

# Supernova neutrino signal detection in NOvA experiment

Andrey Sheshukov

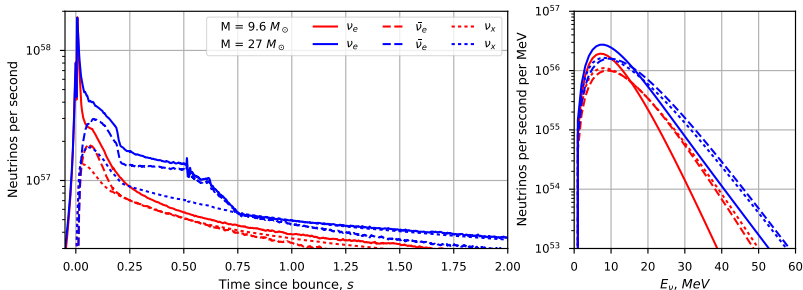
DLNP JINR, Dubna

24.01.2019



## Supernova neutrino signal

Neutrino signal from core-collapse supernova:



- $N_{\nu} \sim 10^{58}$  neutrinos
- $E_{\nu} \sim 10 - 60$  MeV
- $T \sim 10$ s

Models from arXiv:astro-ph/0604300

The models predict different fluxes. Also depends on the mass of the progenitor star.

Can provide valuable information about supernova physics, neutrino physics.

Very rare: 1-3/century in our galaxy.

## Coincidence network

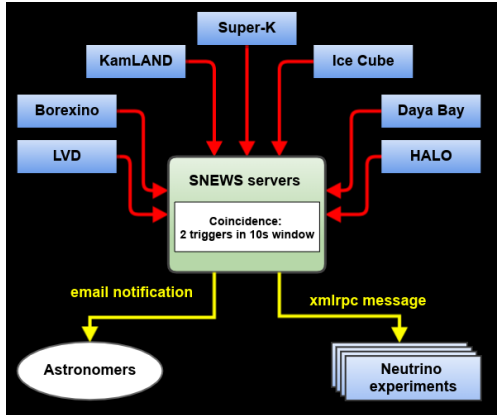
Many neutrino experiments sensitive to the SN neutrino signal.

Experiments capable of detecting this signal in real time are united in SNEWS coincidence network.

- Current mode: combining SN trigger signals from experiments.
- A better approach: combine signal significance from various experiments and do meta-analysis.

Plans for SNEWS v.2.0

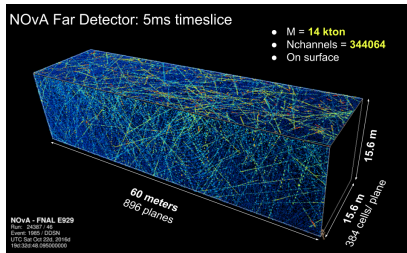
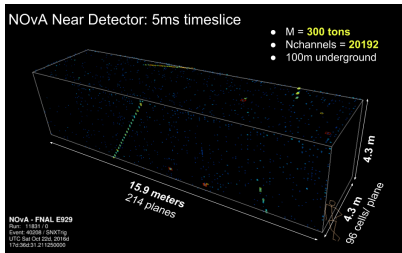
Work towards unified network with GW detectors.



SNEWS: SuperNova Early Warning System

## NOvA detectors

Main goal of the NOvA experiment: study neutrino oscillations in the muon (anti-)neutrino beam, with  $\langle E_\nu \rangle = 2$  GeV.

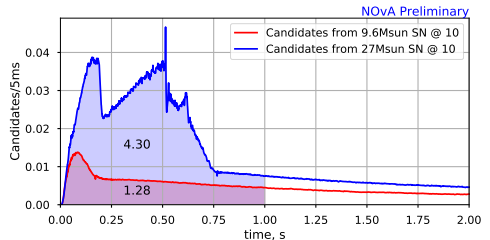
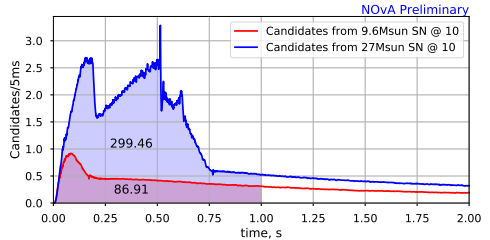
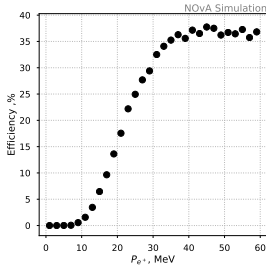


NOvA detectors are not ideal for the supernova signal detection (high background! designed for higher neutrino energies) but can still make a valuable contribution to SNEWS.

- Similar structure  $\Rightarrow$  almost the same reconstruction and data processing,
- Different size and overburden  $\Rightarrow$  very different BG conditions, statistics.

# Detecting supernova neutrinos

Main detection channel:  $\bar{\nu}_e + p \rightarrow e^+ + n$ .



	$N_{bg}$	$N_{sg}@10kpc$
FarDet	2483.21	86.91
NearDet	0.52	1.28

**Table:** Expected number of candidates from the first second of SN, after the reconstruction and selection procedures

# Supernova triggering system

A dedicated triggering system was deployed on NOvA detectors.

Characterized by:

- False trigger rate  $\alpha$
- Detection efficiency for particular supernova signal (model, distance)
- Reaction time.

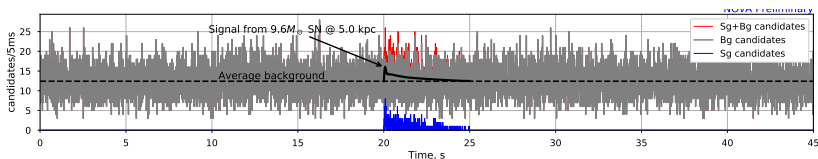
We need to process the data flow on-line:

- Reconstruction of neutrino interaction candidates performed in real time: more than 1800 parallel processes for 5ms data slices.
- Statistical analysis of interactions rate: algorithms should be computationally simple and robust.

## Analyzing time series

Input data from the candidates selection: time series

$$n_i = b_i + s_i$$



The triggering system needs to distinguish between the "background only"  $H_0$  and "background+signal"  $H_1$  hypotheses, using data within a sliding time window

$$\vec{n} = \{n_i\}$$

## Hypothesis testing, significance

- In general: use some test statistics function  $X(\vec{n})$  to discriminate between the hypotheses.
- We then need to know how the  $X(\vec{n})$  is distributed in case of each hypothesis is true:  $P(X|H_0)$ ,  $P(X|H_1)$
- The signal significance is characterized by  $p$ -value:

$$p(X(\vec{n})) = \int_{X(\vec{n})}^{\infty} P(x|H_0) dx$$

- We convert significance in "sigmas" for convenience:

$$z(x) = \text{erf}^{-1} \left( \frac{1 - p(x)}{2} \right)$$

Trigger fires if significance exceeds threshold (whatever definition we use):

$$\alpha = 1/\text{week} \iff p_{thr} = 8.267 \cdot 10^{-9}/5\text{ms} \iff z_{thr} = 5.645\sigma$$



## Simple example: using number of candidates in 1s

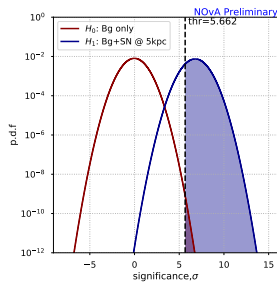
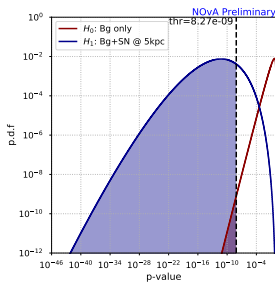
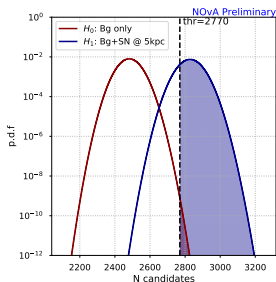
We can use number of candidates in 1s

$$\text{time window: } N = \sum_{i=0}^{200} n_i$$

Assuming  $N$  to have Poisson distribution around the average numbers from table, we can have the distributions for test statistics  $P(X|H_{0,1})$

	$N_{bg}$	$N_{sg}@10kpc$
FarDet	2483.21	86.91

**Table:** Expected number of candidates from the first second of SN



Probability to detect the SN @ 5kpc distance in FarDet is 86.46%, with  $\alpha = 1/\text{week}$

## Simple example: using number of candidates in 1s

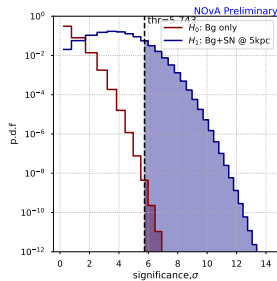
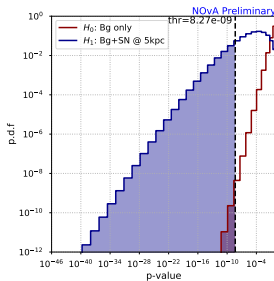
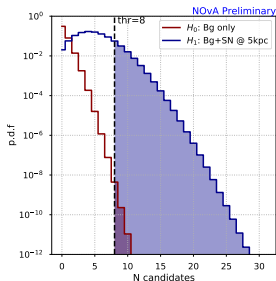
We can use number of candidates in 1s

$$\text{time window: } N = \sum_{i=0}^{200} n_i$$

Assuming  $N$  to have Poisson distribution around the average numbers from table, we can have the distributions for test statistics  $P(X|H_{0,1})$

	$N_{bg}$	$N_{sg}@10kpc$
NearDet	0.52	1.28

**Table:** Expected number of candidates from the first second of SN



Probability to detect the SN @ 5kpc distance in NearDet is 11.66%, with  $\alpha = 1/\text{week}$

## Using signal shape: log likelihood ratio

We can gain more sensitivity, if we use the information about the expected signal shape vs time.

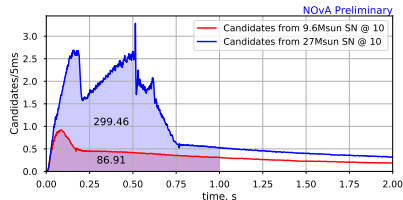
Number of candidates  $n_i$  in each of 5ms time bins should have Poisson distribution:

$$P(n_i|H_0) = B^{n_i} \cdot e^{-B} / n_i!$$

$$P(n_i|H_1) = \frac{(B + S_i)^{n_i} \cdot e^{-(B+S_i)}}{n_i!}$$

The average background rate per 5ms  $B$  is constant.

$$B_{FD} = 12.42 \text{ cand}/5\text{ms}.$$



The average signal candidates rate per 5ms  $S_i$ , varying with the time bin  $i$  (FD).

### Log likelihood ratio

$$\ell(\vec{n}) \equiv \log \frac{P(\vec{n}|H_1)}{P(\vec{n}|H_0)} = \sum_i n_i \cdot \log \left( 1 + \frac{S_i}{B} \right) - \sum_i S_i$$

## Log likelihood ratio (contd)

We can use  $\ell$  as test statistics for hypothesis testing.  
The constant shift  $\sum S_i$  is not important and can be omitted:

### Log likelihood ratio

$$\ell(\vec{n}) = \sum_i n_i \cdot A_i, \quad \text{where } A_i = \log \left( 1 + \frac{S_i}{B} \right)$$

Very convenient for real-time computation:

- A linear combination of the data in considered time window.
- For trigger we want a sliding time window - this becomes a convolution of incoming data  $n_i$  with the kernel  $\hat{A}$ .

Next, we need to know the distributions:  $P(\ell|H_{0,1})$

But a linear combination of Poisson random numbers  $n_i$  is not Poisson (in general).

We still can calculate the distribution  $P(\ell|H)$  in two specific cases.

## Log likelihood ratio distributions: high background

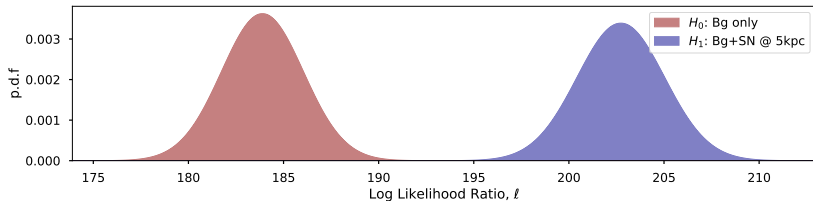
If the background  $B$  in the time bin is high enough,  $n_i$  can be considered normally distributed:

$$P(n_i|H_1) = \mathcal{N}(\mu = B + S_i, \sigma = \sqrt{B + S_i})$$

and linear combination of normal random variables is also normal:

$$P(\ell|H_1) = \mathcal{N}\left(\mu = \sum_i (B + S_i) \cdot A_i, \sigma = \sqrt{\sum_i (B + S_i) \cdot A_i^2}\right)$$

This case can be applied to Far Detector, if we make the time bins large enough: for  $\delta t = 50ms$ ,  $B = 124.2$



## Log likelihood ratio distributions: low background

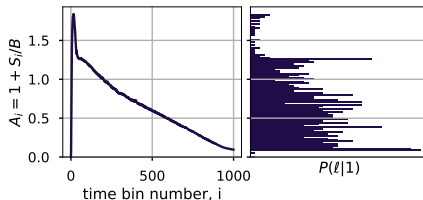
Consider total number of candidates in time window  $N = \sum n_i$ .

$$P(\ell|H_0) = \sum_{N=0}^{\infty} P(\ell|N, H_0) \cdot P(N|H_0)$$

Here  $P(N|H_0) = B^N e^{-B} / N!$  decreases fast, if  $B$  is low. So we can stop at some order.

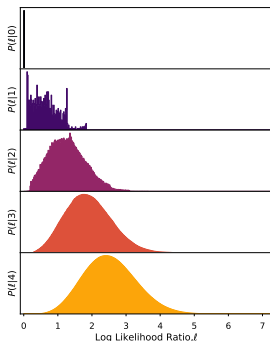
How to calculate  $P(\ell|N)$ ?

- $P(\ell|0)$  is trivial — no candidates means  $\ell = 0$
- $P(\ell|1)$ :  $\ell = A_i$  if candidate gets to the  $i_{th}$  time bin.



- $P(\ell|N + 1)$ :  $\ell = \ell_N + A_i \Rightarrow P(\ell|N + 1) = P(\ell|N) * P(\ell|1)$

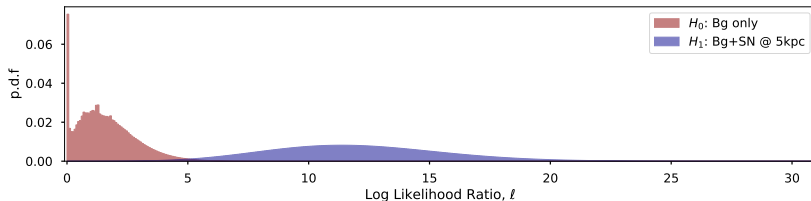
## Log likelihood ratio distribution: low background (continued)



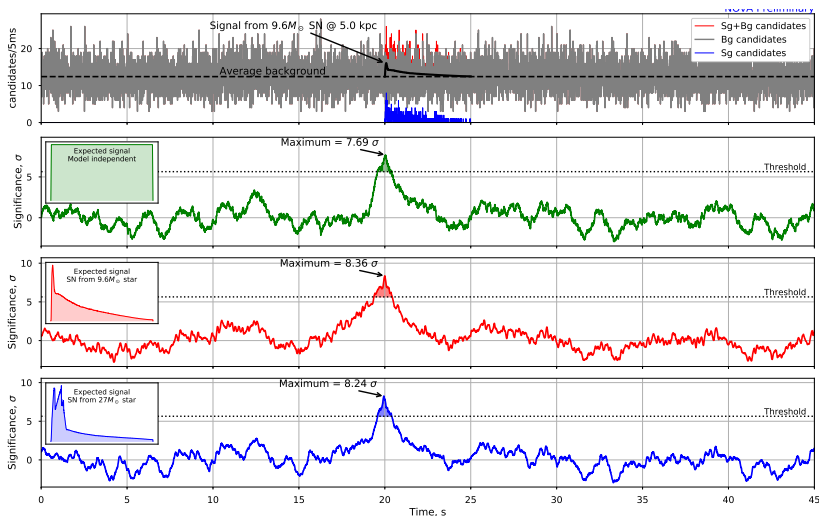
Summing up with correct Poisson probability  $P(N|H_0)$  we get the result distribution.

This is the mode for the Near Detector. Average background rate is 0.5 candidates/sec.

This procedure is rather fast. It is done every time the background level is measured (every 10 minutes)



## Example: triggering on Far Detector



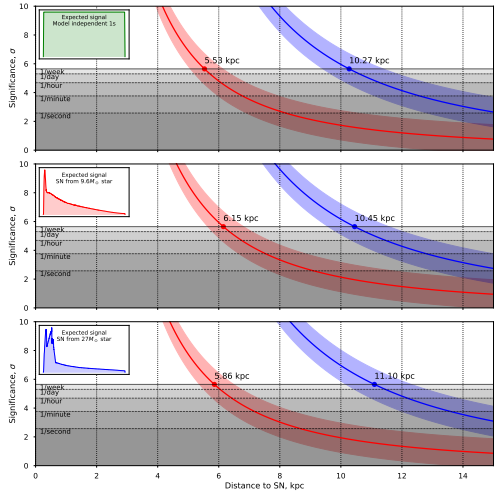


## Significance vs. distance

Different expected signal shapes  $S_i$ .

And we can get the unexpected signal  $\tilde{S}_i$ , different from  $S_i$ .

Note: when  $S_i$  is flat, we get  $\ell \sim \sum n_i$ , i.e. get the simple triggering on the  $N_{cands}$  in a time window.



Significance in the Far detector.

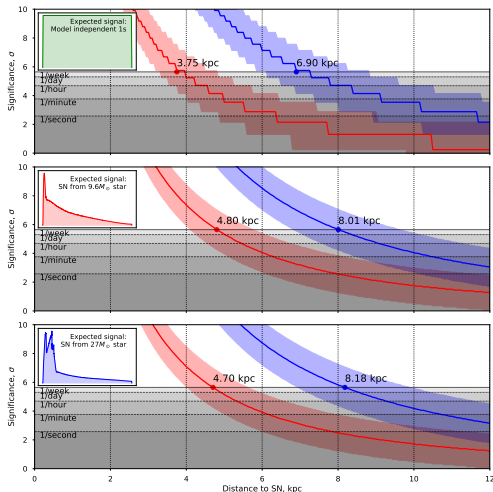
## Significance vs. distance

Different expected signal shapes  $S_i$ .

And we can get the unexpected signal  $\hat{S}_i$ , different from  $S_i$ .

Note: when  $S_i$  is flat, we get  $\ell \sim \sum n_i$ , i.e. get the simple triggering on the  $N_{cands}$  in a time window.

"Steps" from Poisson distribution are visible



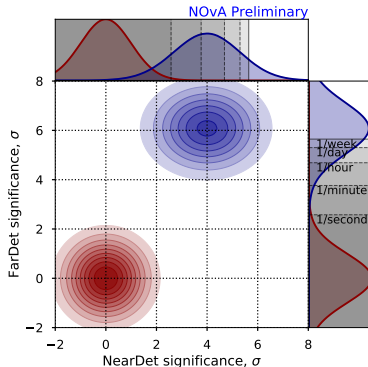
Significance in the Near detector.

## Combining detectors

Currently the detectors perform hypothesis test separately.

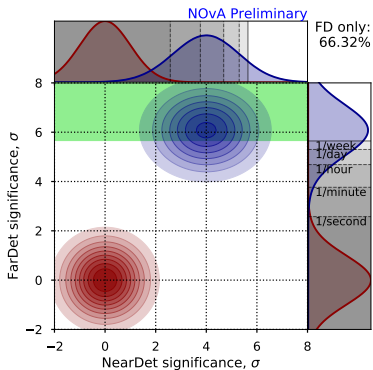
If we can get the synchronized significance scores from both detectors, we can perform meta-analysis using these two parameters.

- We need to define a combined "significance", which can then be used as test statistics:  $S(z_{near}, z_{far})$ .
- The threshold on  $S$  defines a region in  $(z_{near}, z_{far})$  space where the trigger occur.
- The ways to define this function are infinite, depending on what we want:
  - Maximize the efficiency for specific signal?
  - Keep as model independent as possible?
  - Minimize the data flow between detectors?

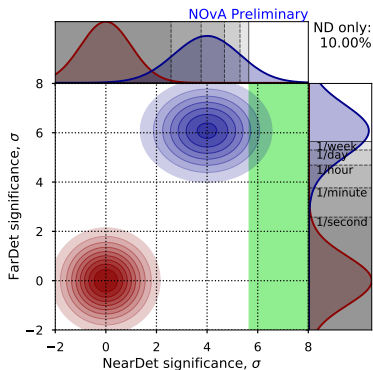


## Combining detectors: examples

The signal (blue distribution) is for  $9.6M_{\odot}$  SN signal at 5 kpc distance.  
The background (red distribution) integral over the green area is fixed to  $\alpha = 1/\text{week}$   
Detectors triggering separately:



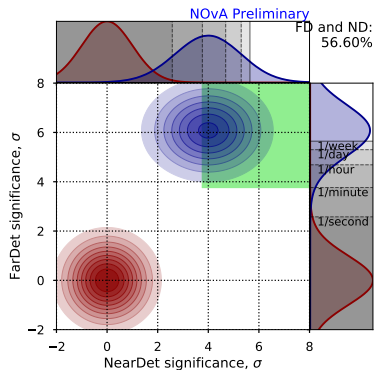
$$S = z_{far}$$



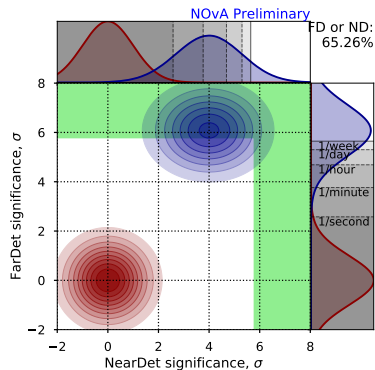
$$S = z_{near}$$

## Combining detectors: examples

The signal (blue distribution) is for  $9.6M_{\odot}$  SN signal at 5 kpc distance.  
The background (red distribution) integral over the green area is fixed to  $\alpha = 1/\text{week}$   
Trigger signals combined (each detector still makes its own decision, but we combine the results):



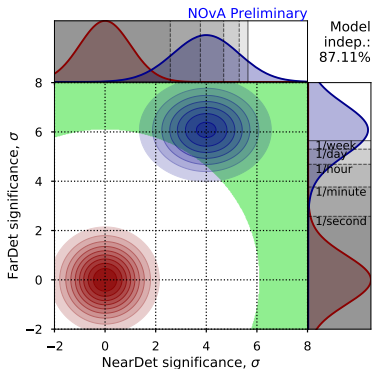
$$S = \min(z_{far}, z_{near})$$



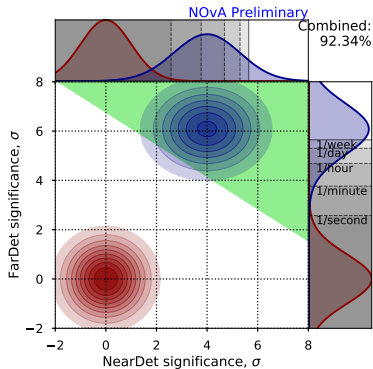
$$S = \max(z_{far}, z_{near})$$

## Combining detectors: examples

The signal (blue distribution) is for  $9.6M_{\odot}$  SN signal at 5 kpc distance.  
The background (red distribution) integral over the green area is fixed to  $\alpha = 1/\text{week}$   
Significance combined (significance score collected for every 5ms time bin):



$$S = \sqrt{z_{far}^2 + z_{near}^2}$$



$$S = a \cdot z_{far} + b \cdot z_{near}$$

## Combining detectors

Mode	$S(z_{far}, z_{near})$	$\epsilon$ for SN @ 6 kpc ( $9.6M_{\odot}$ )	Data sent every
FD only	$z_{far}$	66.32%	1 week
ND only	$z_{near}$	10.0 %	1 week
ND and FD	$\min(z_{far}, z_{near})$	56.6%	55 seconds
ND or FD	$\max(z_{far}, z_{near})$	65.26%	2 weeks
Model indep.	$\sqrt{z_{far}^2 + z_{near}^2}$	87.11%	5 ms
Combined	$a \cdot z_{far} + b \cdot z_{near}$	92.34%	5 ms

Expanding to many experiments network (SNEWS, GWNU):

- Time synchronization will be worse — larger time windows
- Need weighted approach, so less sensitive experiments don't decrease overall sensitivity
- Other signals will have a different position in  $(z_{far}, z_{near})$ . Different detectors sensitive to different signals.
- Mode depends on our requirements, and on the range of  $H_1$  we want to be sensitive to.
- It's hard to stay model independent.

## Summary

- NOvA detectors require slightly different statistical approaches, because of different conditions.
- Using the log likelihood ratio to take into account the expected signal shape improves sensitivity. This is model-dependent, but SN neutrino signals have many common features.
- The calculation of significance is done online. This requires the fast way to calculate  $P(X|H_{0,1})$ ,
- NOvA SN triggering system can be considered as a small coincidence network for SN detection.  
So we can try out various methods of combining the measurements from detectors.
- We still need to define the most promising strategy. Currently we're working in the "OR" mode.



