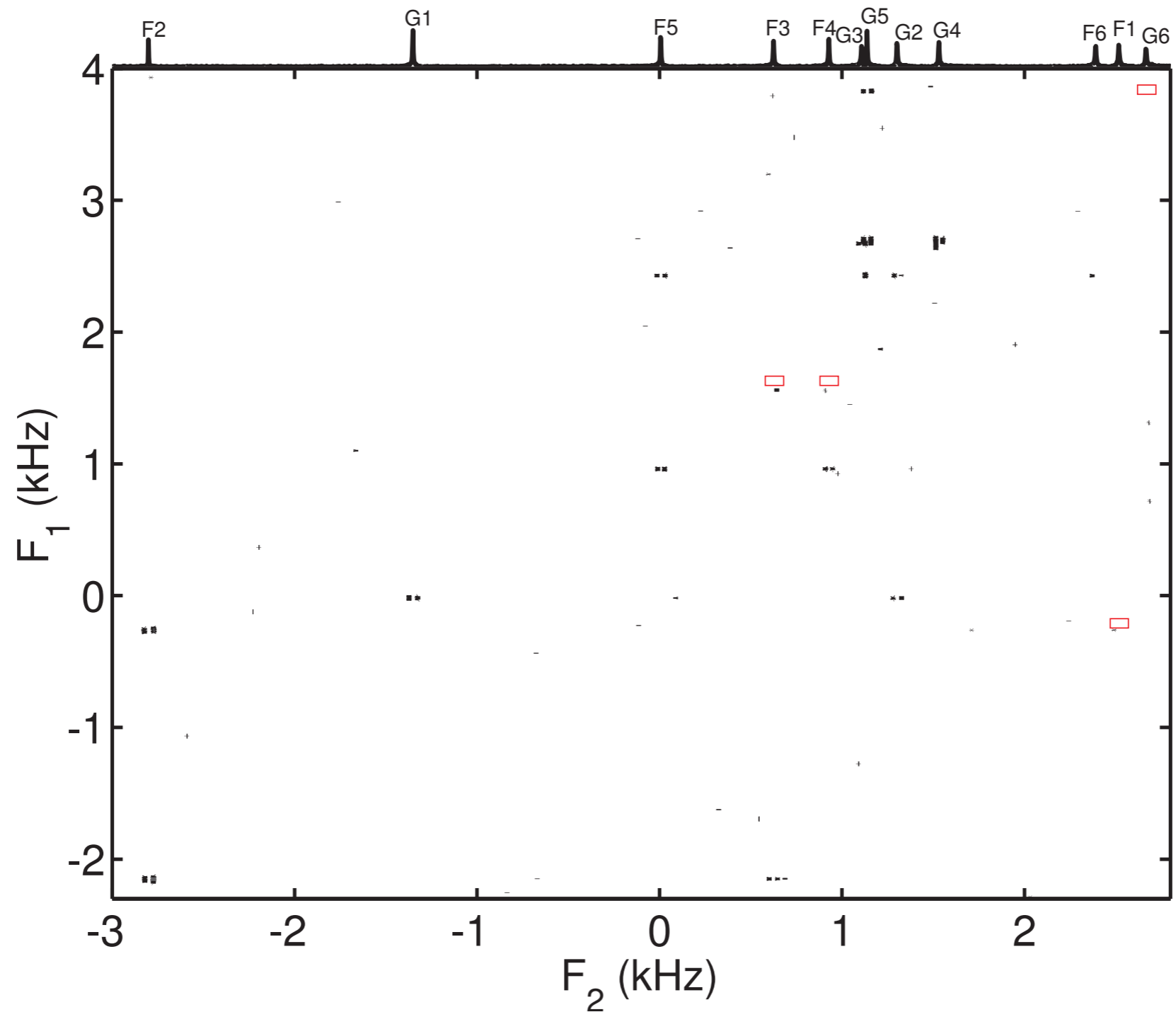
$$\begin{aligned} \min_{p_{ij}} \quad & \sum_{ij} (1 - p_{ij})^2 \|\mathcal{S}_{ij} + \mathcal{S}_{ji}\|^2 + \mu_1 \sum_i \left( 2 - \sum_{j \neq i} p_{ij} \right)^4 \\ & + \mu_2 \sum_{ij} p_{ij} \\ \text{s.t.} \quad & p_{ij} \geq 0 \\ & p_{ij} \leq 1 \end{aligned}$$



# Result



# Without Regularization



# Results

- **> 4X** reduction in scan time
  - compared to skilled interpretation

# Problems

- Can't see past  $O, N$ , etc.
- Still takes too long

# Solutions

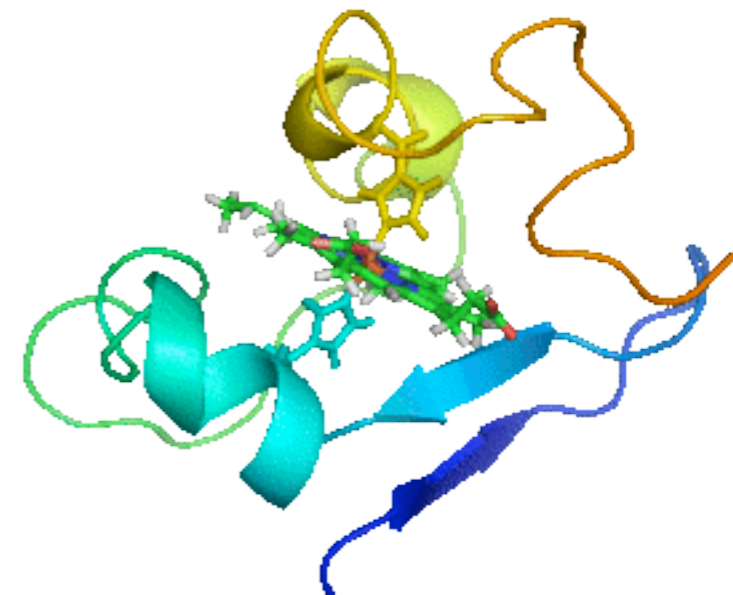
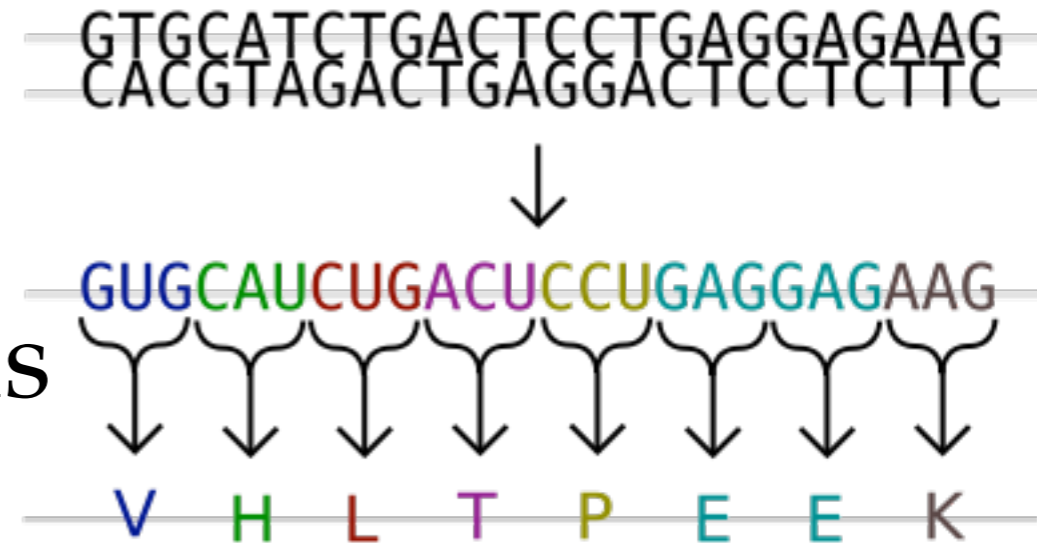
- Can't see past O, N, etc.
  - go Multi-Nuclear
- Still takes too long
  -

# Solutions

- Can't see past O, N, etc.
  - go Multi-Nuclear
- Still takes too long
  - Optimize delay times (k-space sampling)

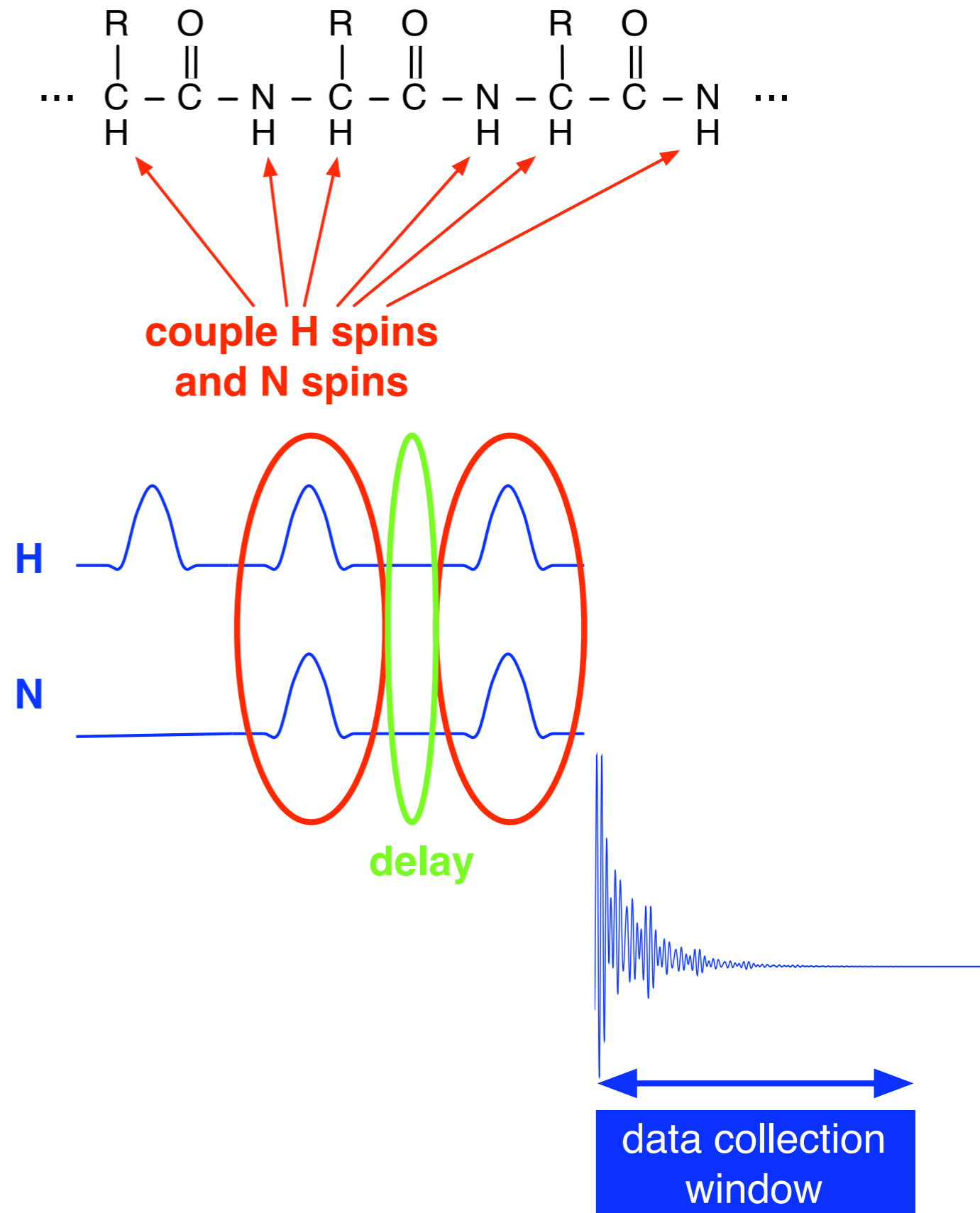
# Protein NMR

- Know DNA Sequences
- Defines Strings of Amino Acids
- Missing Info:
  - Protein Structure
    - only works if folded
  - Protein Function
    - interaction = wiggling



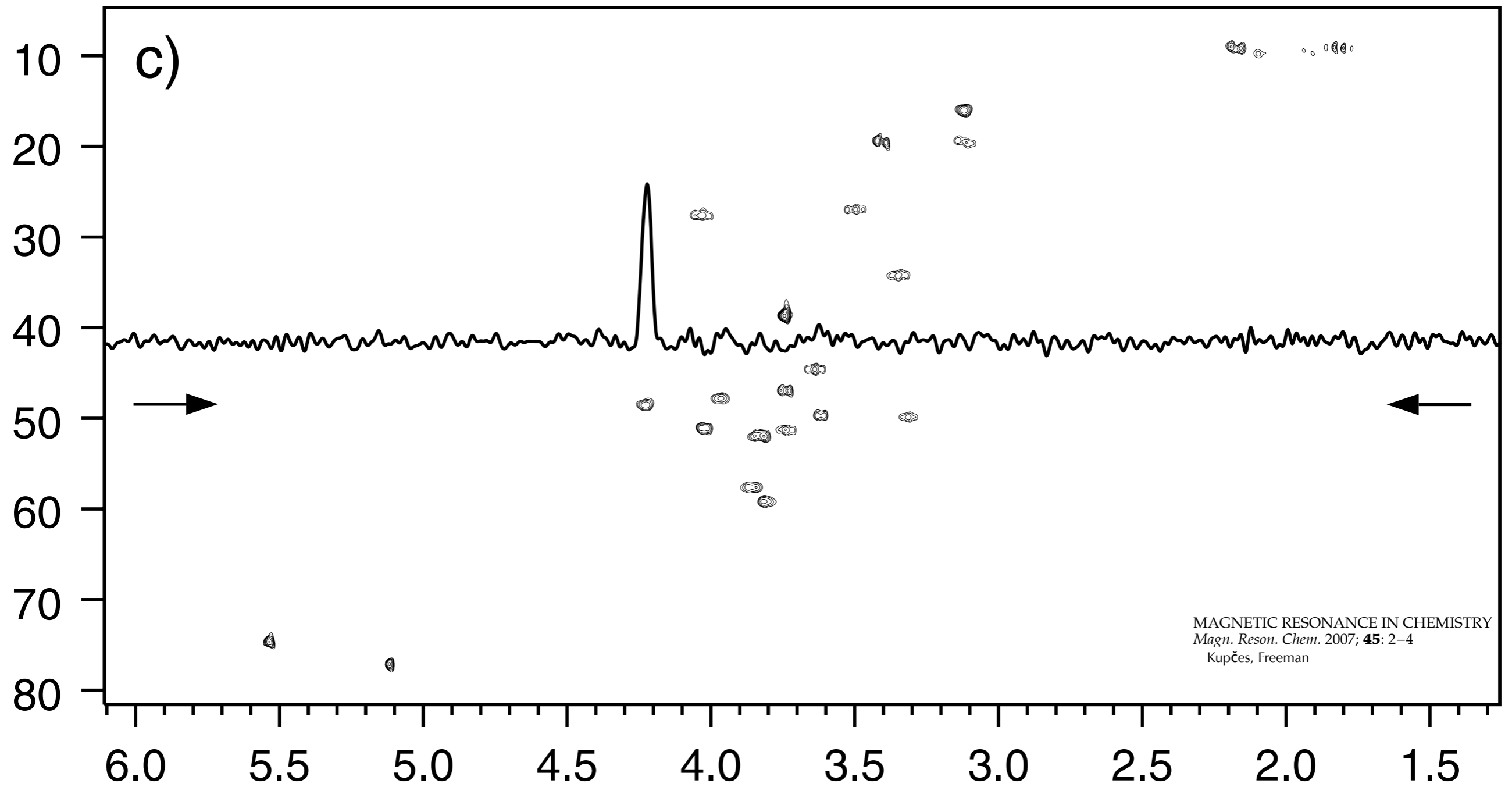
# 2-d NMR

- pulse @ 2 frequencies
- transfer spin state H-N-H
- phase variation proportional to delay (indirect)





# 2-d C-H



# Linear Forward Problem

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$$\tilde{f}(k_i) = \sum_{j=1}^m f(x_j) e^{\sqrt{-1} \langle k_i, x_j \rangle}$$

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$$\begin{pmatrix} \tilde{f}(k_1) \\ \vdots \\ \tilde{f}(k_n) \end{pmatrix} = S \begin{pmatrix} f(x_1) \\ \vdots \\ f(x_m) \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{pmatrix}$$

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$$S_{i,j} = e^{\sqrt{-1}\langle k_i, x_j \rangle}$$

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$$S_{i,j} = e^{\sqrt{-1}\langle k_i, x_j \rangle} \quad \text{is linear}$$

# Moore-Penrose Inverse

$$\begin{pmatrix} f(x_1) \\ \vdots \\ f(x_m) \end{pmatrix} = (S^* S)^{-1} S^* \begin{pmatrix} \tilde{f}(k_1) \\ \vdots \\ \tilde{f}(k_n) \end{pmatrix}$$

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- can invert with M-P pseudo-inverse



# Moore-Penrose Inverse

$$\begin{pmatrix} f(x_1) \\ \vdots \\ f(x_m) \end{pmatrix} = (S^* S)^{-1} S^* \begin{pmatrix} \tilde{f}(k_1) \\ \vdots \\ \tilde{f}(k_n) \end{pmatrix}$$

- can invert with M-P pseudo-inverse
- optimize {k} for M-P

# Worst-Case Noise ~ Conditioning of

$$(S^* S)_{i,j} = \sum_{l=1}^n e^{\sqrt{-1} \langle k_l, x_j - x_i \rangle}$$

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$$(S^* S)_{i,j} = \sum_{l=1}^n e^{\sqrt{-1} \langle k_l, x_j - x_i \rangle}$$

- expected maximum error  
~ 1 / minimal eigenvalue

# Worst-Case Noise ~ Conditioning of

$$(S^* S)_{i,j} = \sum_{l=1}^n e^{\sqrt{-1} \langle k_l, x_j - x_i \rangle}$$

- expected maximum error  
~ 1 / minimal eigenvalue
- constraining eigenvalues  
= Semi-Definite Programming (SDP)

# Real SDP

$$\min_{\{k_i\}} \quad -\lambda$$

subject to  $A - \lambda I \succeq 0$

$$A_{2i-1,2j-1} = \sum_{l=1}^n \cos \langle k_l, x_j - x_i \rangle$$

$$A_{2i,2j} = \sum_{l=1}^n \cos \langle k_l, x_j - x_i \rangle$$

$$A_{2i,2j-1} = \sum_{l=1}^n \sin \langle k_l, x_j - x_i \rangle$$

$$A_{2i-1,2j} = - \sum_{l=1}^n \sin \langle k_l, x_j - x_i \rangle$$

# Trust Region + SDP Step

$$\min_k \quad -\lambda$$

$$\text{subject to} \quad A|_{\tilde{k}} + \sum_{\substack{\alpha = 1 \dots n \\ \beta = 1 \dots r}} (k_{\alpha,\beta} - \tilde{k}_{\alpha,\beta}) \frac{\partial A}{\partial k_{\alpha,\beta}} \Big|_{\tilde{k}} - \lambda I \succeq 0$$

$$\frac{\partial A_{2i-1,2j-1}}{\partial k_{\alpha,\beta}} = - (\sin \langle k_{\alpha}, x_j - x_i \rangle) (x_{j,\beta} - x_{i,\beta})$$

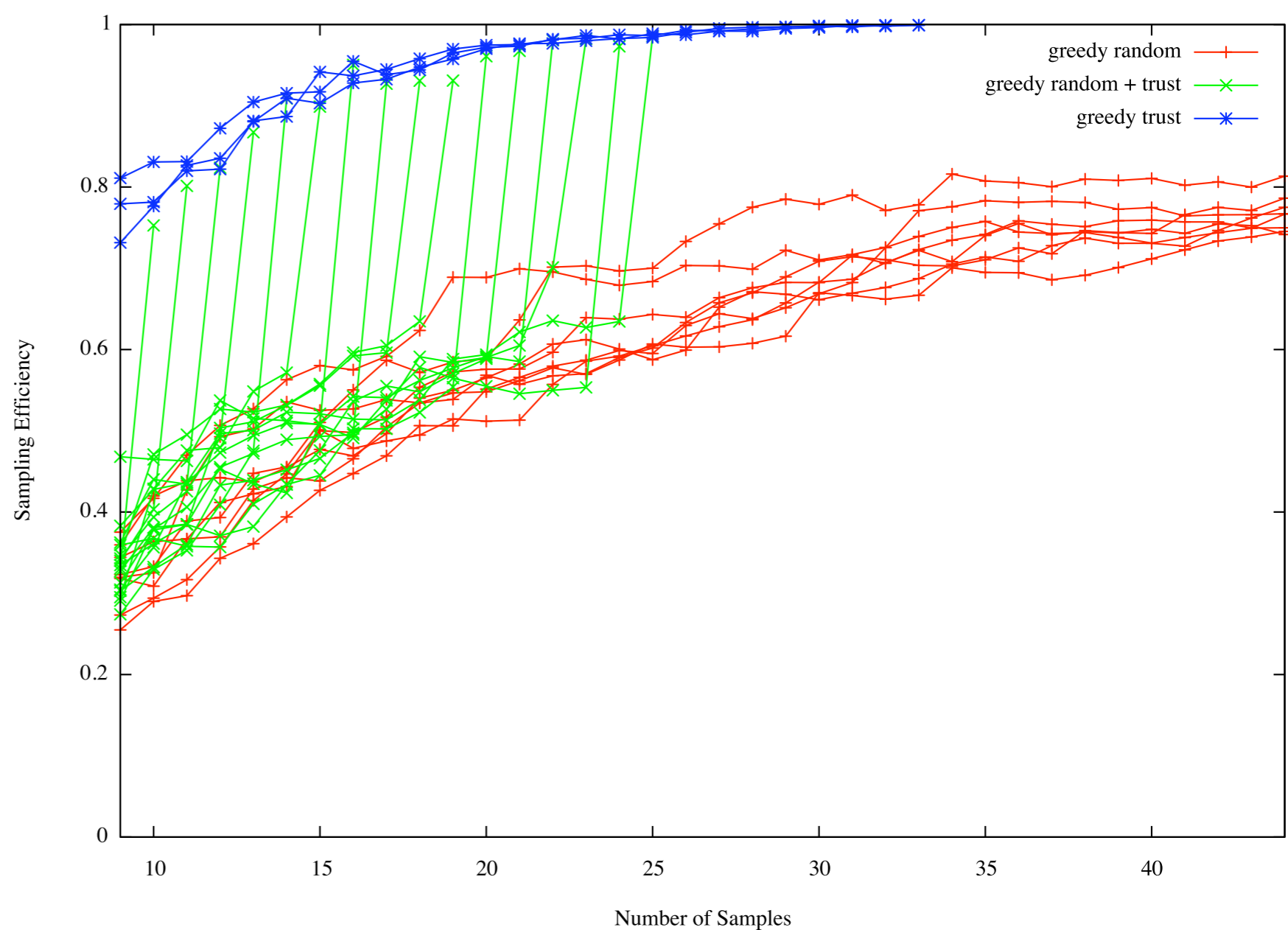
$$\frac{\partial A_{2i,2j}}{\partial k_{\alpha,\beta}} = - (\sin \langle k_{\alpha}, x_j - x_i \rangle) (x_{j,\beta} - x_{i,\beta})$$

$$\frac{\partial A_{2i,2j-1}}{\partial k_{\alpha,\beta}} = (\cos \langle k_{\alpha}, x_j - x_i \rangle) (x_{j,\beta} - x_{i,\beta})$$

$$\frac{\partial A_{2i-1,2j}}{\partial k_{\alpha,\beta}} = - (\cos \langle k_{\alpha}, x_j - x_i \rangle) (x_{j,\beta} - x_{i,\beta})$$

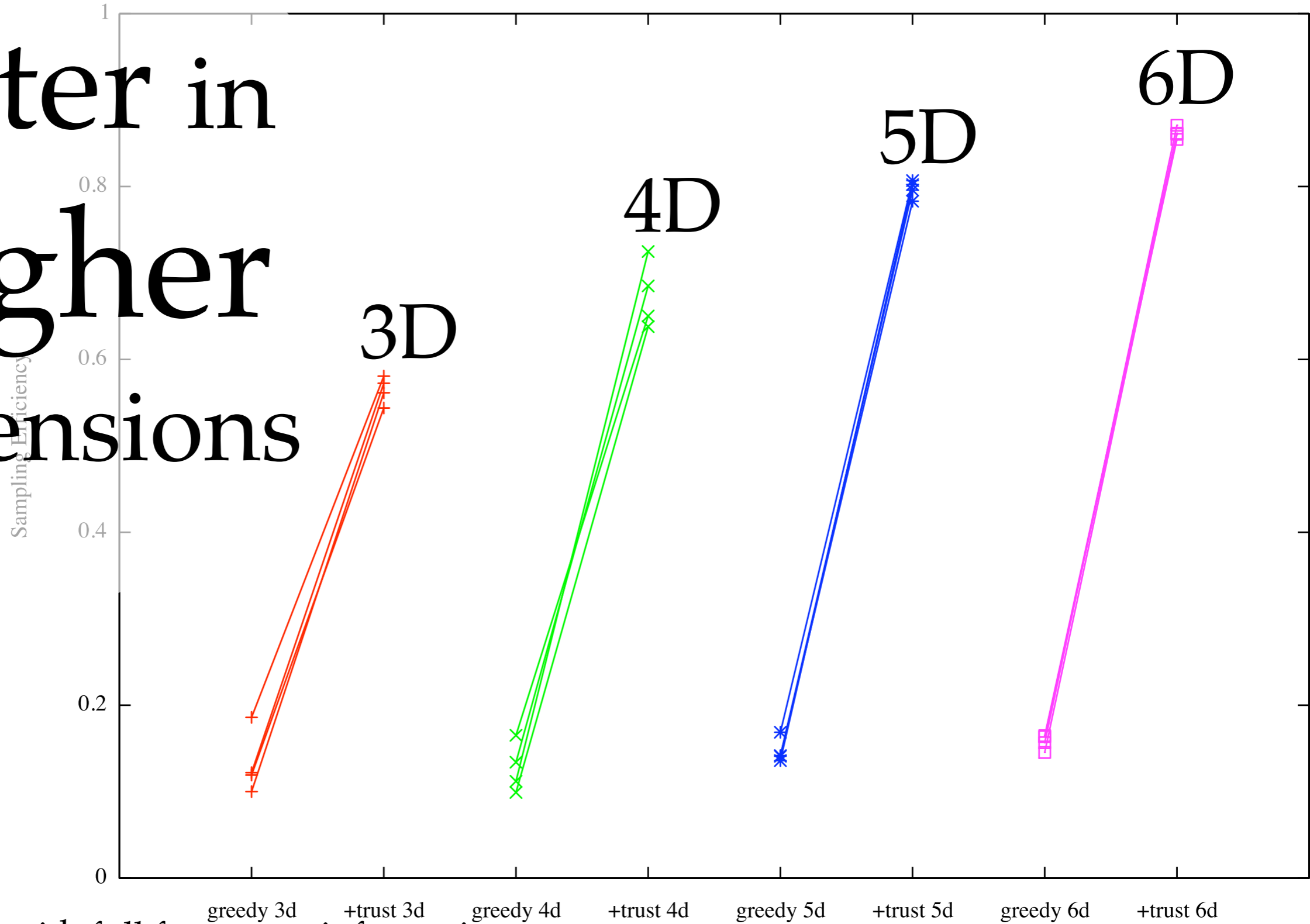
$$|k_{\alpha,\beta} - \tilde{k}_{\alpha,\beta}| \leq \frac{\pi/2}{\max |x_{j,\beta} - x_{i,\beta}|}$$

# Works well in 3D!



- SDP optimization = **100% efficient**
- greedy random < 80% efficient
- 2x more samples with greedy random

# Better in Higher Dimensions



- 17 peaks with full frequency information
- Efficiency increases with dimension (34 samples)
- *fewer* samples required in higher dimensions



# To Do

- Celebrate 4X faster experiments
- Design mixed C-O-N experiments
- Make delay optimization numerically robust

# Thanks to

- Adrian, Dhavide, Hongmei for the invitation
- MITACS and Field's the conference
- NSERC and IBM for funding
- my students for their hard work