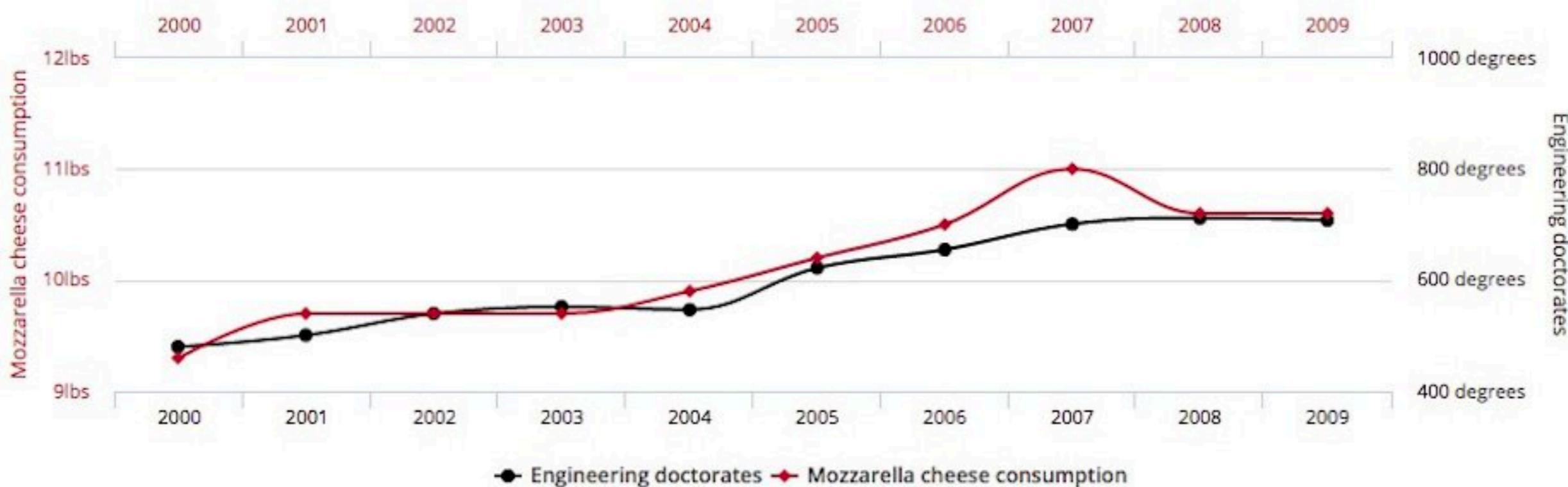


# Per capita consumption of mozzarella cheese correlates with Civil engineering doctorates awarded



Correlation: 95.86% ( $r=0.958648$ )

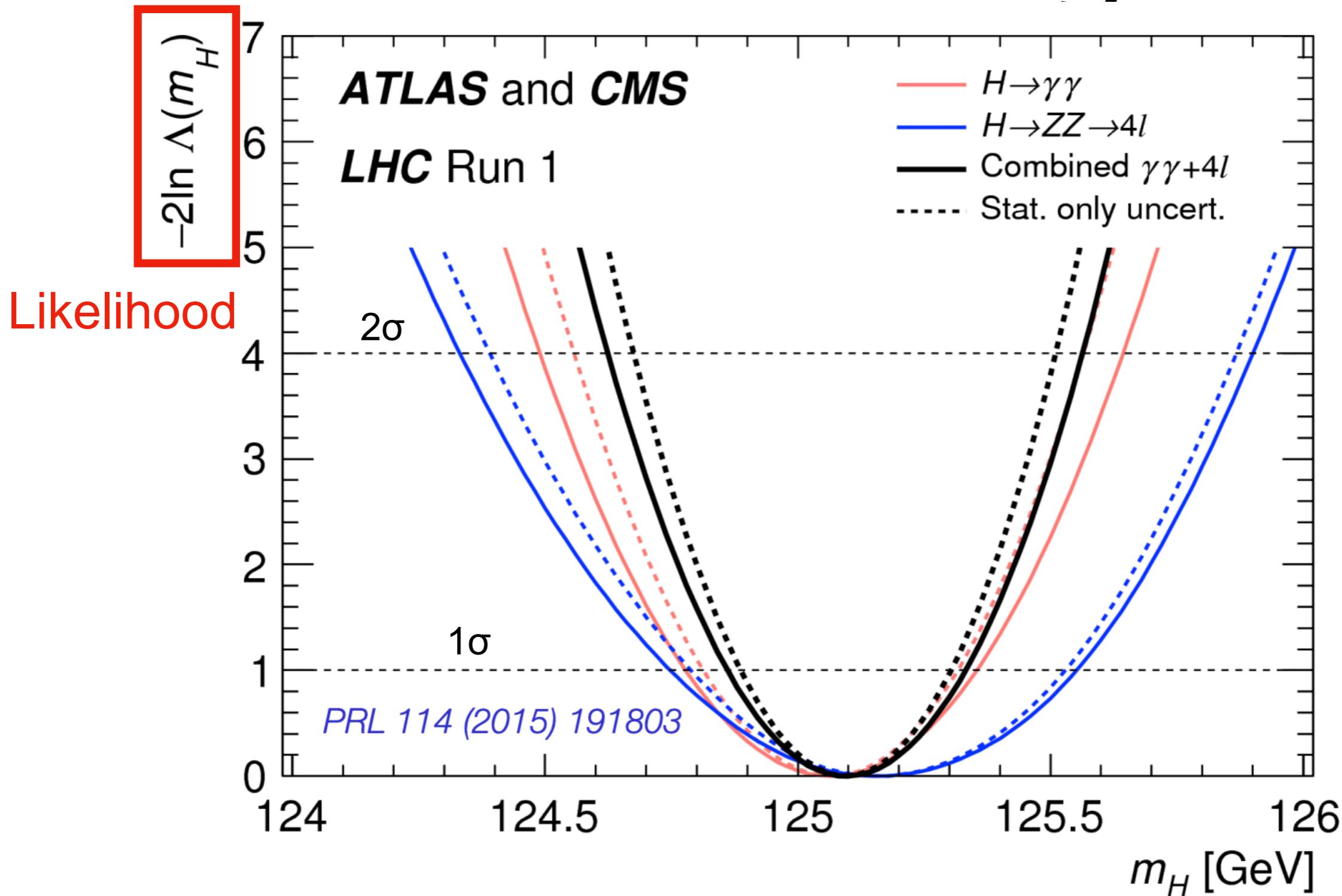


Data sources: U.S. Department of Agriculture and National Science Foundation

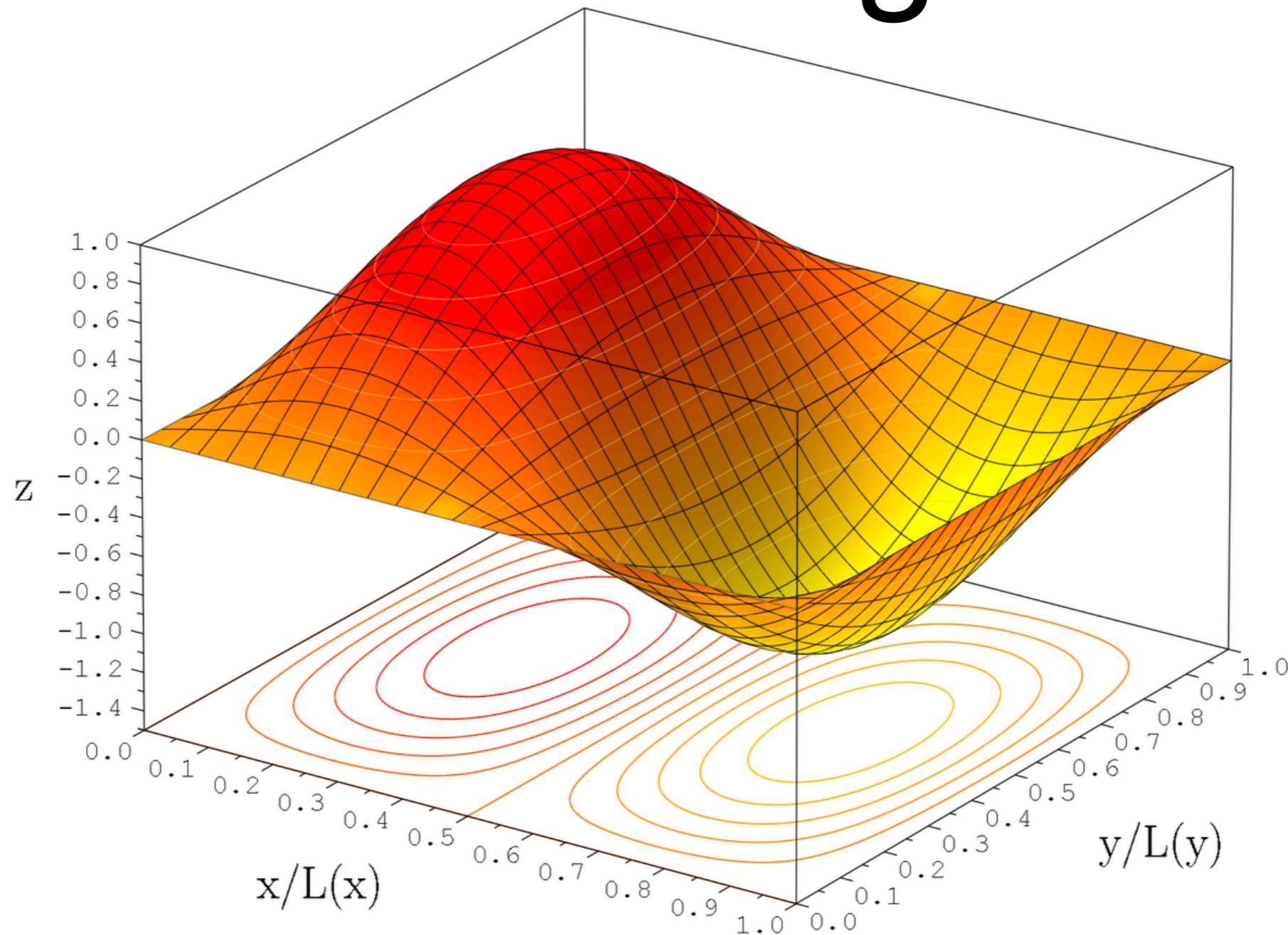
[tylervigen.com](http://tylervigen.com)

# Lecture 7: Correlations

# Understanding Best Fit

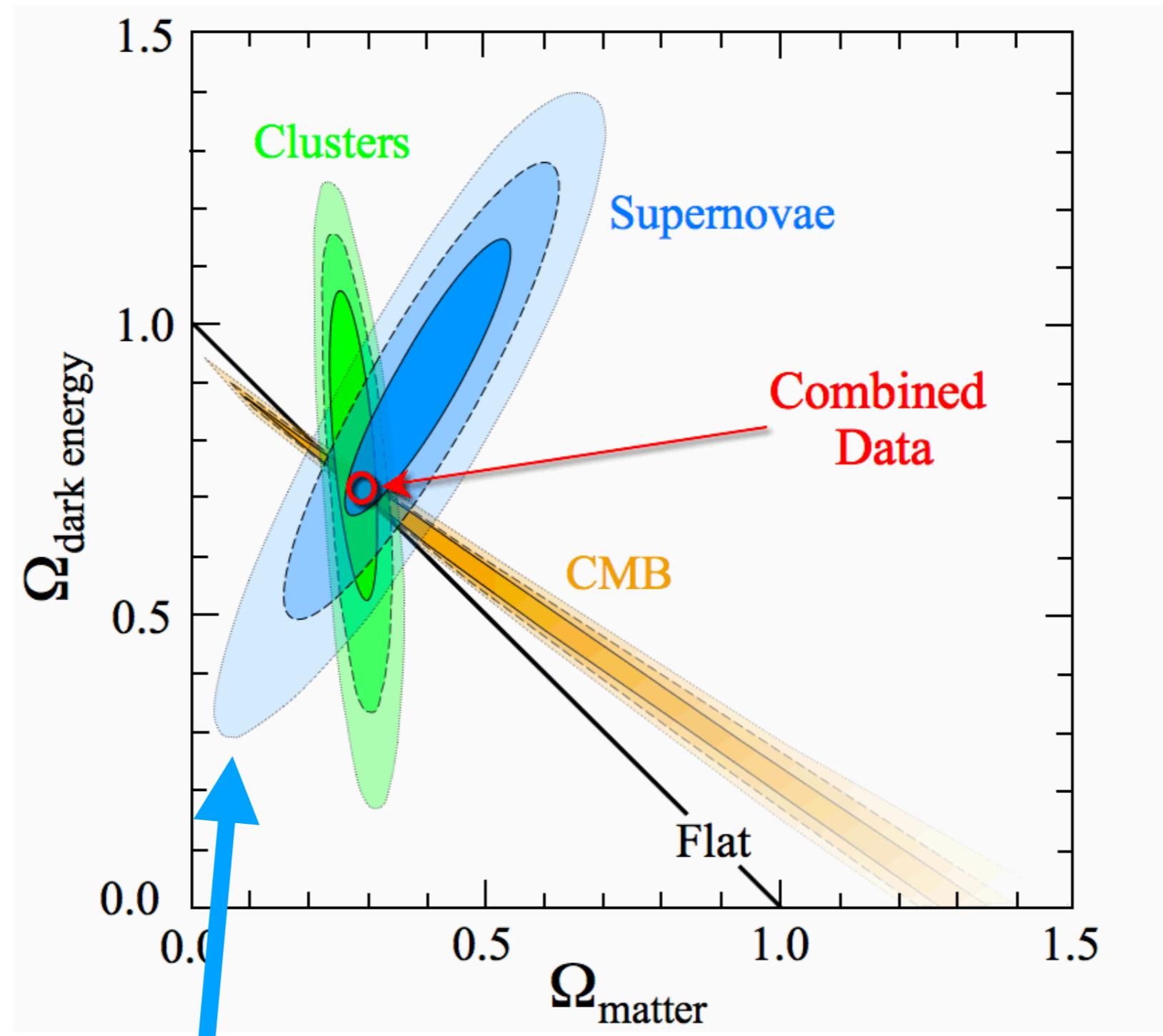


# Minimizing A Surface



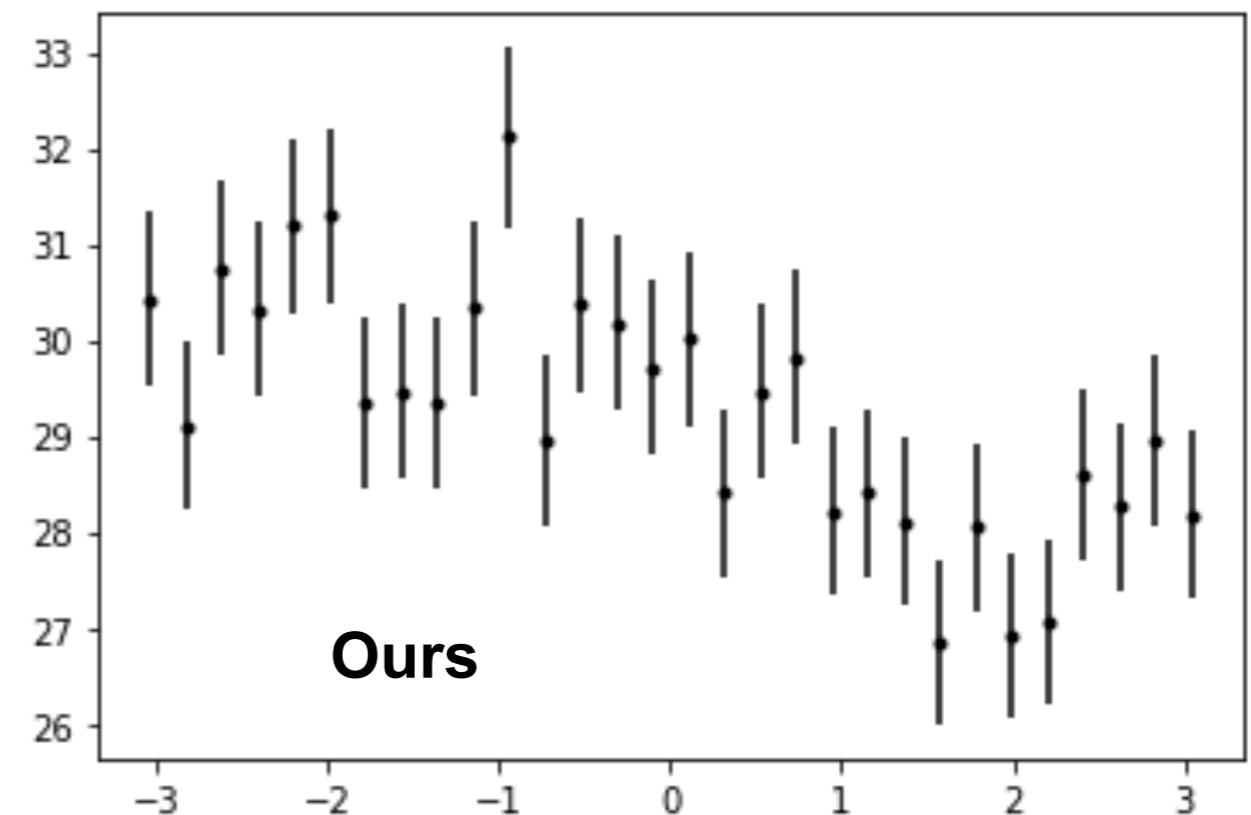
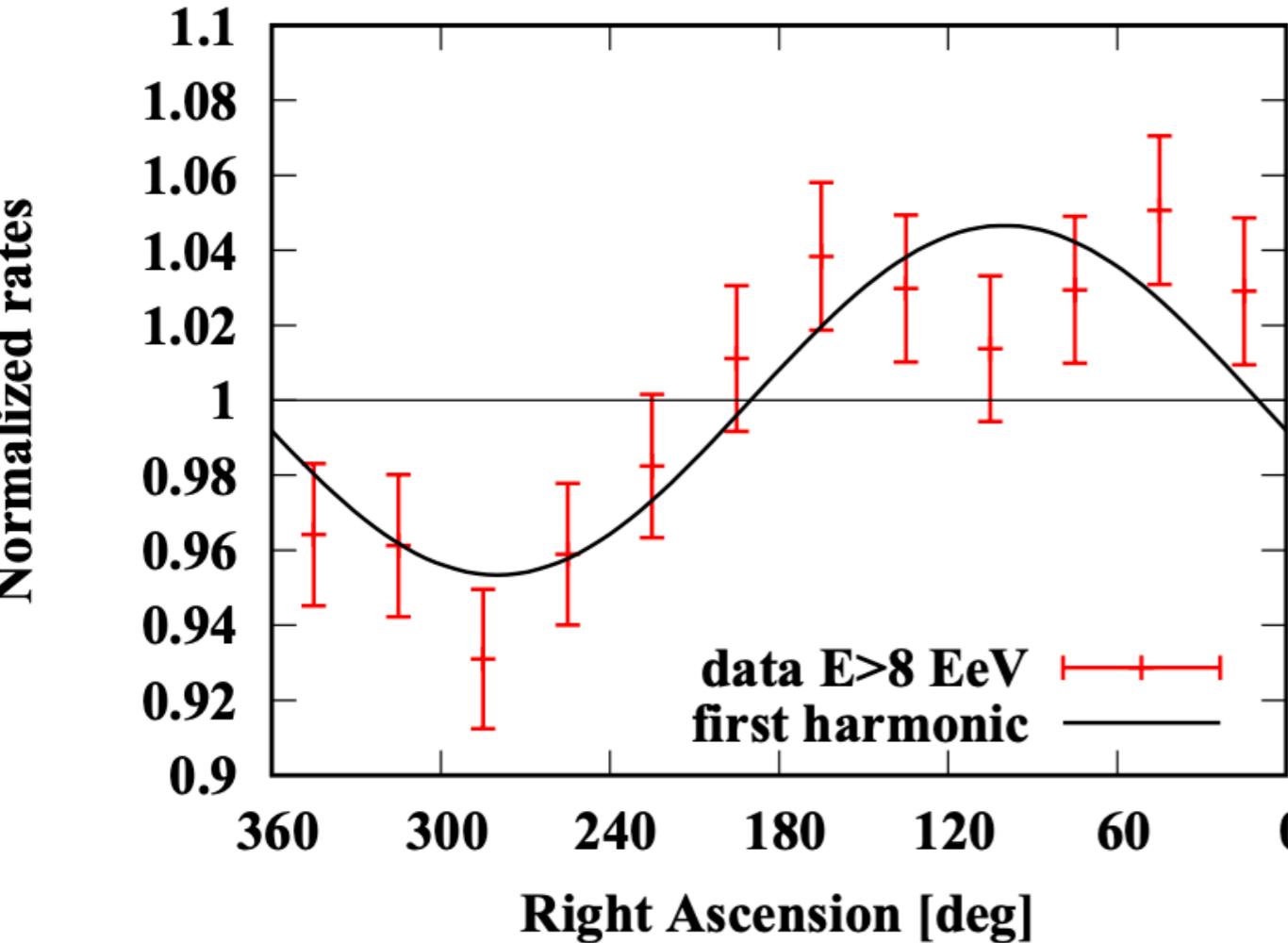
- How do we get to the minimum of that

# Making a 2D Minima



How Can we make the contours on the supernova data?

# Cosmic Ray Data



# Multiple Dimensions

- For N variables the expansion is the same

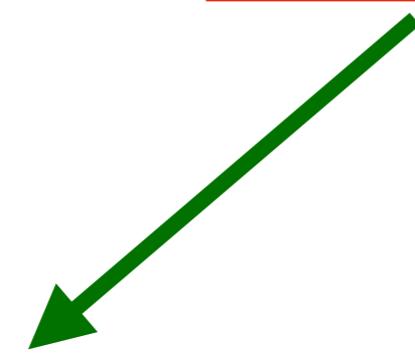
$$\chi^2(x_i, \vec{\theta}) = \chi^2_{min}(x_i, \vec{\theta}) + \frac{1}{2}(\theta_i - \theta_0)^T \frac{\partial^2}{\partial \theta_i \partial \theta_j} \chi^2_{min}(x_i, \vec{\theta}_0)(\theta_j - \theta_0)$$

$\chi^2$  distribution of 1 degree of freedom  
 $V[\chi^2(x)] = 1$

$$\Delta \chi^2 = 2 \Delta \log L = 1$$

For one degree of freedom

Hessian of  
the  $\chi^2$  distribution



This is known as Wilk's Theorem

$$\sigma_{ij}^2 = \left( \frac{\partial^2 \log L}{\partial \theta_i \partial \theta_j} \right)^{-1}$$

# 2D examples

$$\chi^2(x, \vec{\theta}) = \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \begin{pmatrix} \theta_a - \theta_{a-min} & \theta_b - \theta_{b-min} \end{pmatrix} \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \\ \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \begin{pmatrix} \theta_a - \theta_{a-min} \\ \theta_b - \theta_{b-min} \end{pmatrix}$$

$\frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \approx 0$

$$\chi^2(x, \vec{\theta}) = \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \begin{pmatrix} \Delta\theta_a & \Delta\theta_b \end{pmatrix} \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & 0 \\ 0 & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \begin{pmatrix} \Delta\theta_a \\ \Delta\theta_b \end{pmatrix}$$

$$\begin{aligned} \chi^2(x, \vec{\theta}) &= \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \left( \Delta\theta_a^2 \frac{\partial^2 \chi^2}{\partial \theta_a^2} + \Delta\theta_b^2 \frac{\partial^2 \chi^2}{\partial \theta_b^2} \right) \\ &= \chi_{min}^2(x, \vec{\theta}) + \left( \frac{\Delta\theta_a^2}{\sigma_{\theta_a}^2} + \frac{\Delta\theta_b^2}{\sigma_{\theta_b}^2} \right) \end{aligned}$$

# 2D examples

$$\chi^2(x, \vec{\theta}) = \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \begin{pmatrix} \theta_a - \theta_{a-min} & \theta_b - \theta_{b-min} \end{pmatrix} \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \\ \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \begin{pmatrix} \theta_a - \theta_{a-min} \\ \theta_b - \theta_{b-min} \end{pmatrix}$$

$\frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \approx 0$

$$\chi^2(x, \vec{\theta}) = \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \begin{pmatrix} \Delta\theta_a & \Delta\theta_b \end{pmatrix} \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & 0 \\ 0 & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \begin{pmatrix} \Delta\theta_a \\ \Delta\theta_b \end{pmatrix}$$

$$\begin{aligned} \chi^2(x, \vec{\theta}) &= \chi_{min}^2(x, \vec{\theta}) + \frac{1}{2} \left( \Delta\theta_a^2 \frac{\partial^2 \chi^2}{\partial \theta_a^2} + \Delta\theta_b^2 \frac{\partial^2 \chi^2}{\partial \theta_b^2} \right) \\ &= \boxed{\chi_{min}^2(x, \vec{\theta}) + \left( \frac{\Delta\theta_a^2}{\sigma_{\theta_a}^2} + \frac{\Delta\theta_b^2}{\sigma_{\theta_b}^2} \right)} \quad \text{Ellipse} \end{aligned}$$

# Relating all the 2Ds

$$\frac{2}{\sigma^2} = \frac{\partial^2 \chi^2}{\partial \theta_i \partial \theta_j}$$

$$\sigma^2 = 2 \left( \frac{\partial^2 \chi^2}{\partial \theta_i \partial \theta_j} \right)^{-1}$$

**Wilk's Theorem**

$$\begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & 0 \\ 0 & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \rightarrow \begin{pmatrix} \frac{2}{\sigma_a^2} & 0 \\ 0 & \frac{2}{\sigma_b^2} \end{pmatrix}$$

**Wilk's For  
Uncorrelated  
Parameters**

**For correlated  
Paramters  
Can always  
Diagonalize**

$$A^{-1} 2 \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \\ \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix}^{-1} A = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}$$

# 2D Terminology

## Covariance Matrix

$$\begin{pmatrix} \sigma_a^2 & \text{COV}(a, b) \\ \text{COV}(a, b) & \sigma_b^2 \end{pmatrix} = \sum_{i=1}^N \begin{pmatrix} (a_i - \bar{a})^2 & (a_i - \bar{a})(b_i - \bar{b}) \\ (a_i - \bar{a})(b_i - \bar{b}) & (b_i - \bar{b})^2 \end{pmatrix}$$

$$\rho = \begin{pmatrix} 1 & \frac{\text{COV}(a,b)}{\sigma_a \sigma_b} \\ \frac{\text{COV}(a,b)}{\sigma_a \sigma_b} & 1 \end{pmatrix}$$

Correlation Matrix

Correlation Coefficient

# Relating all the 2Ds

$$\frac{2}{\sigma^2} = \frac{\partial^2 \chi^2}{\partial \theta_i \partial \theta_j}$$

$$\sigma^2 = 2 \left( \frac{\partial^2 \chi^2}{\partial \theta_i \partial \theta_j} \right)^{-1}$$

**Wilk's Theorem**

$$\begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & 0 \\ 0 & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix} \rightarrow \begin{pmatrix} \frac{2}{\sigma_a^2} & 0 \\ 0 & \frac{2}{\sigma_b^2} \end{pmatrix}$$

**Wilk's For Uncorrelated Parameters**

**For correlated Paramters  
Can always Diagonalize**

$$A^{-1} 2 \begin{pmatrix} \frac{\partial^2 \chi^2}{\partial \theta_a^2} & \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} \\ \frac{\partial^2 \chi^2}{\partial \theta_a \partial \theta_b} & \frac{\partial^2 \chi^2}{\partial \theta_b^2} \end{pmatrix}^{-1} A = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}$$

# 2D Terminology

## Covariance Matrix

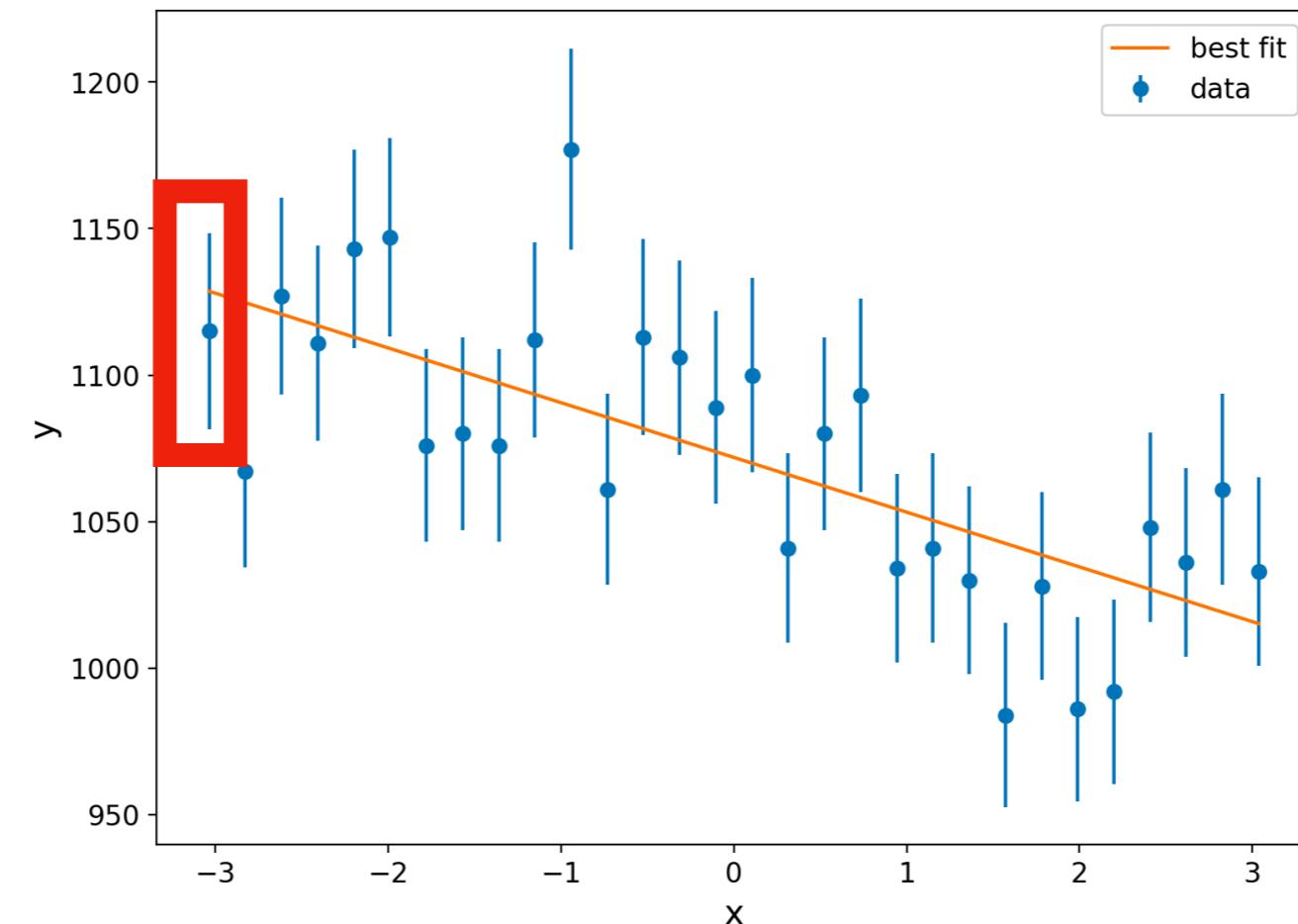
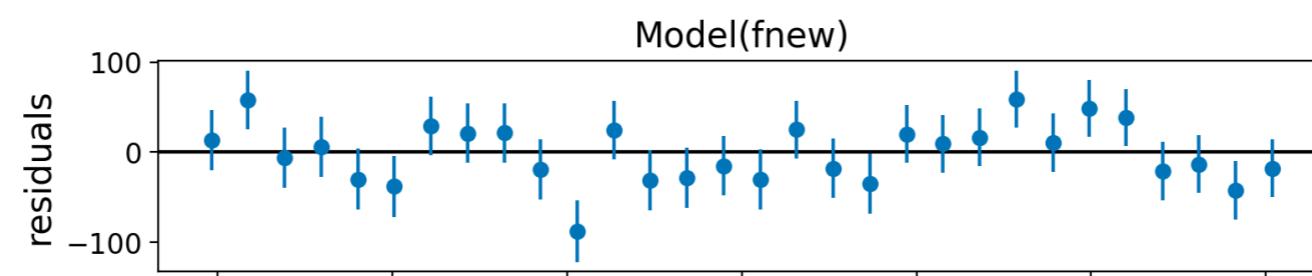
$$\begin{pmatrix} \sigma_a^2 & \text{COV}(a, b) \\ \text{COV}(a, b) & \sigma_b^2 \end{pmatrix} = \sum_{i=1}^N \begin{pmatrix} (a_i - \bar{a})^2 & (a_i - \bar{a})(b_i - \bar{b}) \\ (a_i - \bar{a})(b_i - \bar{b}) & (b_i - \bar{b})^2 \end{pmatrix}$$

$$\rho = \begin{pmatrix} 1 & \frac{\text{COV}(a,b)}{\sigma_a \sigma_b} \\ \frac{\text{COV}(a,b)}{\sigma_a \sigma_b} & 1 \end{pmatrix}$$

Correlation Matrix

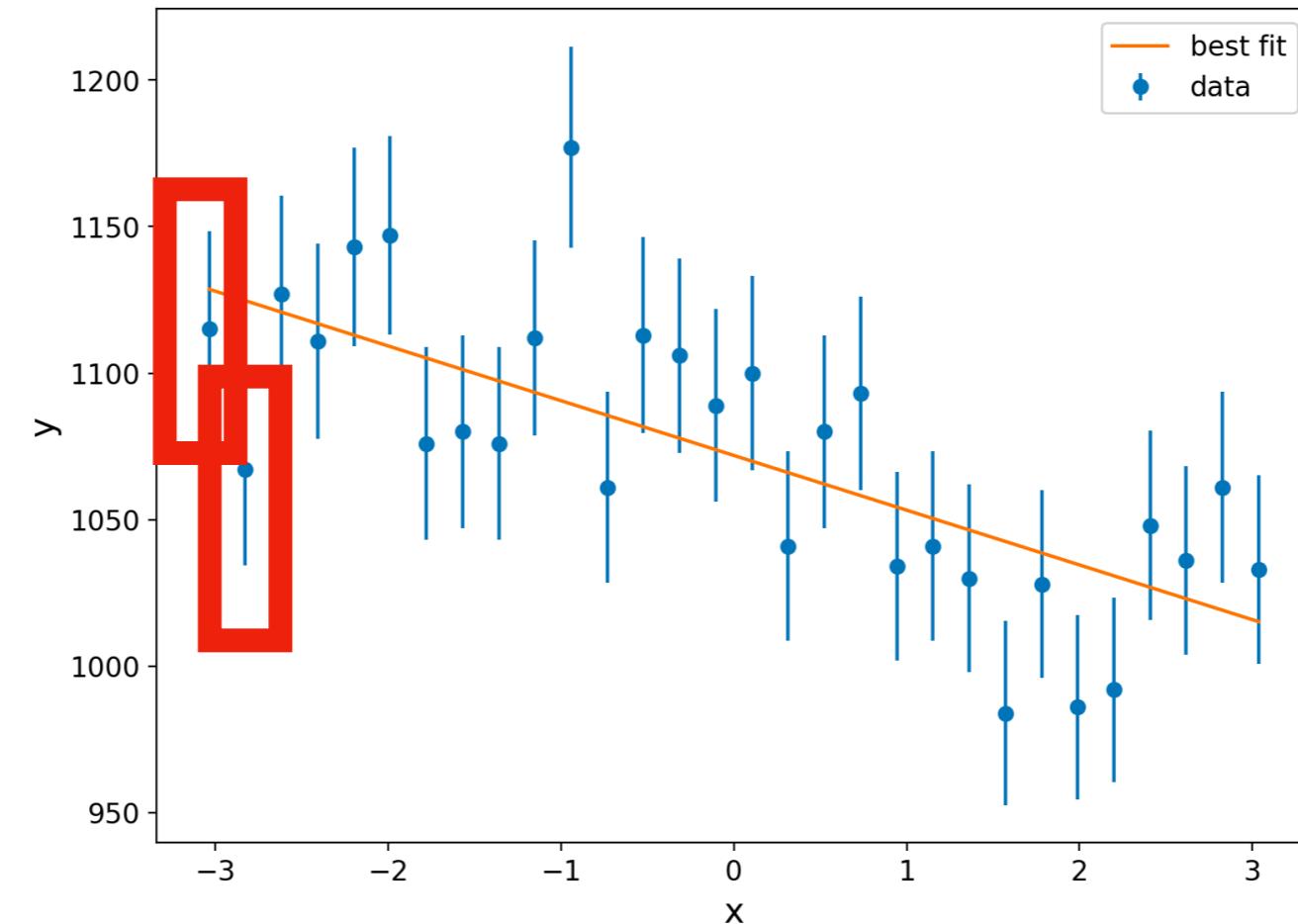
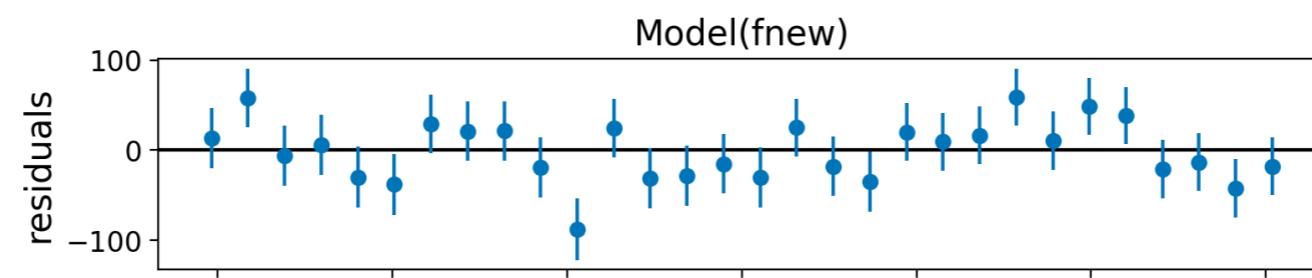
Correlation Coefficient

# Toys



Poisson Fluctuate this bin

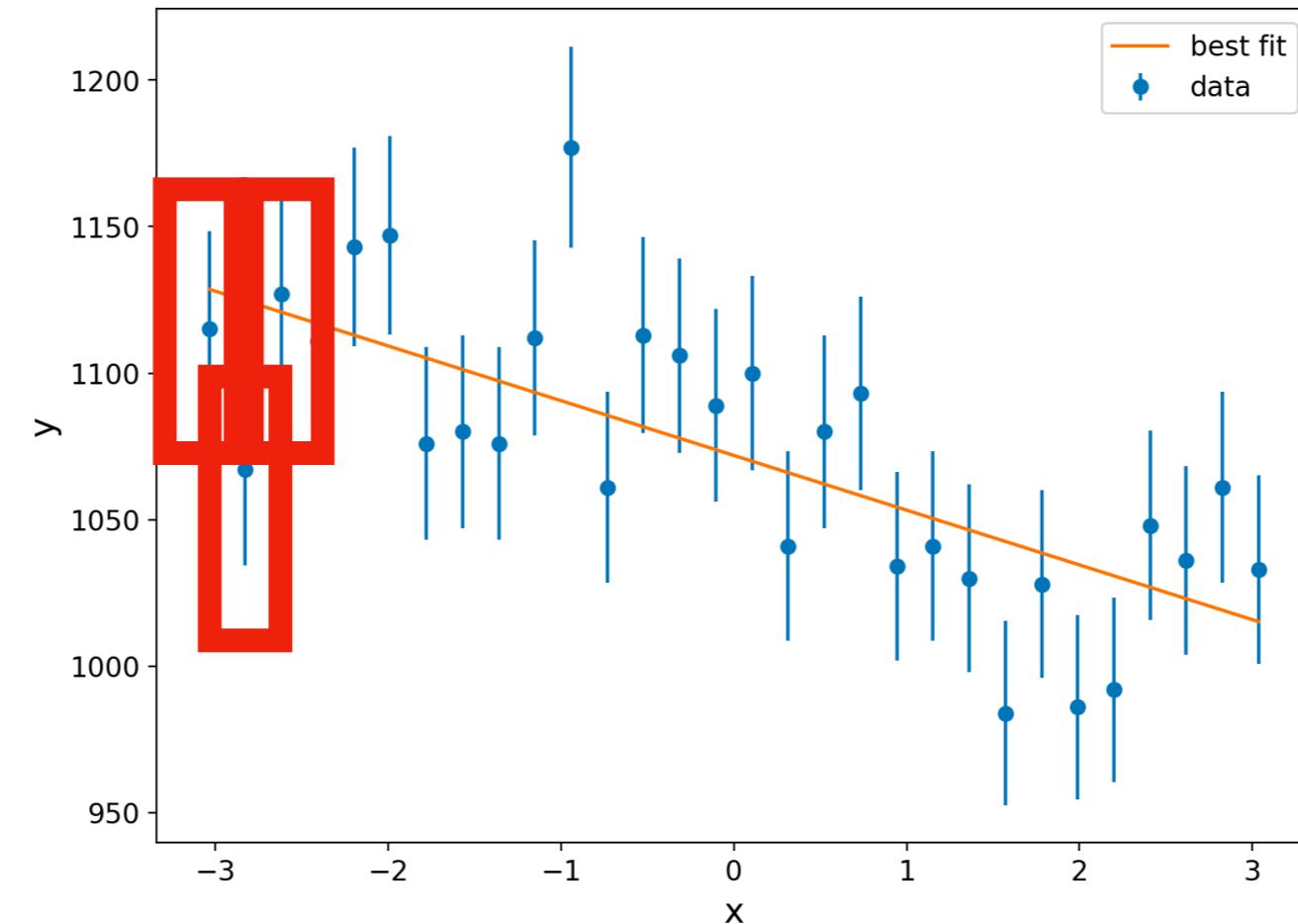
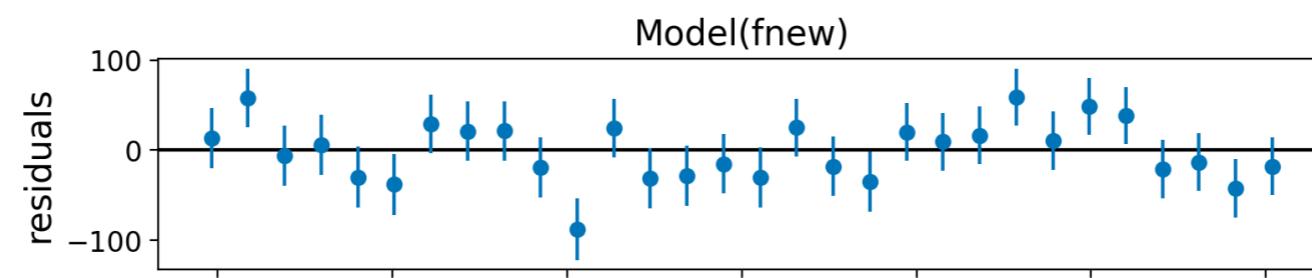
# Toys



Poisson Fluctuate this bin

Poisson Fluctuate this bin

# Toys

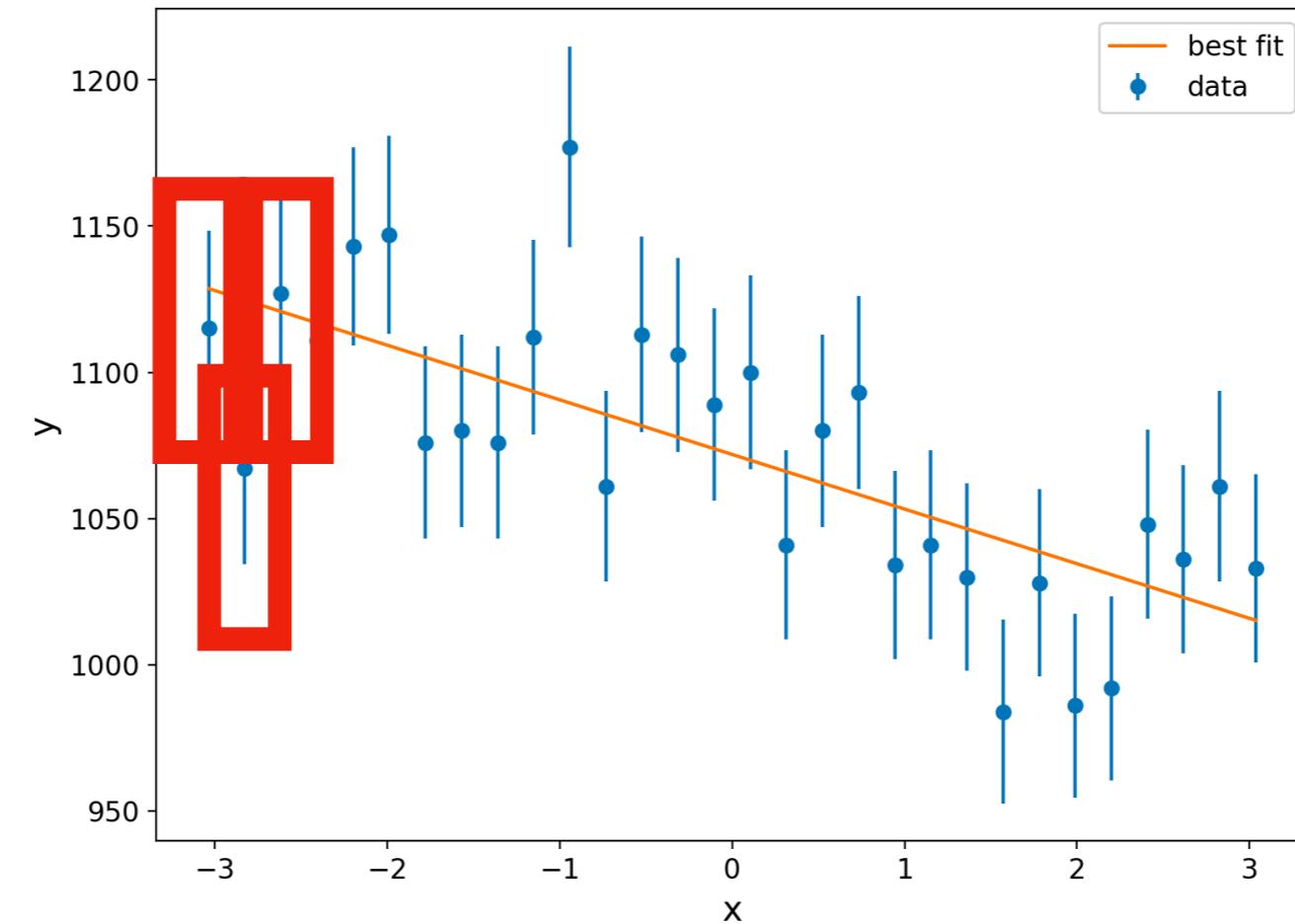
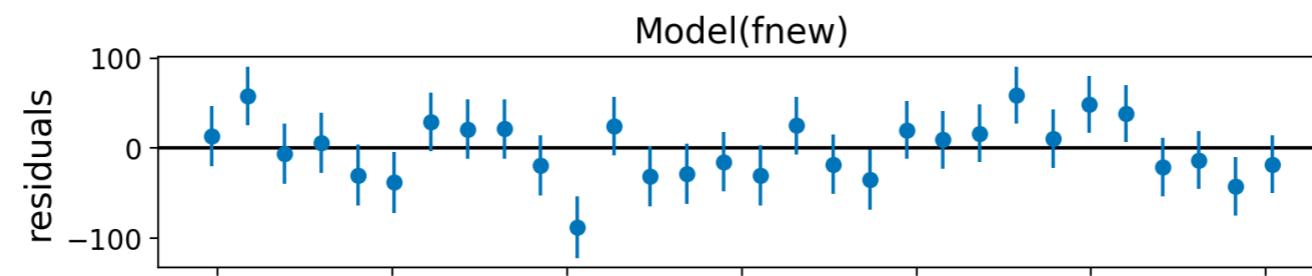


Poisson Fluctuate this bin

Poisson Fluctuate this bin

Poisson Fluctuate this bin

# Toys

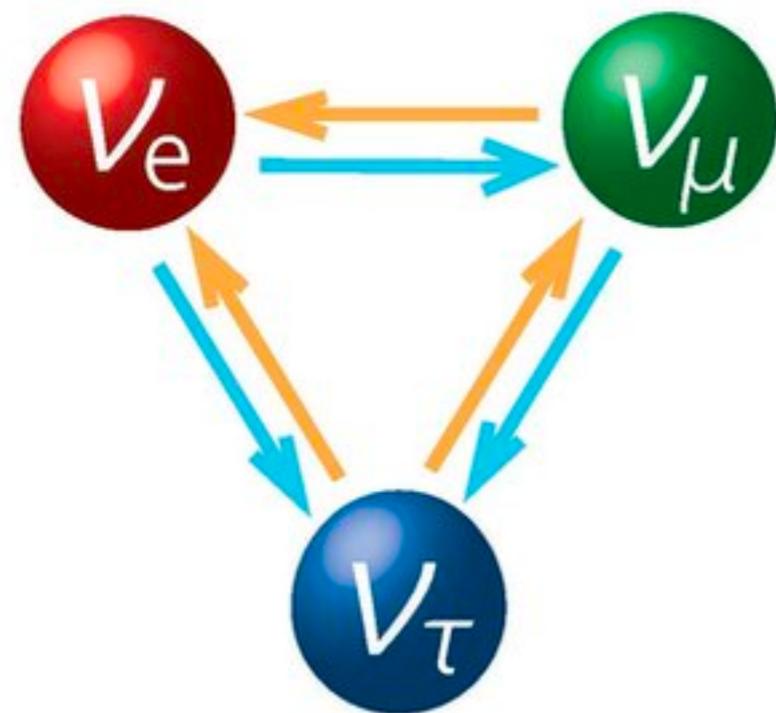


Poisson Fluctuate this bin

Poisson Fluctuate this bin

....

Poisson Fluctuate this bin



Neutrinos oscillate into other neutrinos

# Nobel Prize

The Nobel Prize in Physics 2015

Takaaki Kajita  
Arthur B. McDonald

Share this



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Mahmoud

Takaaki Kajita

Prize share: 1/2



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Mahmoud

Arthur B. McDonald

Prize share: 1/2

- Nobel prize was recently awarded for neutrino oscillations
  - This is a second award on neutrino properties

# Neutrino Mixing

Particle  
Eigenstates

$$U = \begin{pmatrix} U_{e1} & U_{e2} & U_{e3} \\ U_{\mu 1} & U_{\mu 2} & U_{\mu 3} \\ U_{\tau 1} & U_{\tau 2} & U_{\tau 3} \end{pmatrix} \quad s_{ij} \equiv \sin \theta_{ij}, \quad c_{ij} \equiv \cos \theta_{ij}$$

$$| \nu_\alpha \rangle = \sum_{i=1}^3 U_{\alpha i}^* | \nu_i \rangle$$

Mass  
Eigenstates

$$= \begin{pmatrix} c_{13}c_{12} & c_{13}s_{12} & s_{13}e^{-i\delta} \\ -c_{23}s_{12} - s_{13}s_{23}c_{12}e^{i\delta} & c_{23}c_{12} - s_{13}s_{23}s_{12}e^{i\delta} & c_{13}s_{23} \\ s_{23}s_{12} - s_{13}c_{23}c_{12}e^{i\delta} & -s_{23}c_{12} - s_{13}c_{23}s_{12}e^{i\delta} & c_{13}c_{23} \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0 & 0 \\ 0 & c_{23} & s_{23} \\ 0 & -s_{23} & c_{23} \end{pmatrix} \begin{pmatrix} c_{13} & 0 & s_{13}e^{-i\delta} \\ 0 & 1 & 0 \\ -s_{13}e^{i\delta} & 0 & c_{13} \end{pmatrix} \begin{pmatrix} c_{12} & s_{12} & 0 \\ -s_{12} & c_{12} & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

# Neutrino Mixing

$$P_{\alpha \rightarrow \beta} = | \langle \nu_\beta(t) | \nu_\alpha(t) \rangle |^2$$

$$= \left( \sum_{j=1}^3 U_{\beta j} U_{\alpha j}^* e^{-i \frac{m_j L}{2E}} \right) \left( \sum_{i=1}^3 U_{\beta i}^* U_{\alpha i} e^{i \frac{m_j L}{2E}} \right)$$

As we evolve over time the particle eigenstates oscillate through the mass states

$$P_{\alpha \rightarrow \beta} = \delta_{\alpha \beta} - 4 \sum_{i > j} \Re[U_{\alpha i}^* U_{\alpha j} U_{\beta i} U_{\beta j}^*] \sin^2 \left( \frac{\Delta m_{ij}^2}{4E} L \right)$$

$$+ 2 \sum_{i > j} \Im[U_{\alpha i}^* U_{\alpha j} U_{\beta i} U_{\beta j}^*] \sin^2 \left( \frac{\Delta m_{ij}^2}{2E} L \right)$$

# Neutrino Mixing

Master Formula

$$P_{\mu \rightarrow \mu} \simeq 1 - 4s_{23}^2 c_{23}^2 (s_{12}^2 + c_{12}^2) \sin^2 \left( \frac{1.27 \Delta m_{atm.}^2}{E} L \right)$$

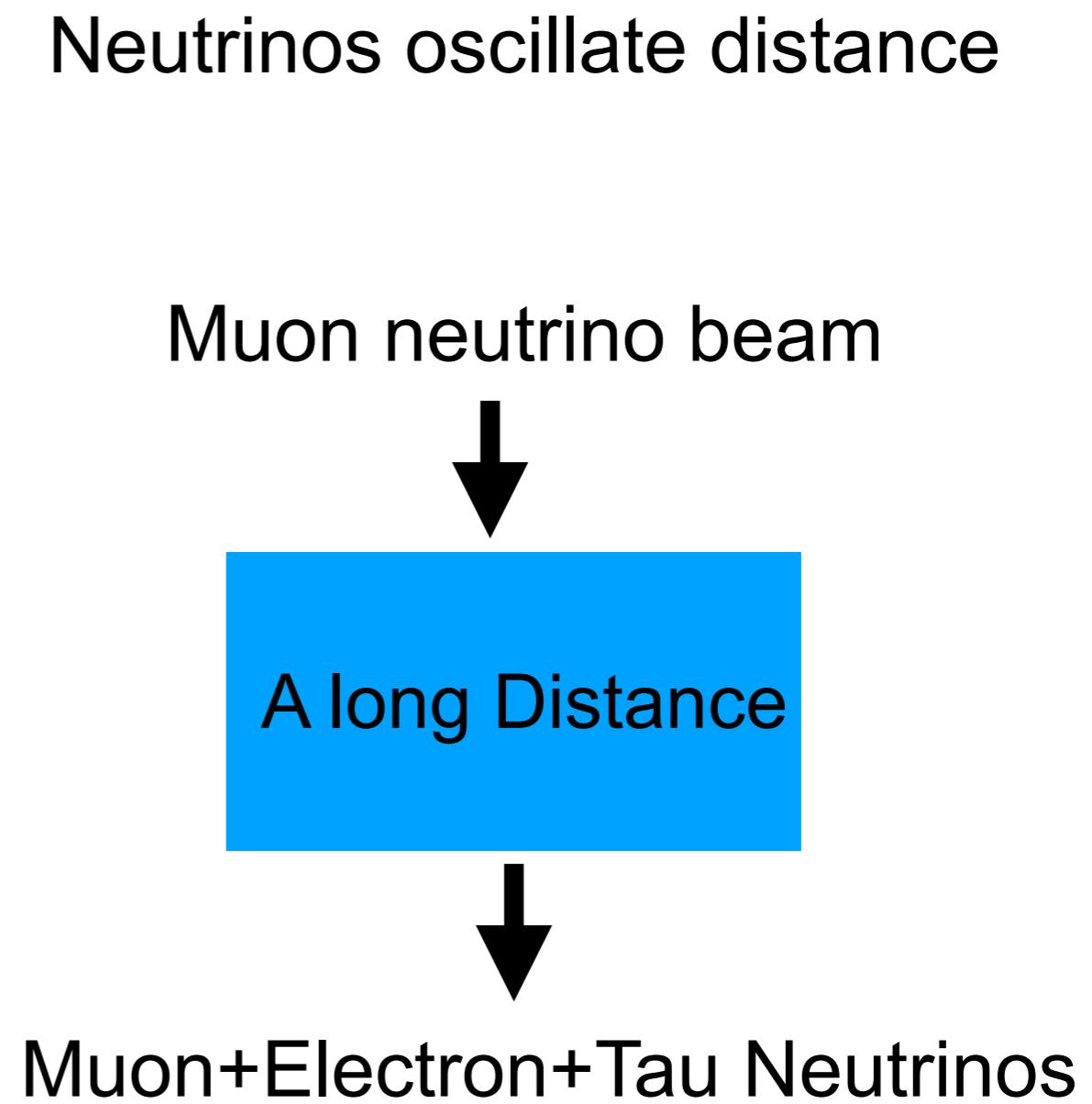
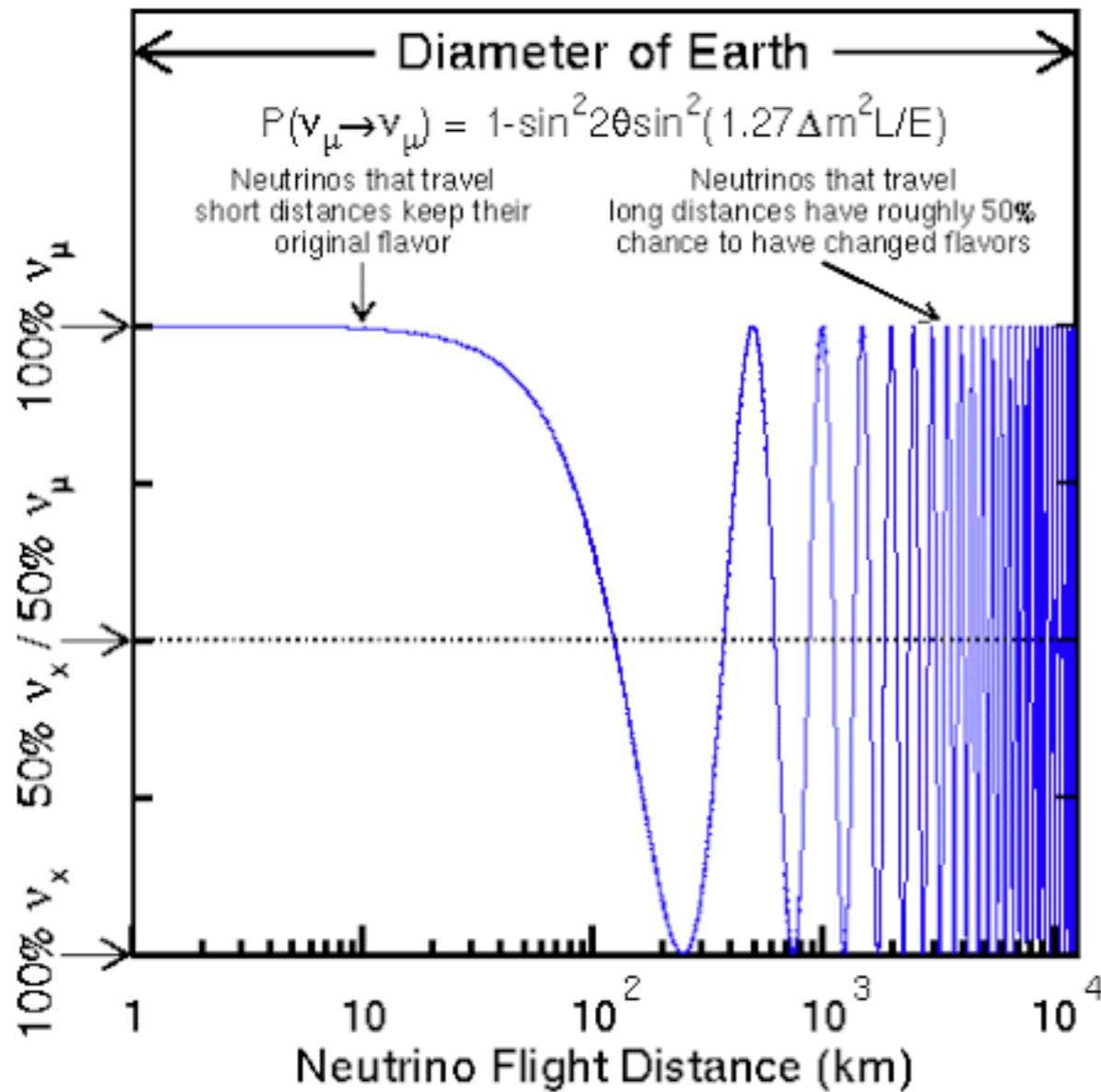
$$\simeq 1 - \sin^2 2\theta_{23} \sin^2 \left( \frac{1.27 \Delta m_{atm.}^2}{E} L \right),$$

As we evolve over time the particle eigenstates oscillate through the mass states

$$P_{\alpha \rightarrow \beta} = \delta_{\alpha \beta} - 4 \sum_{i > j} \Re[U_{\alpha i}^* U_{\alpha j} U_{\beta i} U_{\beta j}^*] \sin^2 \left( \frac{\Delta m_{ij}^2}{4E} L \right)$$

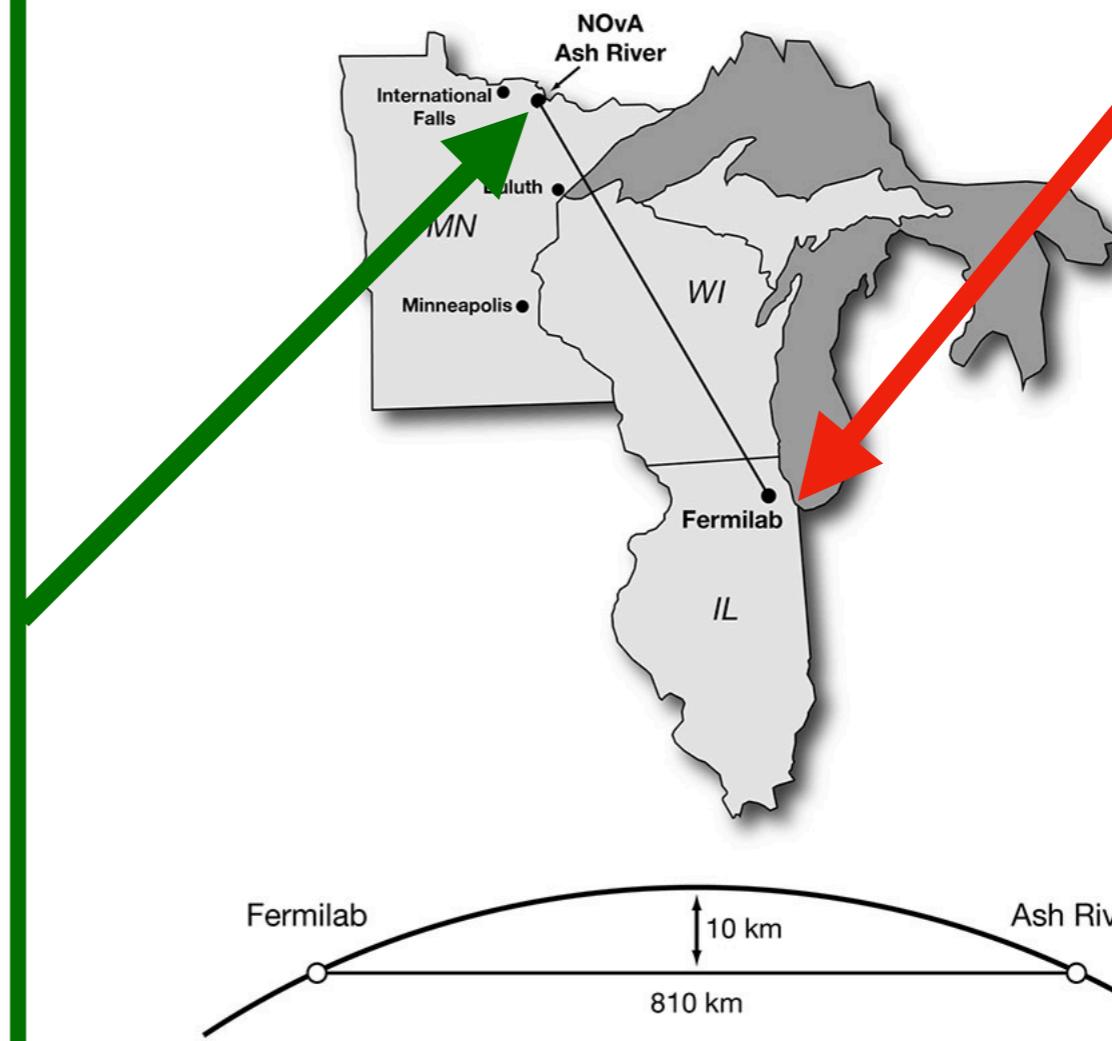
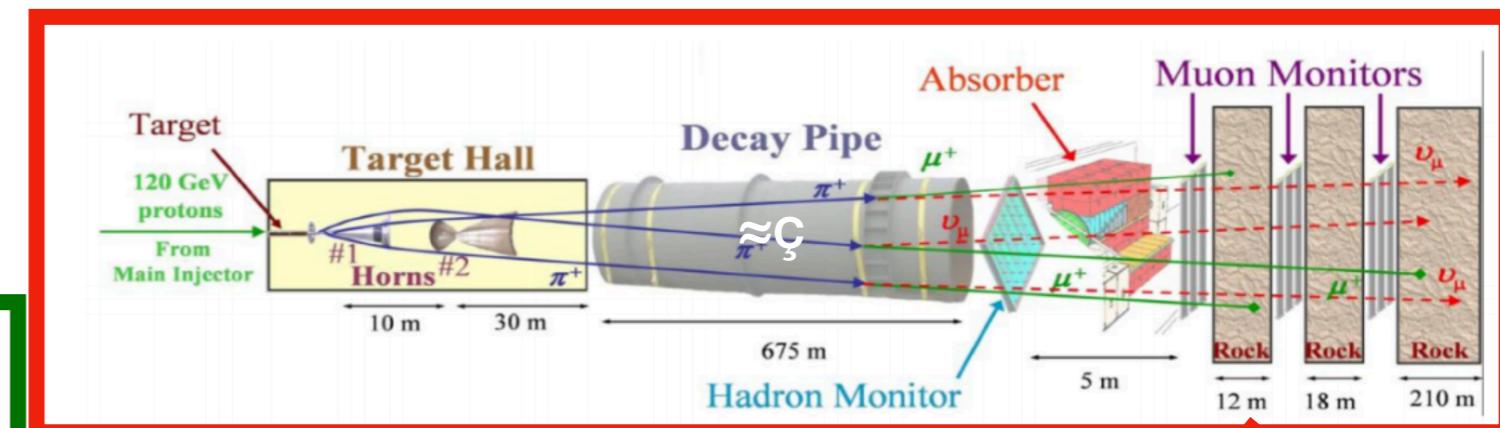
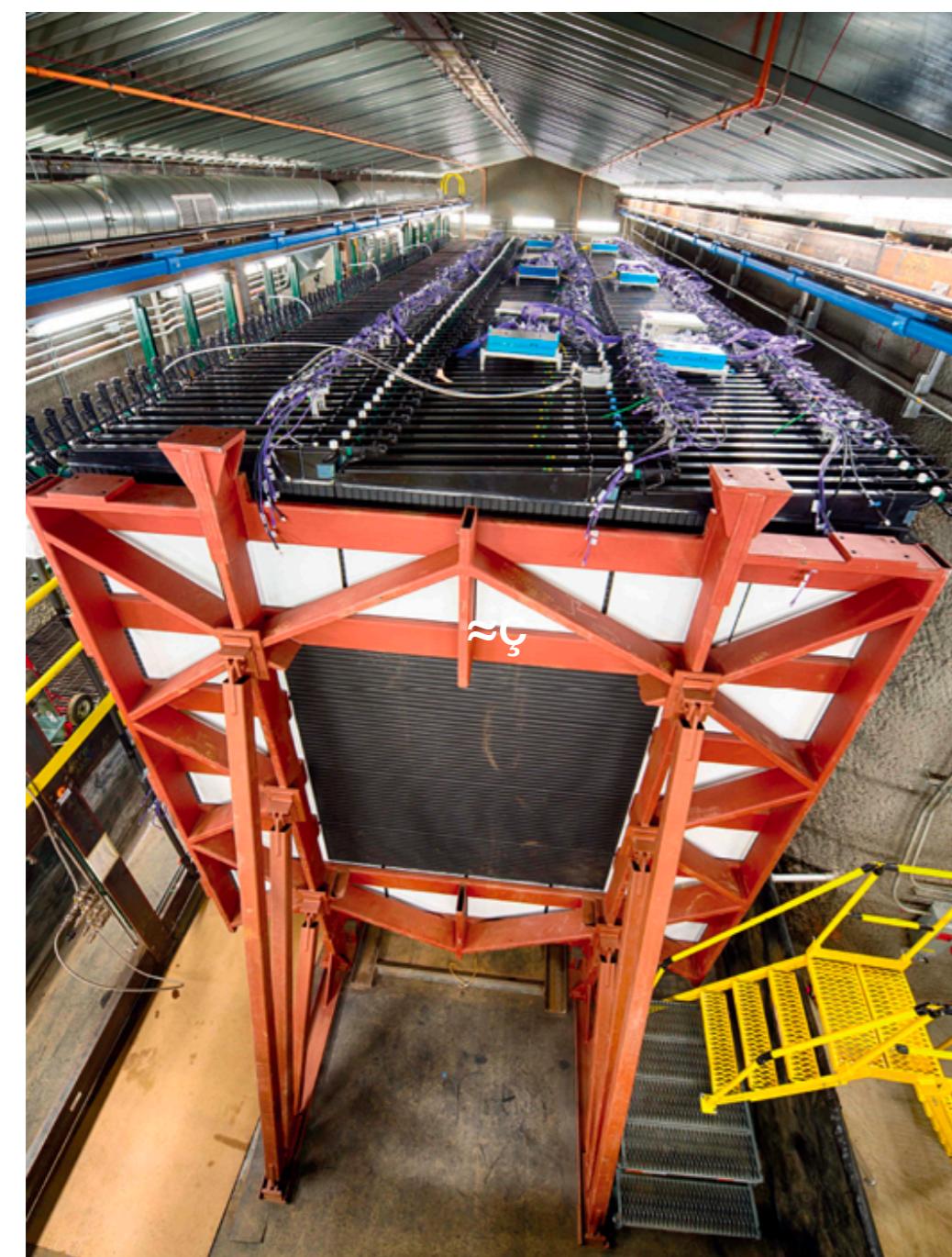
$$+ 2 \sum_{i > j} \Im[U_{\alpha i}^* U_{\alpha j} U_{\beta i} U_{\beta j}^*] \sin^2 \left( \frac{\Delta m_{ij}^2}{2E} L \right)$$

# Observing Oscillations

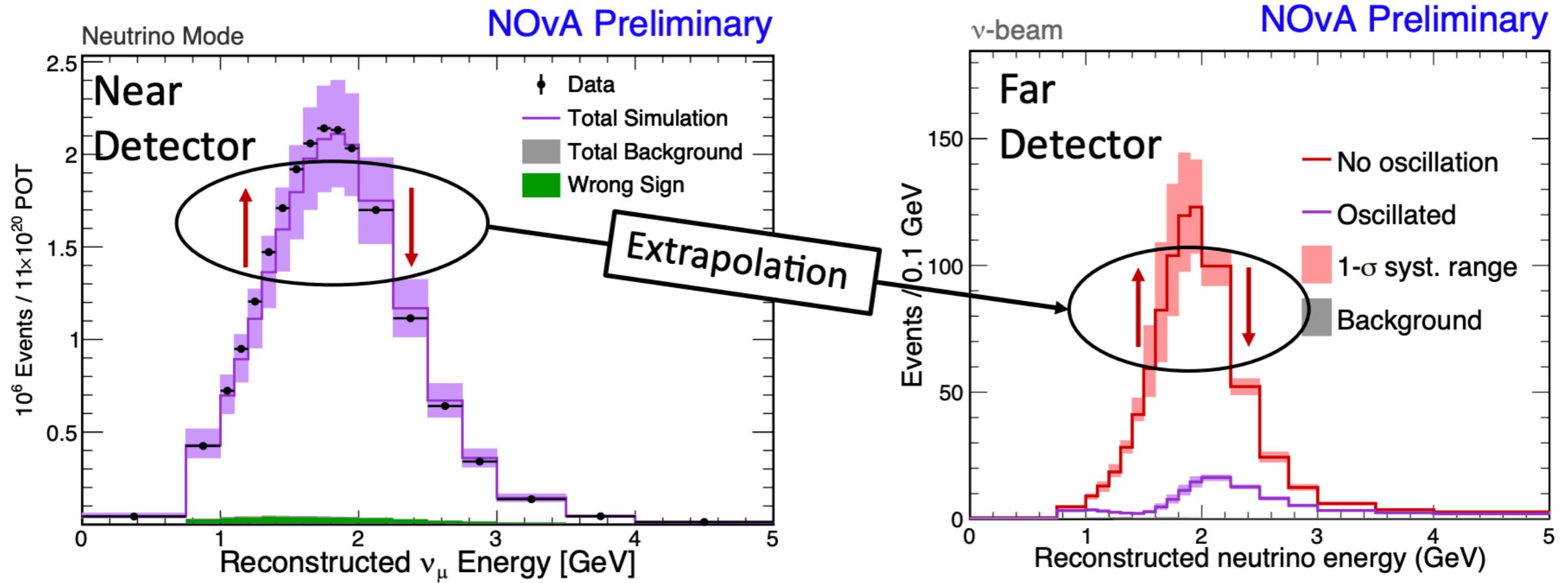


# NOvA Detector

Neutrino Beam  
From Fermilab (Near Chicago)  
To Minnesota (Near Canada)

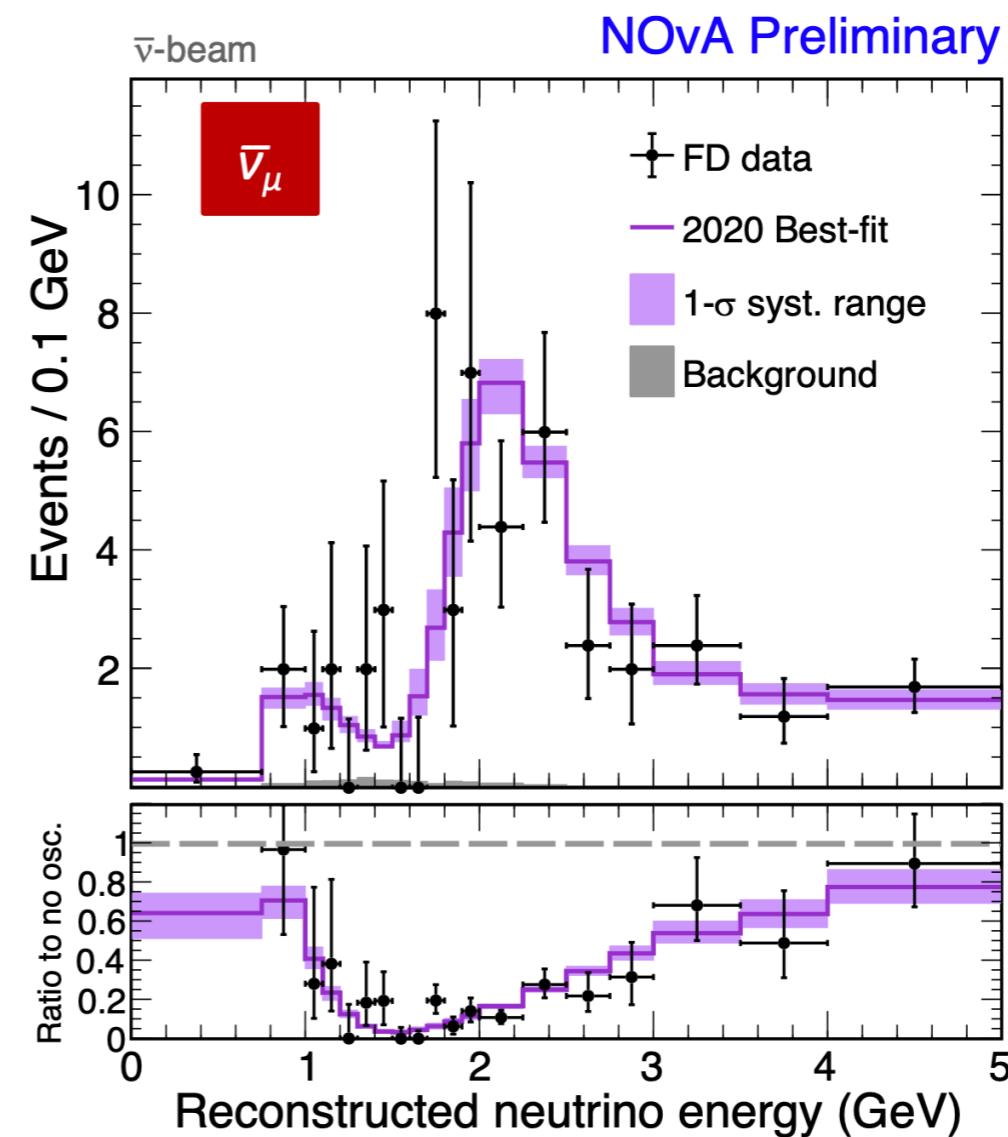
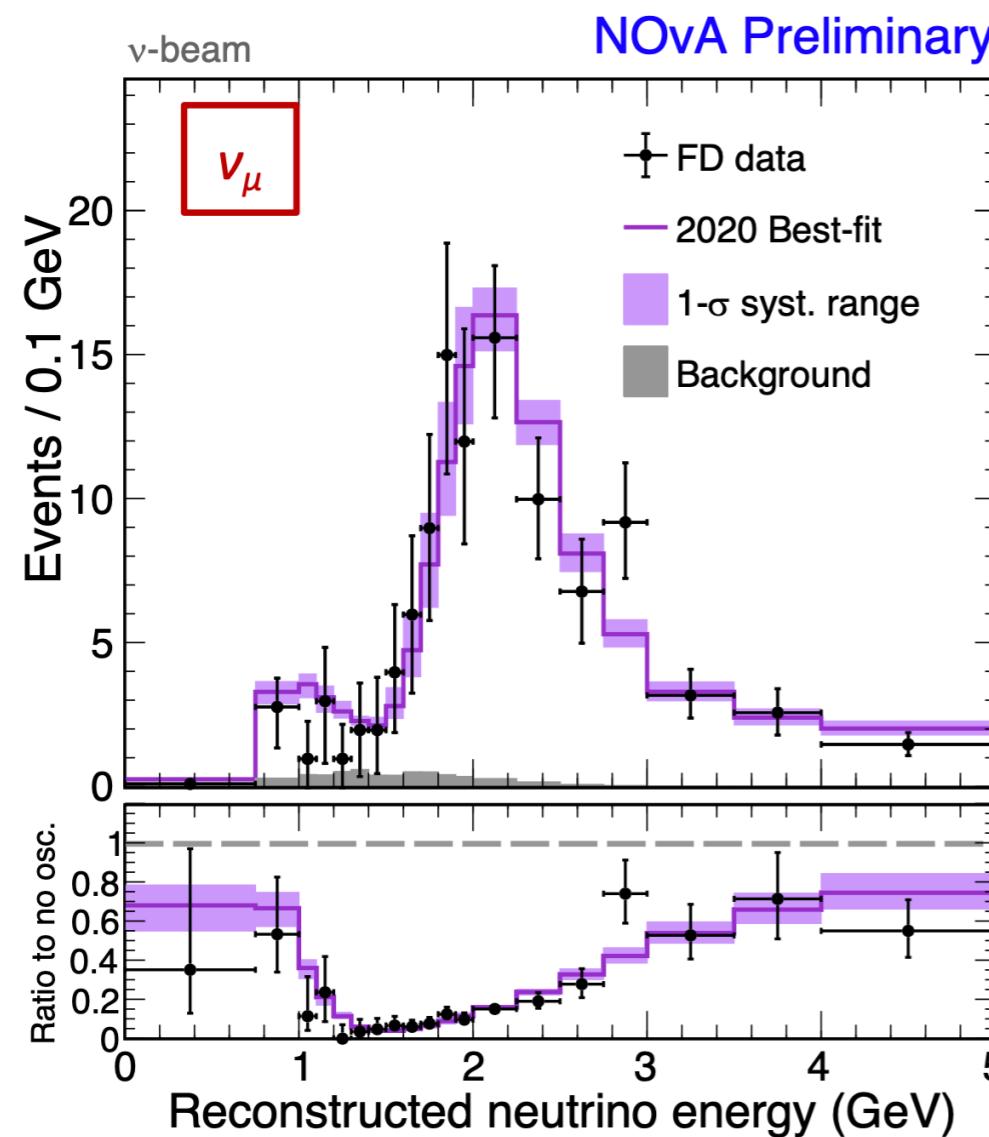


# NOvA Data



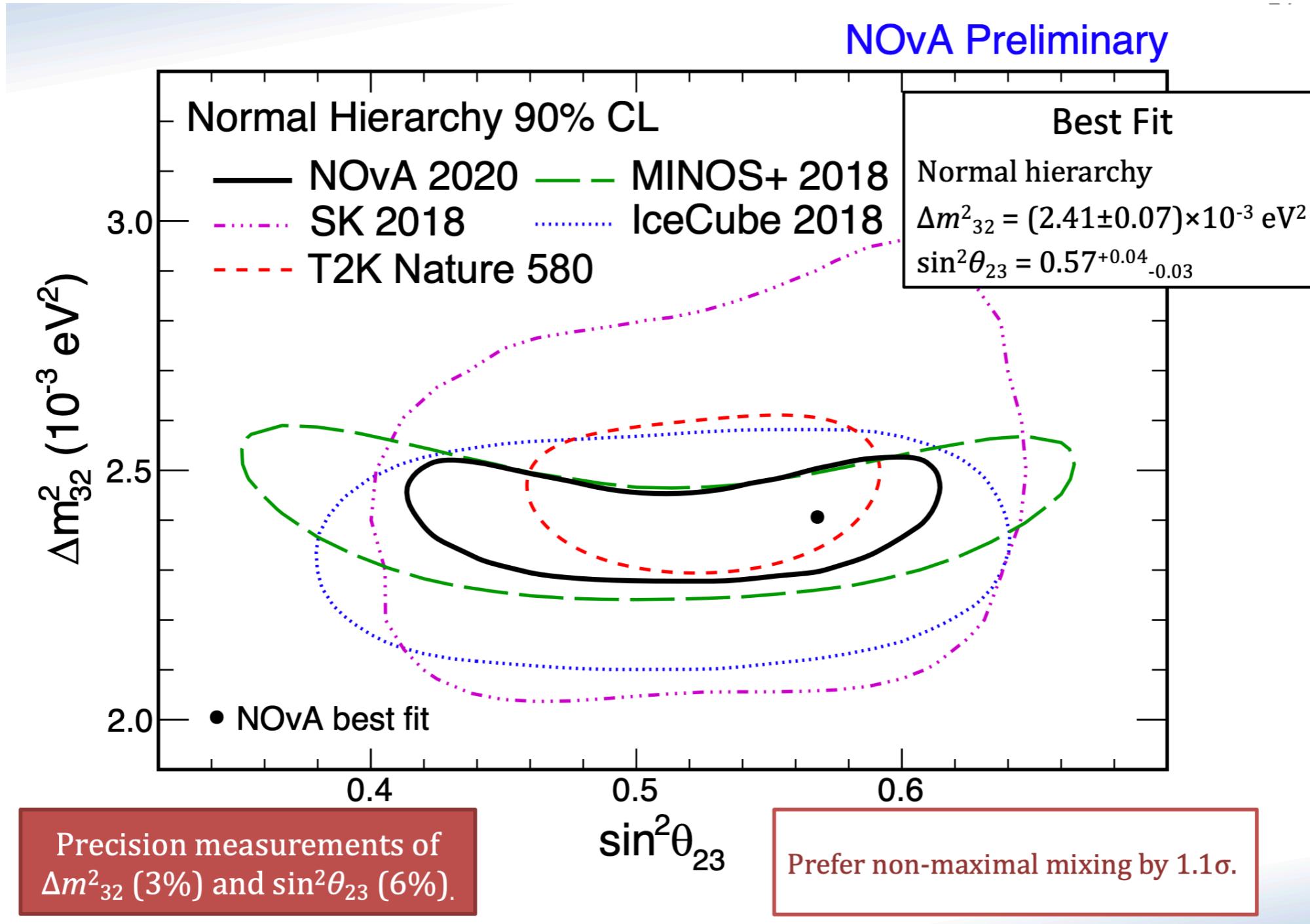
- With the input detector we can predict the output dist
  - In this way we predict it without any oscillations
  - The oscillation depends on our formula

# NOvA Data



- With the input detector we can predict the output dist
-

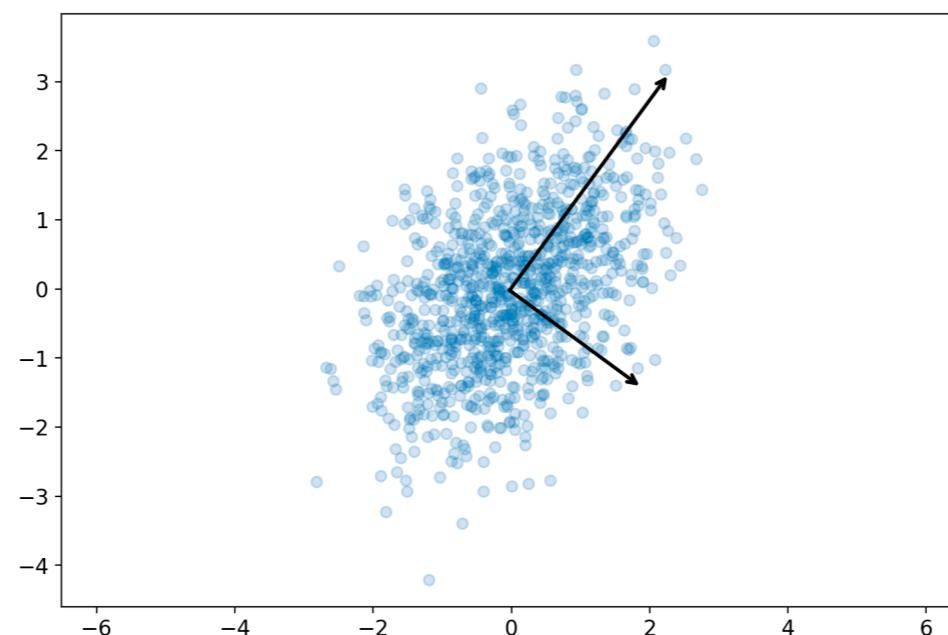
# NOvA Result



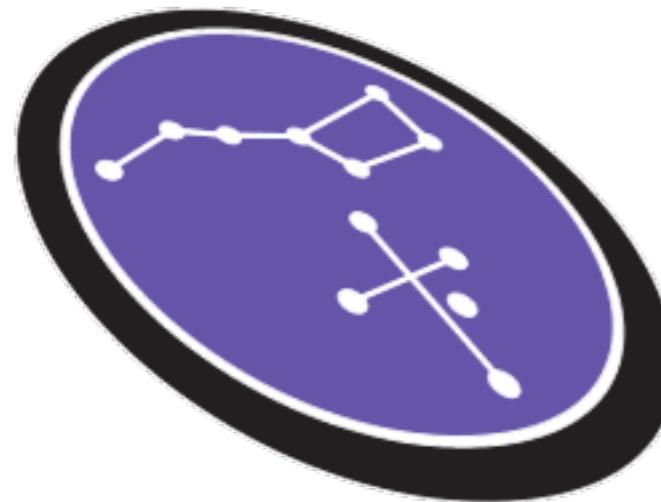
- From those plots: Lets look at those results

# Principal Component Analysis<sup>27</sup>

- Just taking the Eigen-vectors/values of an n-d space
  - Sorted by Eigenvalues, which give rank
  - Number of Eigenvalues above threshold is dimension



# SDSS



# SDSS

