PHYS 575A/B/C

Autumn 2012

Radiation and Radiation Detectors

Course home page:

http://depts.washington.edu/physcert/radcert12/575website/

7: more on statistical data analysis

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Course calendar (revised)

week	date	day	topic	text
1	10/1/15	Thurs	Introduction, review of basics, radioactivity, units for radiation and dosimetry	Ch. 1, notes
2	10/6/15	Tues	Radioactive sources; decay processes;	Ch. 1, notes
3	10/13/15	Tues	Photomultiplier tubes and scintillation counters; Counting statistics	Chs. 3, 8, 9 (I-V)
3	10/15/15	Thurs	**LAB: Room B248** Scopes, fast pulses; PMTs and scintillation counters; standard electronics modules	Chs. 4, 9, 16, 17
4	10/20/15	Tues	Overview of charged particle detectors	Ch. 4
4	10/22/15	Thurs	**LAB: Room B248** Coincidence techniques; nanosec time measurement, energy from pulse area	Chs. 17, 18
5	10/27/15	Tues	Interaction of charged particles and photons with matter; counting statistics; gas detectors; Proposal for term paper must be emailed to JW by today	Chs. 2, 3; Chs. 5, 6, 7
6	11/3/15	Tues	ionization chambers; solid-state detectors	Chs. 11, 12, 13
7	11/10/15	Tues	Statistics for data analysis; Case studies: classic visual detectors (cloud and bubble chambers, nuclear emulsion, spark chambers)	Ch. 19, notes
8	11/17/15	Tues	Case studies: Cosmic ray detectors (Auger, Fermi gamma ray observatory); Cherenkov detectors: atmospheric Cherenkov, triggering Cherenkov	Ch. 19, notes
9	11/24/15	Tues	Case studies: neutrino detectors (IceCube, Daya Bay, Majorana), Detecting neutrons; high energy accelerators;	Ch. 19, notes Ch. 14, 15, 18
10	12/1/15	Tues	Finish case studies; begin student presentations	Notes
11	12/8/15	Tues	Student presentations	-
11	12/10/15	Thurs	Student presentations	

Tonight

Announcements

- Presentation dates: Tues Dec 1, Tues Dec 8, and Thurs Dec 10
  - See class web page for link to signup sheet

- NEW Schedule and signup table for term project presentations. This is a Google spreadsheet in the UW Google Docs filespace; log in with your UW NetID username and password (NOT your personal Google username) for access. Sign in to the slot you want, then exit, and let me know you did so by email.

I will arbitrarily assign slots for those not signed up by November 29

As of today:

PHYS 575 Au-15: Report Presentations			
Please send me your presentation ppt/pdf (or URL) at least 1 hour before class on your date			
Day	Time	Name	Topic
12/1/2015	7:00 PM	Per Provencher	Low Background Laboratories
	7:20 PM	Rick McGann	Neutron Generation and Effects on Materials and Electronics
	7:40 PM	Chris Provencher	Bremsstrahlung
	8:00 PM	Charles Ko	Radiometric Dating
	8:20 PM		
12/8/2015	6:40 PM	Diana Thompson	NORM
	7:00 PM	Shawn Apodaca	Fast Neutron Time of Flight and Spectroscopy
	7:20 PM	Erin Board	Cosmic Radiation and Shielding
	7:40 PM		
	8:00 PM		
	8:20 PM		
12/10/2015	6:40 PM	Nathan Hicks	Methods of Radionuclide Production for Medical Isotope Usability: Meeting the Demand
	7:00 PM	Farrah Tan	QCD
	7:20 PM	Nicolas Michel-Hart	microXRF
	7:40 PM	Michael Esuabana	proton-Boron11 fusion
	8:00 PM		
	8:20 PM		

Using statistics to evaluate detector data

- Hypothesis testing: what is probability that data were due to effects of some physics model, not mere chance (random fluctuations)?
  - Test: Is model valid, if so to what confidence level?
  - Example: are Super-Kamiokande neutrino data consistent with expectations from assumption neutrinos are massless? With what confidence limit can we exclude mere chance?

    (We've already discussed chi-squared test methods)
- Parameter estimation: *assuming* some model represents the data, what are the best estimates of its parameters, given these data?
  - Find best-fit values, and confidence limits on them
  - Example: assuming data are due to neutrino "oscillations" (evidence of mass), what are best estimates of the model parameters θ and Δm^2 ? How well do the data constrain these estimates?
- We'll discuss three common methods:
  - Maximum likelihood (most general method for parameter estimation)
  - Least squares fitting (special case of ML; aka "χ^2 method")
  - Kolmogőrov-Smirnov methods

Max Likelihood fitting

Given a set of N observations $\{\underline{x}\}_N$ we want to find best-fit values for the m parameters θ_j in the assumed (model) PDF $f(x|\underline{\theta})$

- Probability of obtaining exactly the data set we observed is:

  $P(\underline{x}|\underline{\theta})= f(x_1|\underline{\theta})\Delta x_1\, f(x_2|\underline{\theta})\Delta x_2 \ldots f(x_N|\underline{\theta})\Delta x_N$

  (= Prob of $(x_1 \leq x < x_1+\Delta x_1)$.and.$(x_2 \leq x < x_2+\Delta x_2)$.and. ...)

  So $f(x_1) \bullet f(x_2) \bullet f(x_2) \ldots = \Pi_i\, f(x_i|\underline{\theta})$

  $= \Pi_i\, f(x_i|\underline{\theta})\Delta x_i$ = prob of observing the exact set of data we have, given $\underline{\theta}$

  Note that here we regard $\underline{x}$ as variables and $\underline{\theta}$ as given parameters

- Reverse roles: now treat $\underline{x}$ as fixed (by the experiment) and $\underline{\theta}$ as variables, and write the joint PDF for all data again as function of $\underline{\theta}$, given x's

  $L(\underline{\theta}|\underline{x}) = \Pi_i\, f(x_i|\underline{\theta})$ ***Likelihood function***

  $L(\underline{\theta}|x)$ = probability of parameters in model being $\underline{\theta}$, given set of x's observed

  Now L is $L(\underline{\theta}) \rightarrow$ PDF for $\underline{\theta}$, given results of our experiment $\{\underline{x}\}_N$

- Best fit values for parameters $\underline{\theta}$ = those which give *maximum likelihood*
  – use simple calculus to find set of θ_i that maximizes L : $\partial L/\partial \theta_j = 0$

Max Likelihood method

- With m parameters to be fitted, we get m simultaneous eqns:
  minimize: set $\partial L/\partial \theta_j = \partial \{\Pi_i f(x_i|\underline{\theta})\}/\partial \theta_j = 0 \qquad 1 \leq j \leq m$

  Usually easier to deal with log-likelihood (product → sum):
  $\partial \log L/\partial \theta_j = \partial \log \{\Pi_i f(x_i|\underline{\theta})\}/\partial \theta_j = \partial \Sigma_i \{\log f(x_i|\underline{\theta})\}/\partial \theta_j = 0$
  - This requires $L(\underline{\theta})$ be differentiable (at least numerically)
    - we are looking for peak in L as a function of $\underline{\theta}$
  - equations may require numerical solution: find *global maximum* in $L(\underline{\theta})$ hypersurface
    - if L_{MAX} is at boundary of $\underline{\theta}$ range, may need to extend to *unphysical region* in $\underline{\theta}$ space to properly evaluate fit
  - Behavior of $L(\underline{\theta})$ near maximum gives estimates of confidence limits on parameters: how sharply peaked is the hypersurface?
- For ML estimators, "best" means maximum joint probability
  - Not necessarily best by other criteria (eg, *minimax* = minimize *maximum* deviation from data, minimum variance estimator, bias): choose criterion
  - ML is easy to use, and does not require binning (arbitrary choice of bin size, loss of detailed info)

Example: fit to transverse momentum data

- Transverse momentum in proton-proton interactions
  - Produced particles (pions) go mostly in forward direction
    - Transverse component of their momentum is limited

Theory suggests exponential distribution for $x = p_T$: $f(x;\theta)=(1/\theta)\exp(-x/\theta)$

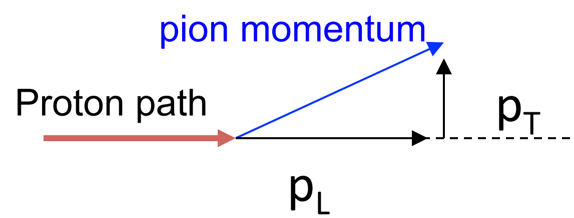
with $\theta = \langle p_T \rangle$ (average p_T)

- $L(\theta)= \Pi_i (1/\theta)\exp(-x_i/\theta)$
- $\log L(\theta)= \Sigma_i (\log(1/\theta) - x_i/\theta)$
- $\partial \log L/\partial \theta = \Sigma_i (-2/\theta +2 x_i/\theta^2)$

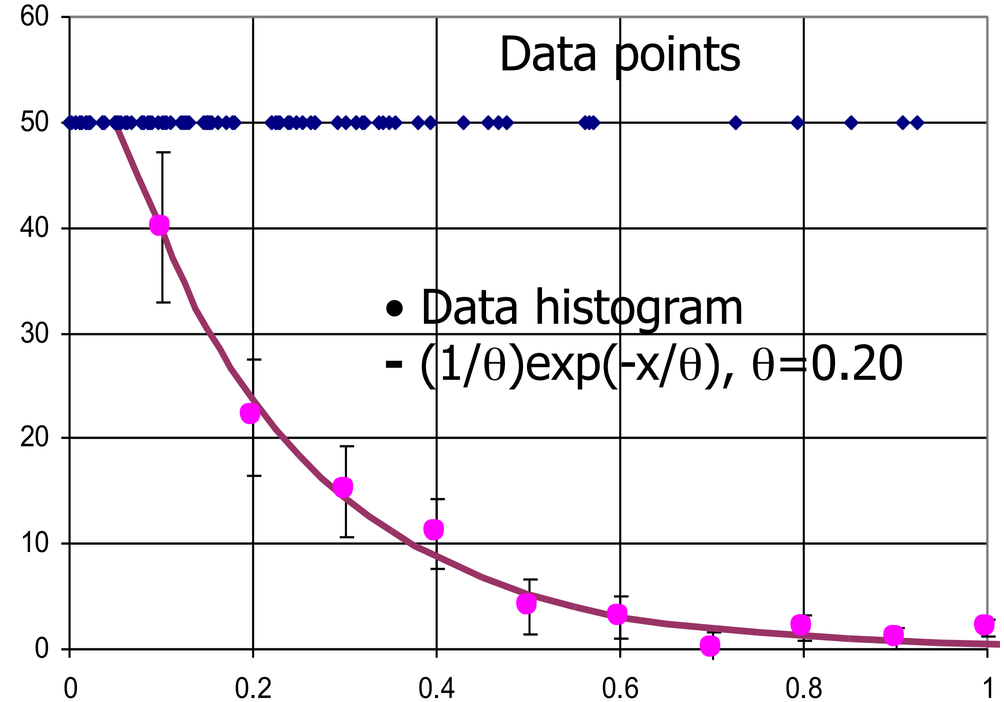
$$= -N/\theta + (\Sigma_i x_i)/\theta^2$$

$$N\theta = \Sigma_i x_i$$

so $\log L$ = max for $\theta^{ML} = (1/N) \Sigma_i x_i$ (just the arithmetic mean of p_T data)

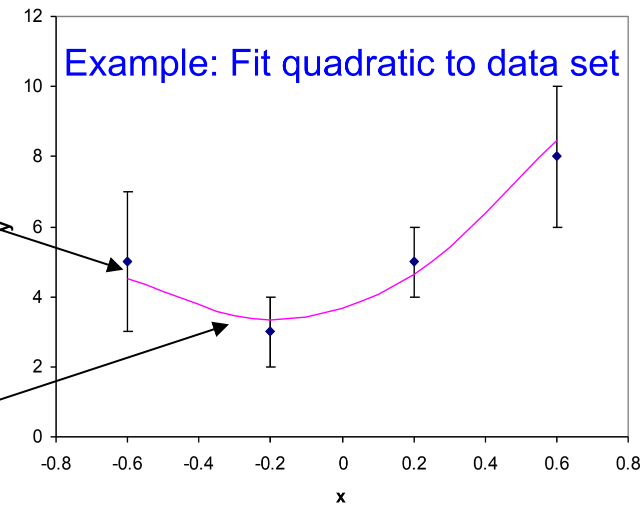


ML example: fit to p_T distribution



- Line of dots at top = individual data points' p_T values
  - For this data set, $\theta^{ML} = (1/N)\ \Sigma_i\ x_i = 0.20$
- Plotted points = histogram of data with bin width 0.1 MeV/c
  - Error bars are $\sqrt{N_{bin}}$ (assumes each bin's contents are Poisson distributed)
- Curve = ML fit (uses all pts, *not* a fit to the histogram)

Least Squares methods



Observations $y(x_i) \pm \sigma_i$
y=*dependent* variable
(measured values)

Function $f(x; a,b,c)=a+bx+cx^2$
x=*independent* variable
(values set by experiment)

- LSQ is popular due to long history, ease of use
  - no optimum properties in general, but:
    - For an $f(x; \theta)$ that is *linear* in θ, LSQ estimators are unique, unbiased and minimum-variance (all the statistician's virtues!)
- LSQ principle: given
  - N observations $\{y_i(x_i)\}$, each with associated weight W_i, and
  - A model function which yields predicted values $\eta_i = f(\underline{x}; \underline{\theta})$

Then the best estimates $\underline{\theta}^{LSQ}$ are those which minimize

$\chi^2 = \Sigma_N W_i (y_i - f(x_i ; \underline{\theta}))^2$

This minimizes the deviation of the predicted values from the data *in the sense of least squares*

LSQ is a *special case of ML*

Weight W_i is proportional to accuracy (inverse of uncertainty) for each measurement

- If W_i =1 for all i, we have an *unweighted LSQ* fit:
  - $\chi^2 = \Sigma_N (y_i - \eta_i)^2$
- If W_i are unequal, we usually take $W_i = 1/\sigma_i^2$
  - σ_i^2 = uncertainty in data point i
  - $\chi^2 = \Sigma_N W_i (y_i - \eta_i)^2$
- For counting data we usually take uncertainty √N : √f(x) → $\sigma_i^2 = f(\underline{x}) = \eta_i$
  - $\chi^2 = \Sigma_N ((y_i - \eta_i)^2)/ \eta_i$ (η_i = model's prediction for y)
- When precisions cannot be assumed equal but details are unknown, people often take $\sigma_i^2 = y_i$ for simplicity:
  - $\chi^2 = \Sigma_N ((y_i - \eta_i)^2)/ y_i$ (Observed value of y)

- LSQ makes no *requirement* on distribution of observables about $f(\underline{x}; \underline{\theta})$: "distribution-free estimator" but if* $y_i(x_i)$ are normally distributed about $f(\underline{x})$,
  1. LSQ is the *same as ML:*
     - $L(x;\theta)=\Pi_N$ $(1/\text{sqrt}(2\pi\sigma_i) \exp[-(y_i- \eta_i)^2 /(2 \sigma_i^2)]$ (normal distribution)
     - Maximize Ln L= $\Sigma_N -(y_i- \eta_i)^2 /\sigma_i^2 \rightarrow$ minimize $\Sigma_N (y_i- \eta_i)^2/\sigma_i^2$ (max L = min χ^2)
  2. χ^2 at minimum will obey the χ^2 -distribution: lets us get quantitative estimates of goodness of fit and CLs
     - LSQ fits are often (mis)named χ^2 fits for this reason

* if not - people often use χ^2 anyway!

LSQ example

To minimize $\chi^2 = \Sigma_N W_i (y_i - f(x_i ; \underline{\theta}))^2$,

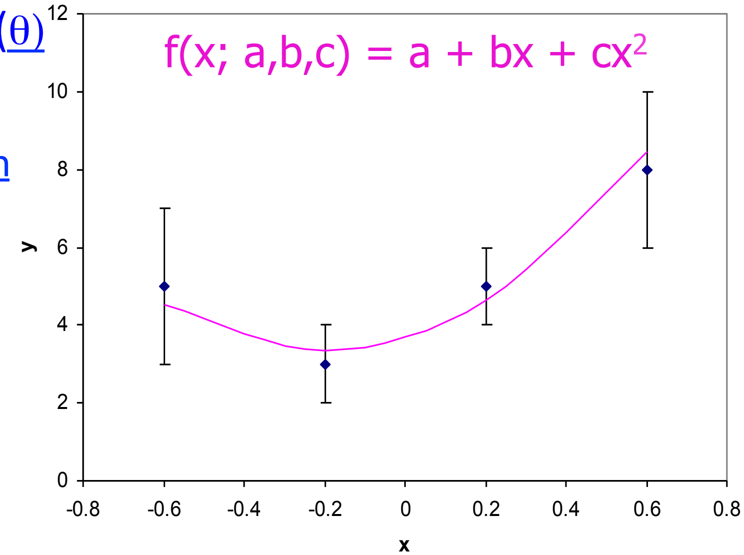
Take derivatives to get m equations in m unknowns ($\underline{\theta}$)

- Results from parabola example :

x	y(data)	fitted η	$\varepsilon = (y_i - \eta)/\sigma$	χ^2 contribution
-0.6	5	4.53	0.235	0.055
-0.2	3	3.34	-0.338	0.114
0.2	5	4.65	0.354	0.125
0.6	8	8.45	-0.227	0.051

a = 3.7 $\pm$ 2.0
b = 2.8 $\pm$ 0.75
c = 7.8 $\pm$ 0.54

χ^2 = 0.346
DOF=N-L=4-3=1
$P(\chi^2,1)$= 0.56



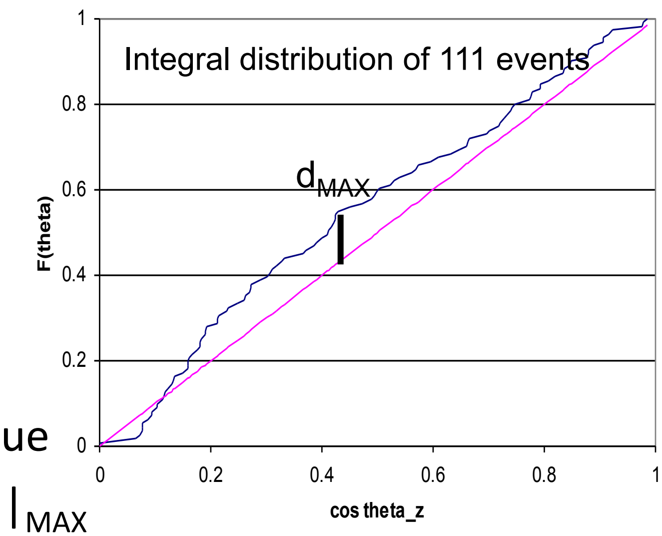
- Notes:
  - $\varepsilon = (y_i - \eta)/\sigma$ = "(normalized) residual" for point i
  - Error bars here seem overestimated: fit is "too good"
  - Variances σ_i^2 on parameters are given by diagonal elements of covariance matrix → uncertainties on parameters = $\sqrt{\sigma_i^2}$

* covariance matrix is obtained while solving the set of simultaneous linear eqns for the fit

Binning-free fits and tests

- χ^2 test and LSQ depend upon binning data (histograms)
  - Binning = loss of information (integration over bin)
  - impractical for low-statistics data with wide range
- Kolmogorov-Smirnov method is binning-free, like ML
  - Uses each data point's exact value to form integral distribution
    - Integral distribution has "deep" connection to statistical theory
  - Procedure:
    - construct integral distribution F(x) for data
      - Sort data (observed y values) in order of x_i
      - $F(<x_1) = 0$
      - $F(x_i) = F(x_{i-1}) + 1/N$
      - $F(\geq x_N) = 1$

      so F rises monotonically from 0 to 1
    - compare to $F_0(x|H_0)$ = cumulative distr if H_0=true
    - find *maximum deviation* $d_{MAX} = |F(x) - F_0(x|H_0)|_{MAX}$



Evaluating K-S test results

- All this is nice, but we need to connect the statistic d_{MAX} to confidence levels…
  - Kolmogorov found the PDF for d_{MAX} for us (under certain limitations)
- Distribution of $d_{MAX} = f_{KS}(d_{MAX};N)$ is known for "large" N (N > ~80)
  - *independent* of form of $F_0(x)$: distribution-free test
  - For the record, formula is: $P_{KS}(d_{MAX}(N) \geq [z/\sqrt{N}]) = 2 \Sigma_{k=1}^{\infty} (-1)^{k-1} \exp(-2k^2z^2)$

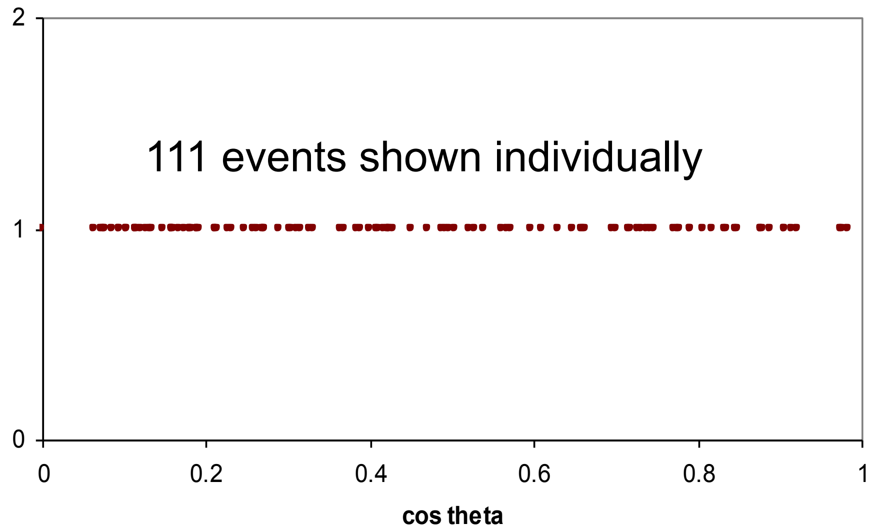
    (so $z = d_{MAX}\sqrt{N}$)
- Notice $P_{KS}=P_{KS}(z \geq d_{MAX}\sqrt{N})$: so extreme values are $P_{KS}(0)=1$, $P_{KS}(\infty)=0$
  - To test H_0 = two data sets come from same F(X),

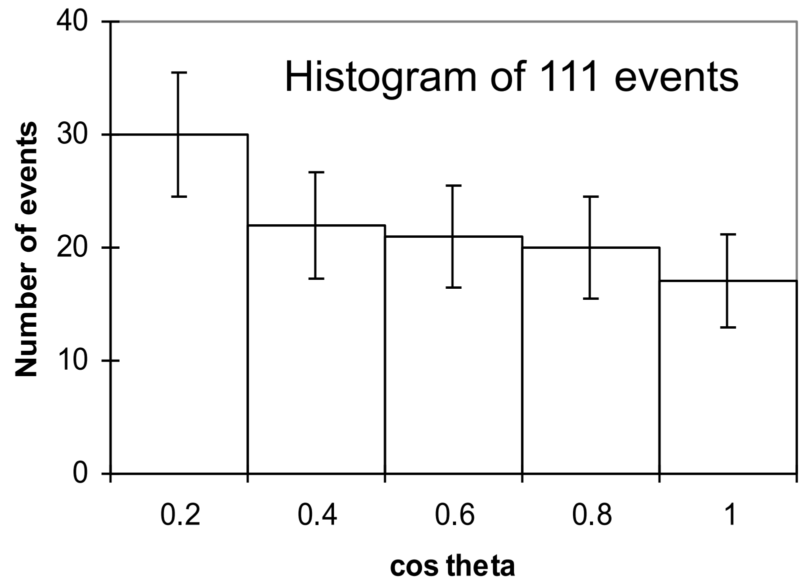
  find $d_{MAX} = |F_1(x) - F_2(x)|_{MAX}$ and use KS function to evaluate probability with

  $N = \text{sqrt}[(n_1 n_2)/(n_1+ n_2)$
- Use $f_{KS}(d_{MAX})$ to find significance level α of data compared to H_0, or to find $\pm\alpha$ *confidence bands*
  - Can't be used if F_0 uses parameters derived from the data: then $P_{KS}(d_{MAX}(N))$ is no longer applicable

KS vs χ^2 example

- Super-K angular distribution for upward-going neutrinos:
  - is it significantly inconsistent with **no** angular dependence (flat)?

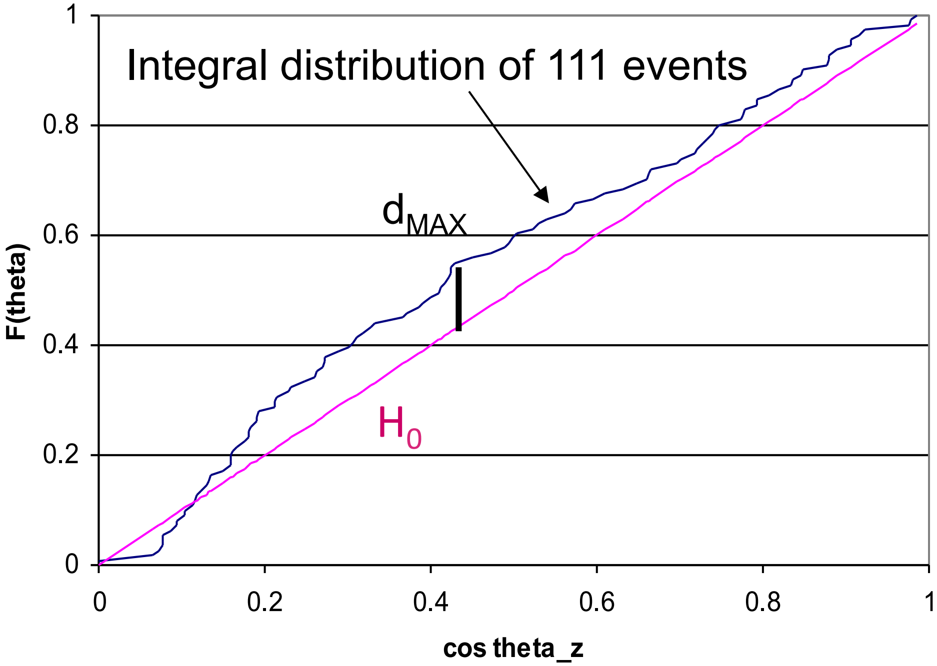




  - For this histogram, we find χ^2 = 3.8 for 4 DOF (hypothesis: n_i=<n>, constant)
    - $\rightarrow$ P(constant) ~ 50%
    - Can't claim apparent non-uniformity is unlikely to be from mere chance
  - So χ^2 test says "not inconsistent with H_0", but non-uniform trend is evident
    - Can we do better than (weak) χ^2 test ?

Now try Kolmogorov-Smirnov test

- Again, H_0 = **no** angular variation
  - (uniform in $\cos\theta$)
  - $f_0(\cos\theta)$=constant, $-1< \cos\theta < +1$
  - $F_0(\cos\theta=-1) = 0$; $F_0(\cos\theta=+1) = 1$
- Plot the integral distribution for the data, and compare to F_0 :



–Notice each data point enters the integral distribution and contributes to the test: information content is not integrated away by binning

•Find maximum difference (vertical deviation):

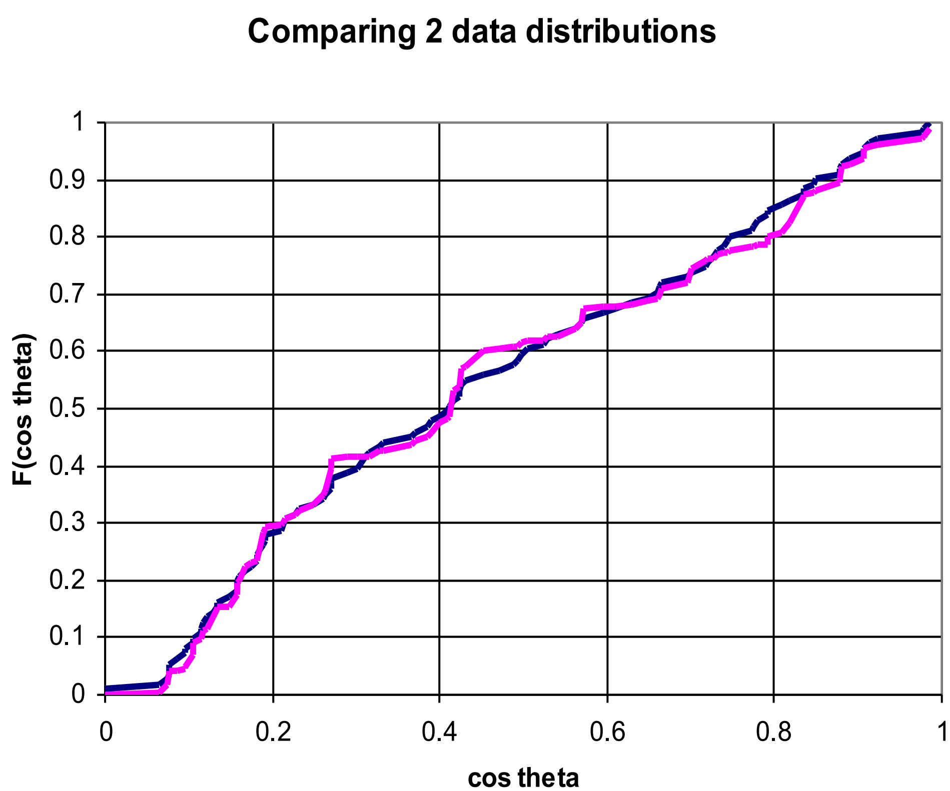
–d_{MAX} = 0.12 (for N=111 events)

–From table of KS probabilities: $P(\geq d_{MAX};N)= \alpha$

- $P(\geq 0.12; 111)= 0.10$
- Only a 10% chance the observed distribution (or one with worse d_{MAX}) could occur by chance, if the underlying distribution is uniform, according to K-S

Testing for consistency

- Can also use KS test to compare two data sets for consistency
  - Two data distributions: what is probability they are drawn from the same distribution and the samples differ by chance?
  - Common application: check for changes in detector behavior vs time

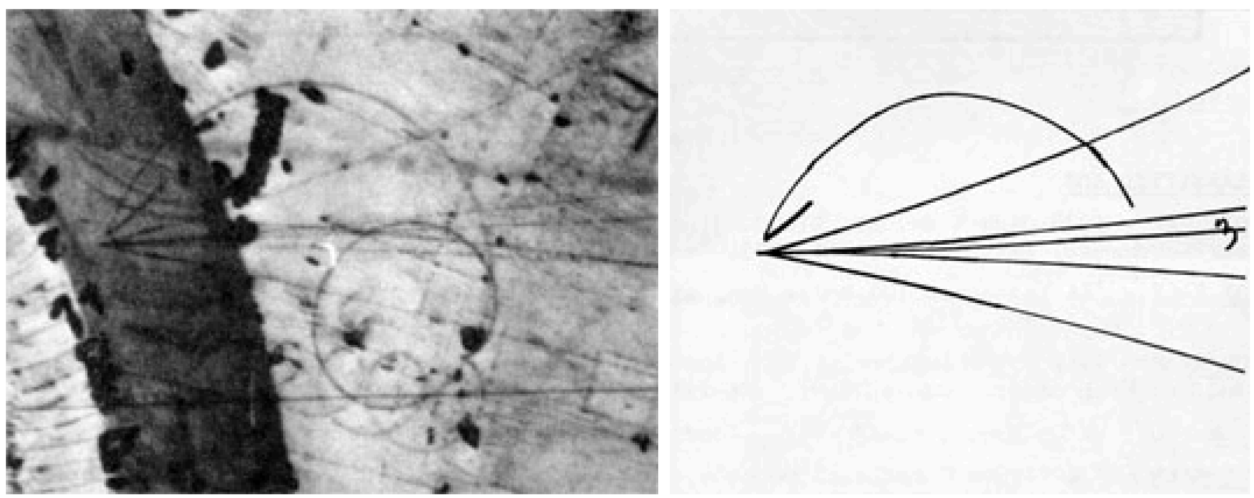


Bubble chambers

Same principle as cloud chamber, but uses a different phase transition

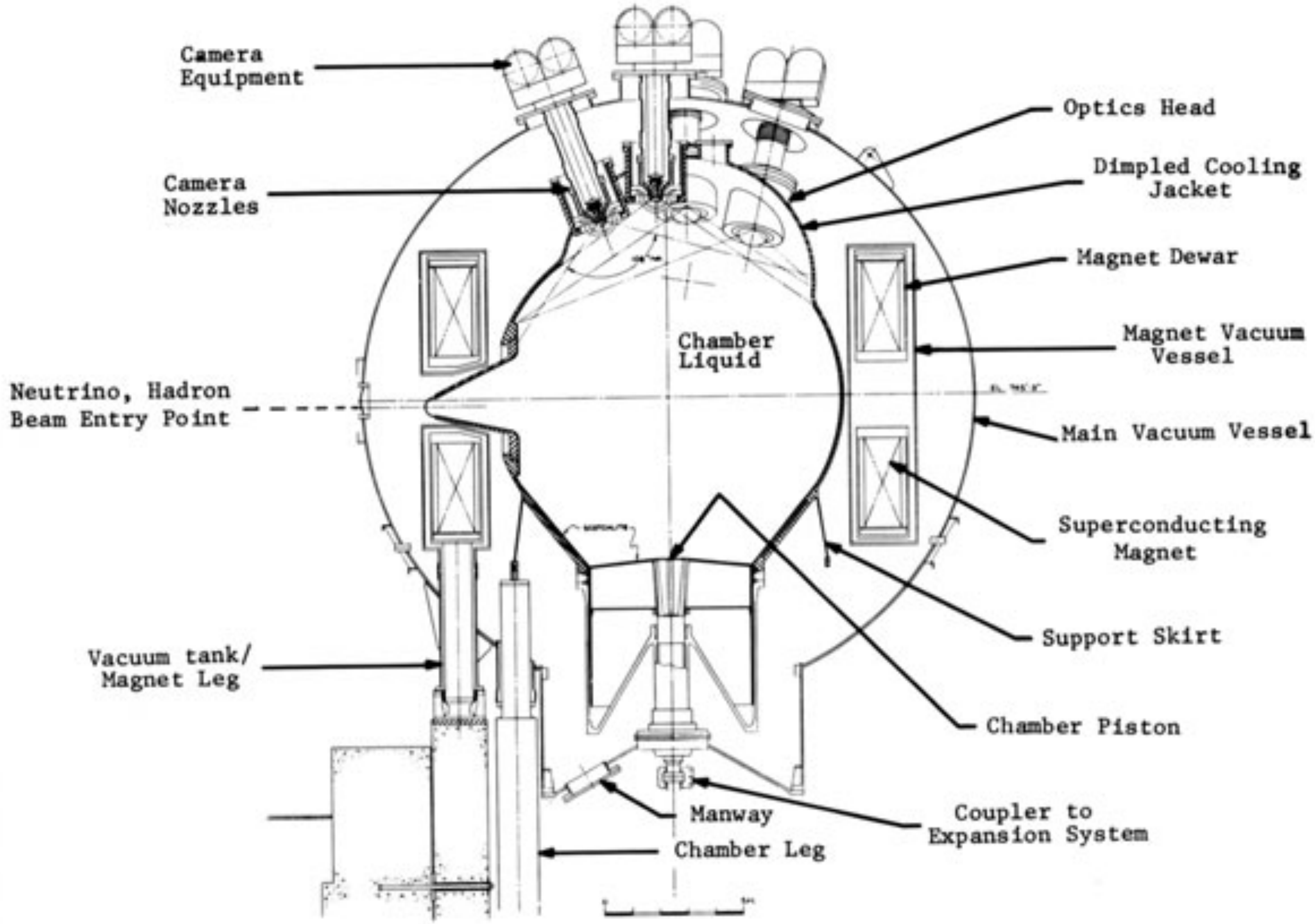
- Keep a cryogenic fluid near its boiling point
  - Typically hydrogen, deuterium, helium or argon; for heavy-nucleus target, Freon
- Drop pressure suddenly when particles of interest are present (beam spill, or use trigger counters)
- Boiling (bubble formation) occurs preferentially along ionization trails
- Snap photos quickly, before boiling becomes widespread, from 3 angles
  - Typically: high-resolution 70mm aerial surveillance film

- Measure track coordinates on film from each camera, reconstruct track paths in 3D

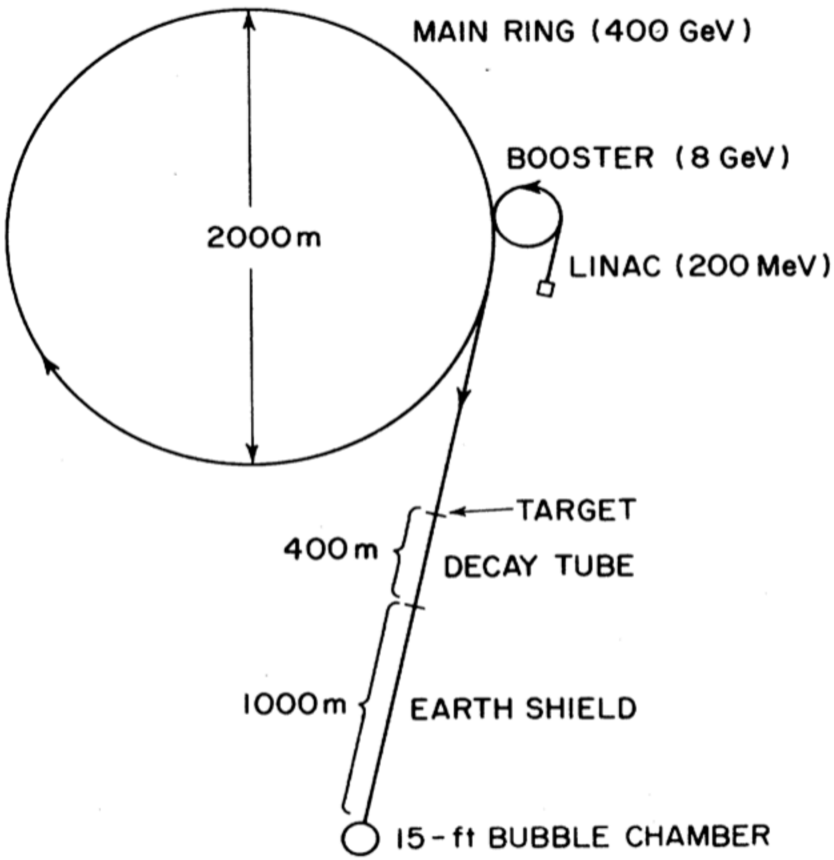


An example of a rare neutrino event taken by Experiment 45 in the Fermilab 15-Foot Bubble Chamber. The neutrino (not visible) enters from the left and produces 5 charged prongs. In addition, the decay of a neutral lambda hyperon to a "V" is observed just above the interaction point.

Bubble chamber example: 15ft BC at Fermilab

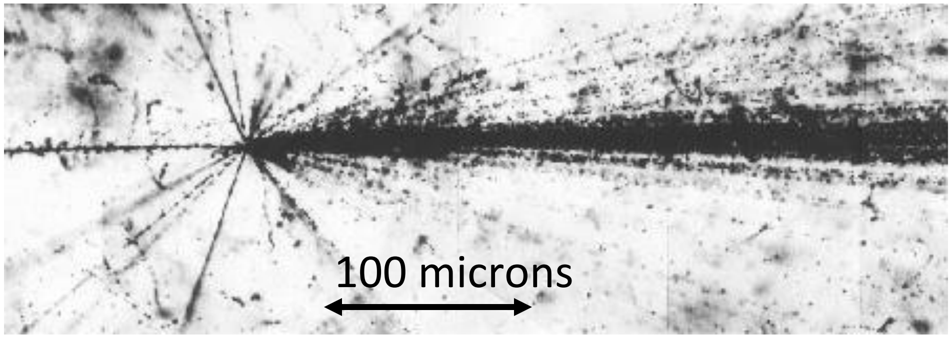


Bubble chamber example: 15ft BC at Fermilab



Neurino beamline at Fermilab, c. 1975

Nuclear emulsion



- Photographic emulsion, hypersensitized to react to ionizing particles
  - Photographic emulsion = Silver Bromide crystals suspended in gelatin (1850s)
  - First emulsion sensitive to minimum-ionizing tracks: 1947
    - Used to discover the pion, many other early particle physics discoveries
- Until 1960s, used in solid blocks of ‘pellicles’
  - Pour melted gel on plate glass, peel off slabs (~ 500 microns thick) when cool
  - Stack pellicles for exposure, unstack and develop afterwards
  - Typically exposed with beam parallel to pellicle’s width
  - Observe particle tracks through microscopes
    - Emulsion = Dense medium, so only very high energy tracks do not stop
- 1970s: “emulsion chamber” technique developed in Japan
  - Couldn’t afford big pellicle stacks!
  - Coat thin plastic base on both sides with thin emulsion layers (50 microns)
  - Observe tracks passing through perpendicularly

Emulsion chambers

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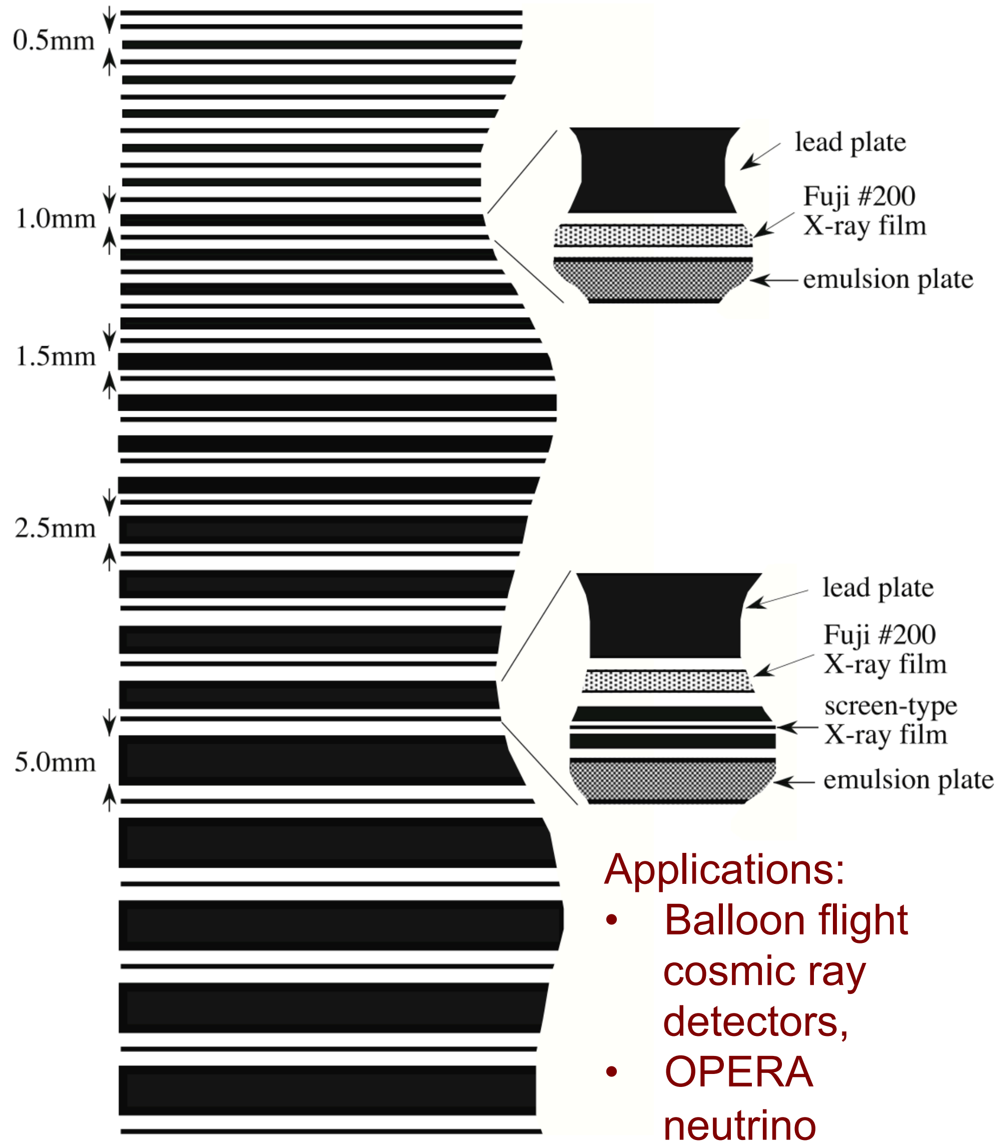


Applications:

- Balloon flight cosmic ray detectors,
- OPERA neutrino detector

Contemporary application of nuclear (photographic) emulsion

Make a calorimeter using thin layers of emulsion and Pb plates

X-ray film shows visible spots around >100 GeV electron shower cores

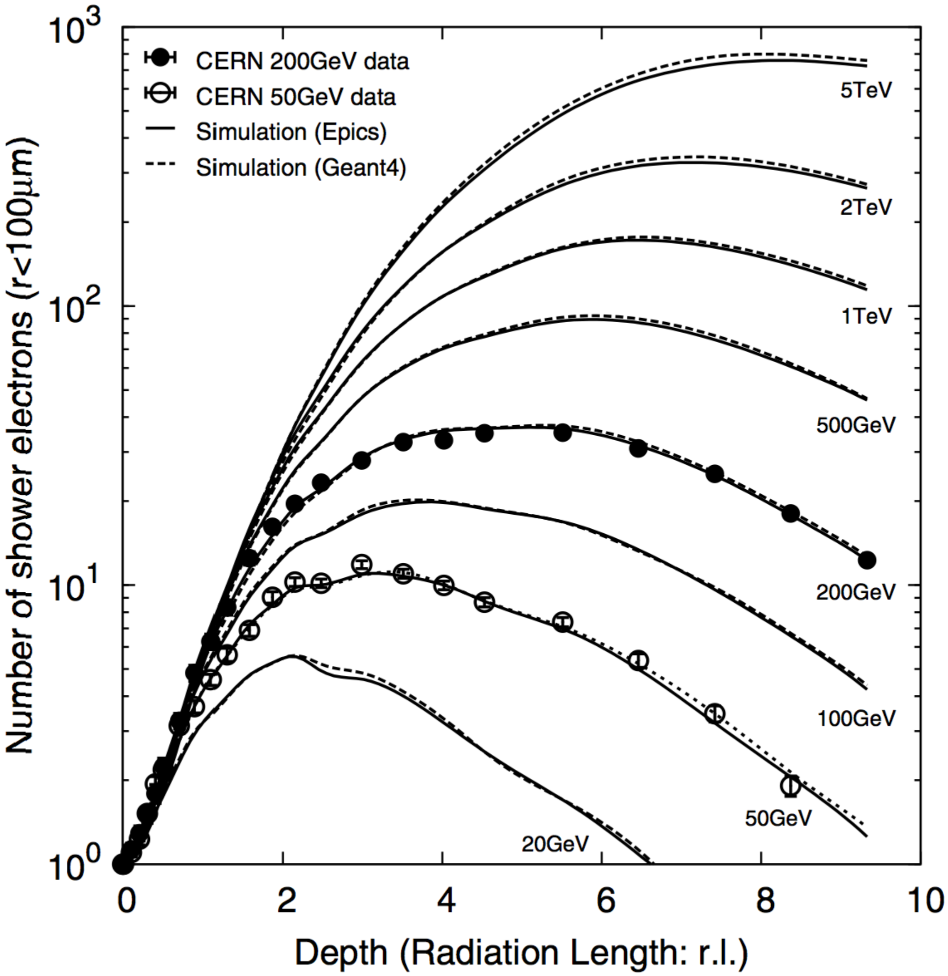
Use x-ray films to locate showers, trace back to initiating particle

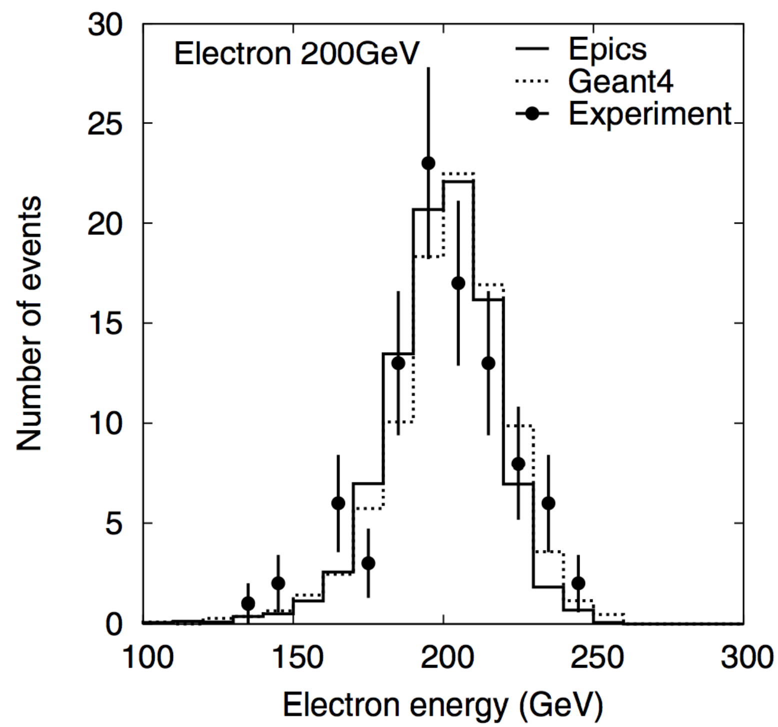
Separate electrons from protons with high reliability

Automated microscopes developed to analyze emulsions

Emulsion chambers

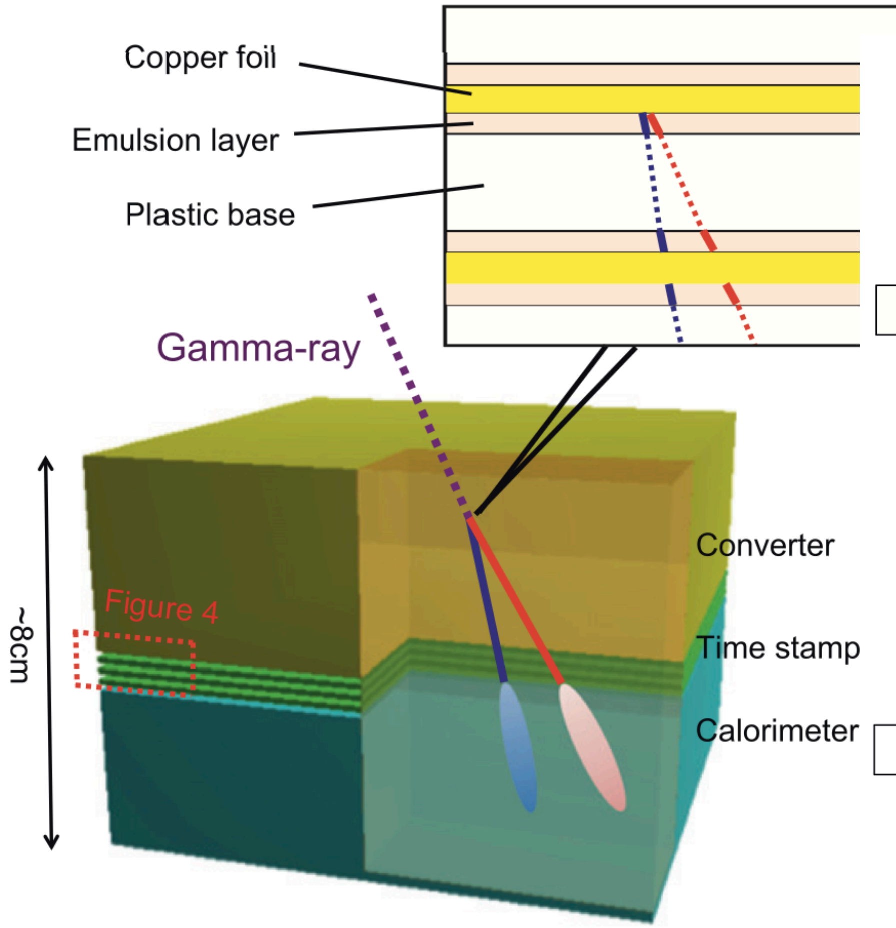
Count number of electron tracks in shower vs depth in Pb plates to get energy
Well-developed calibrations using accelerator beams

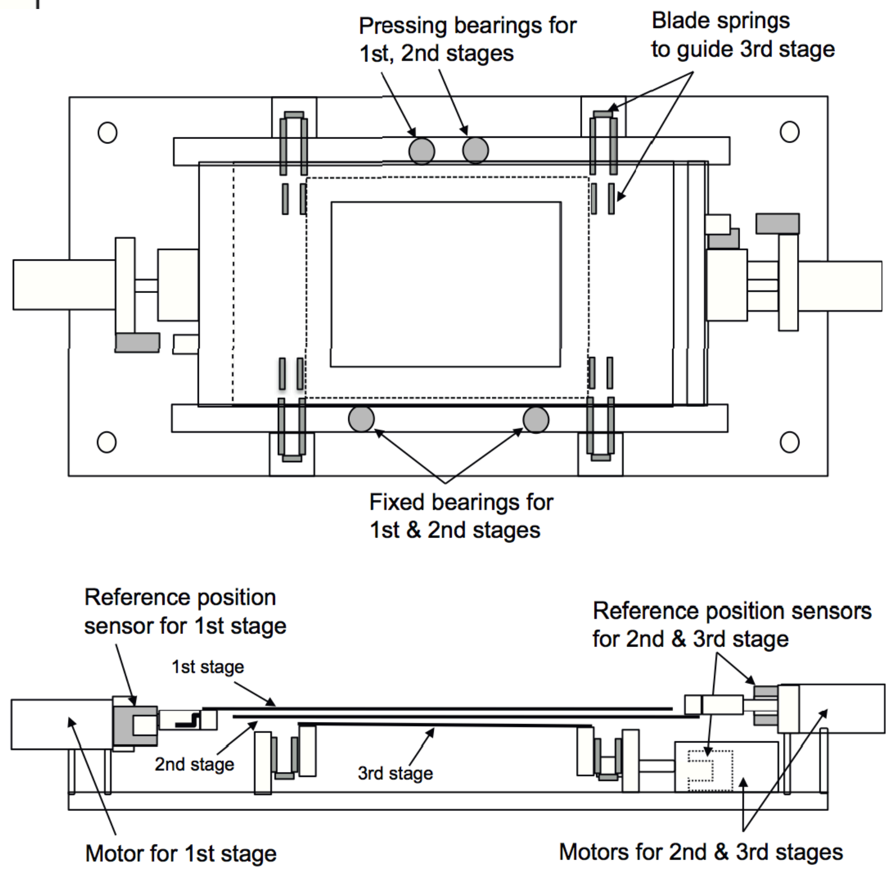




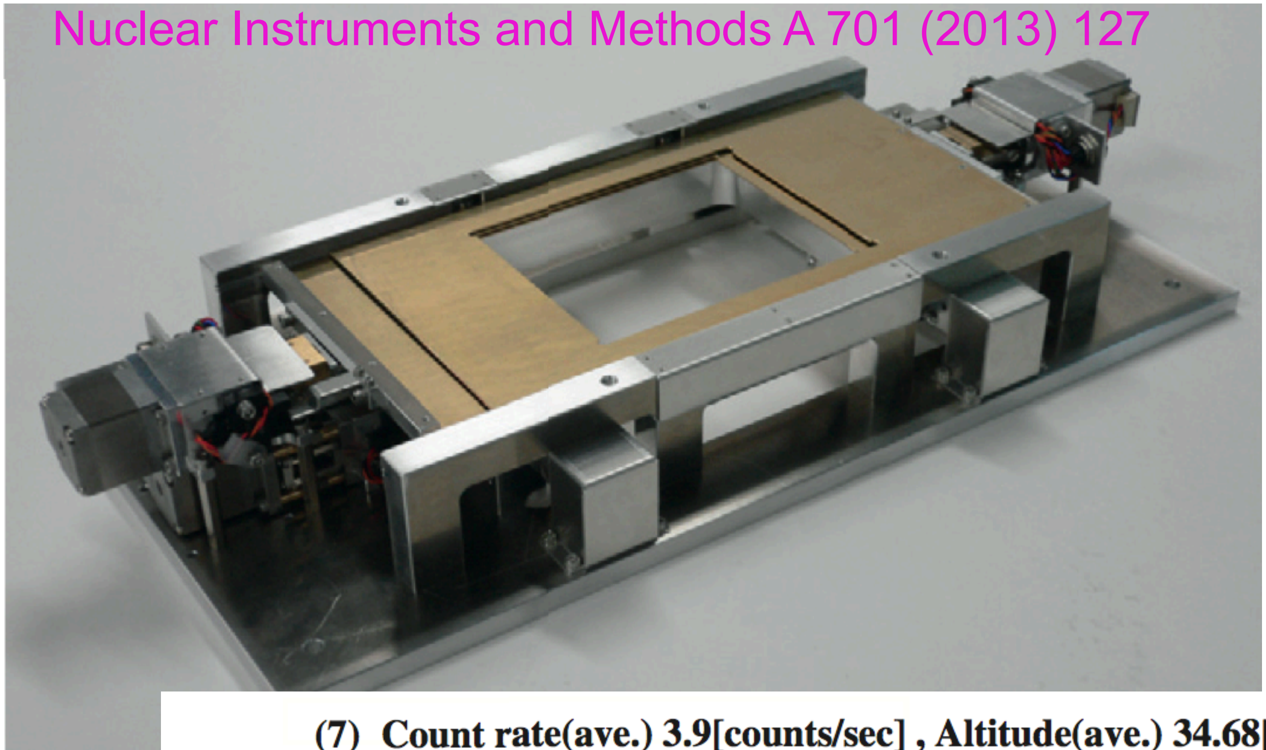
Time stamping for Emulsion chambers

"Shifter" device in main calorimeter moves film layers at constant rate, displacement tells when event was recorded

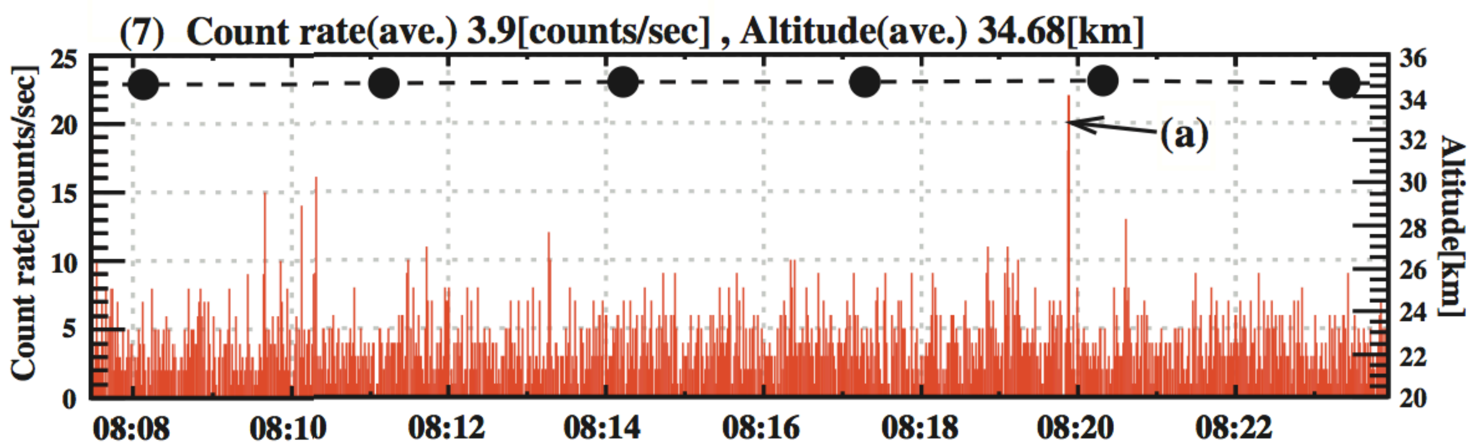




Shifter used in recent balloon flight



Find high-multiplicity cosmic-ray events by checking track counts (from automatic scanner) vs time



Hybrid emulsion/bubble chamber detector

Goal: Particles carrying the charm quark were first observed in 1974 in ee collisions at 3 GeV at SLAC

Search for charmed mesons produced in hadronic interactions was a major effort during 1975 ~ 80: example, Fermilab E-564

Production by deep inelastic interactions of neutrinos or muons was a convenient approach: cleaner kinematics and fewer backgrounds

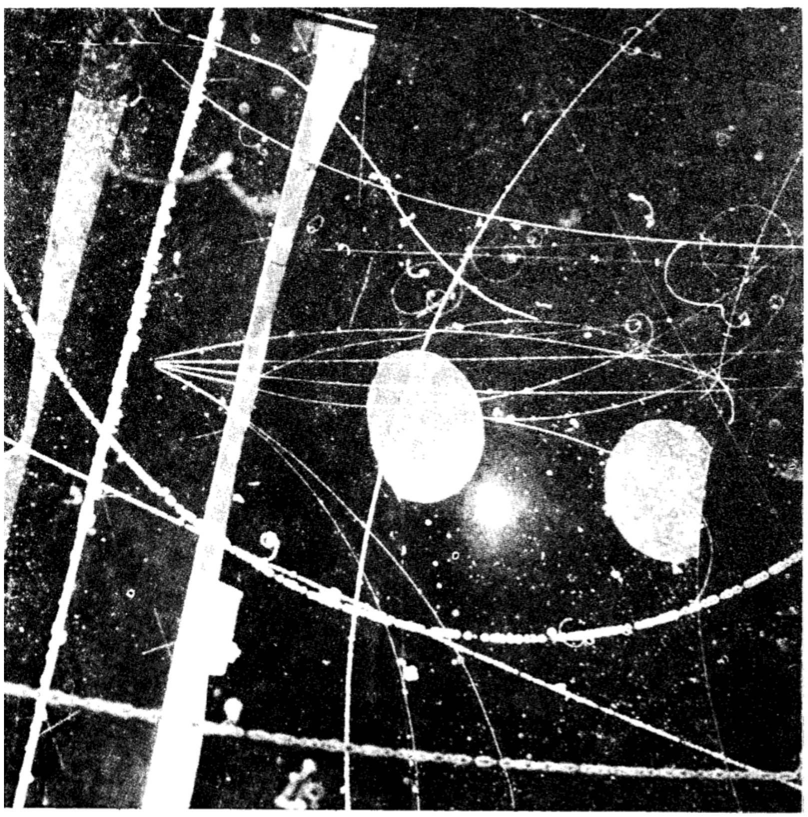
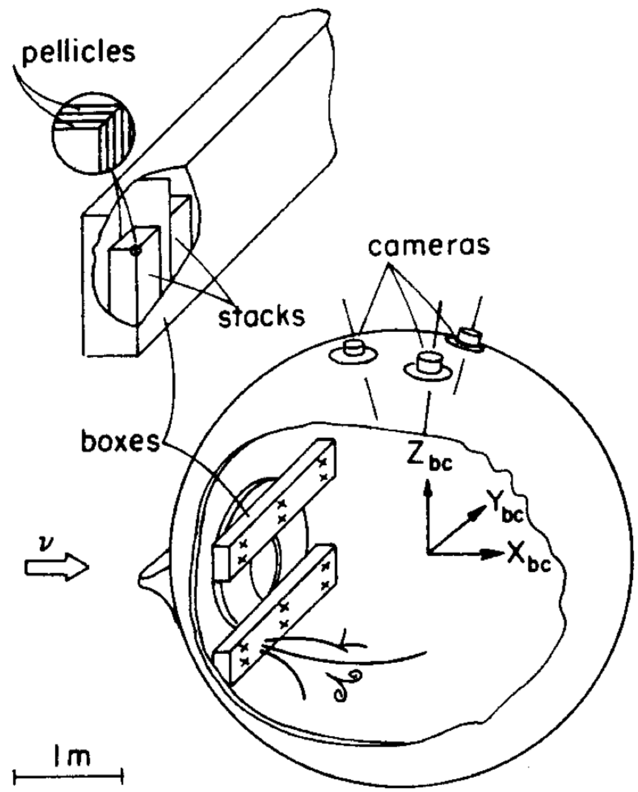
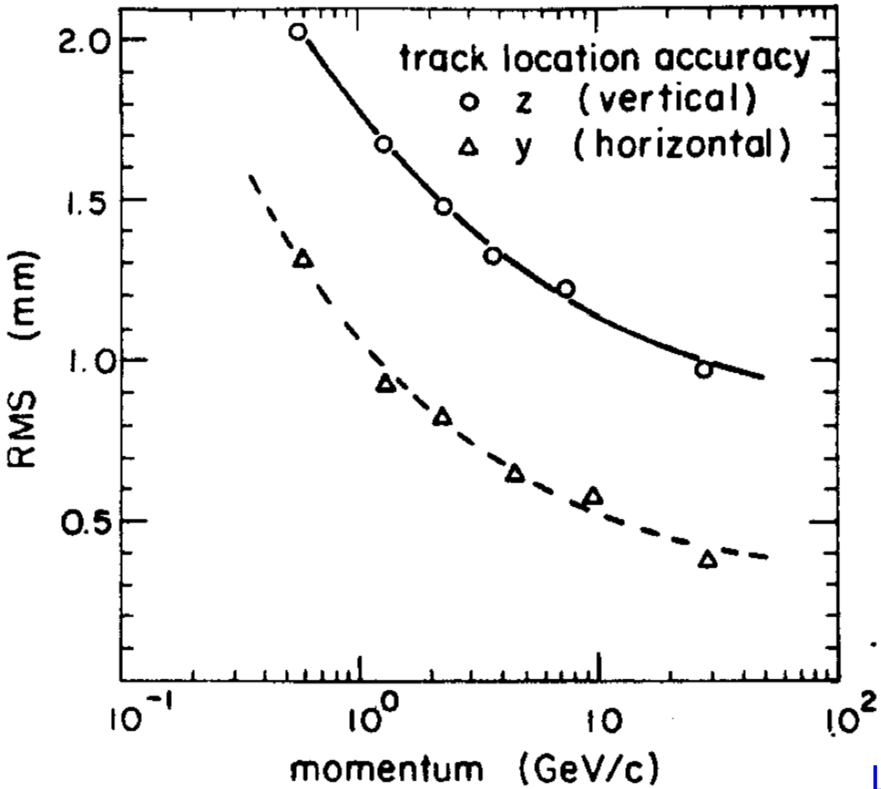


Fig. 2. A bubble chamber picture with an emulsion event candidate





E-564

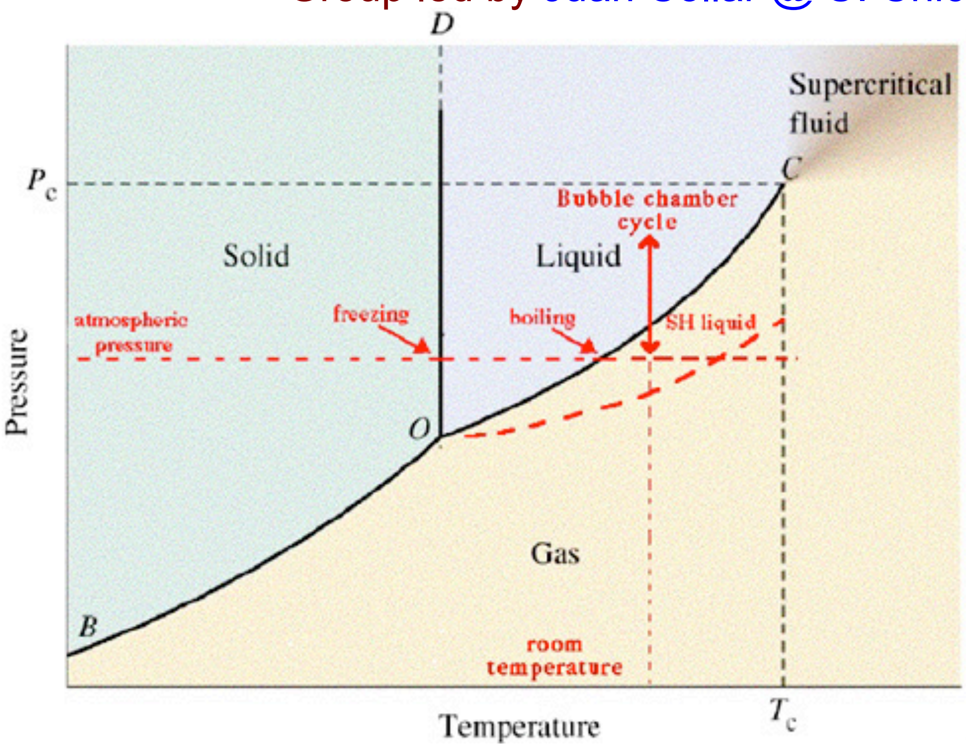
- Nuclear emulsion pellicles (slabs) 5x20 cm x 400 microns thick, in 22 stacks of 200
- Produced and processed at Serpukhov, USSR
- Scanned thousands of BC pictures to find a few hundred neutrino events in emulsion
- Total of 3 charmed mesons identified

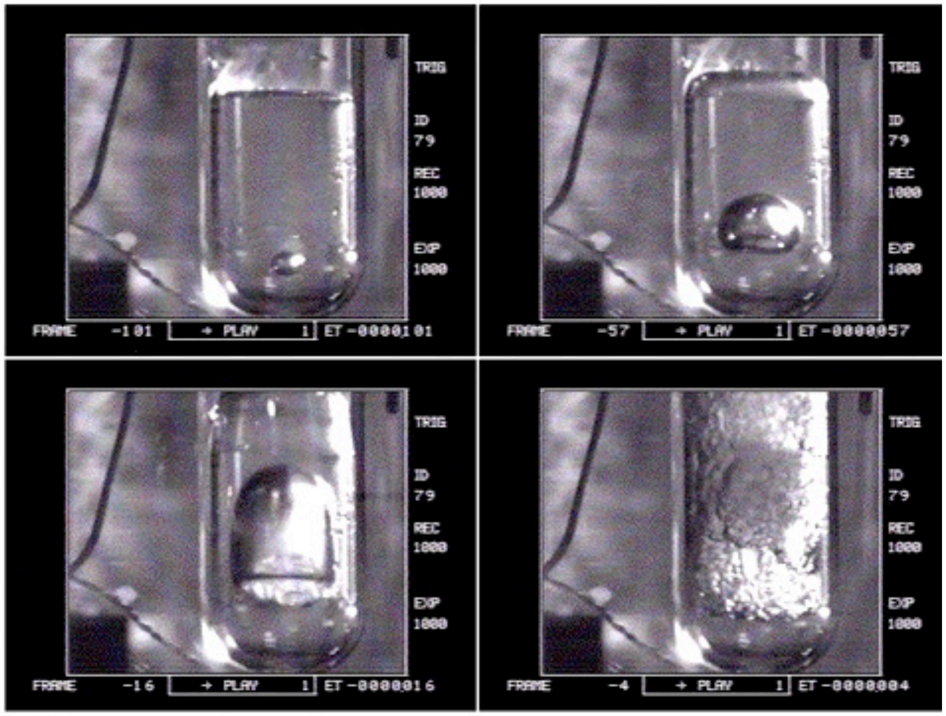
Number of:	Run 1 (Liquid deuterium)	Run 2 (Liquid He + Ne)	Total
BC pictures scanned	237000	280000	517000
events selected and measured	2800	3300	6100
total predictions	1140	1340	2480
"good" predictions	700	600	1300
events scanned in emulsion	930	700	1630
found events	90	194	284
neutrino interactions	51	102	153
charged current events	43	85	128
decay candidates	2	3	5

Contemporary bubble chambers for WIMP searches

"The degree of superheat can be tuned so as to have complete insensitivity to the minimum-ionizing backgrounds that plague these searches, while still being responsive to low-energy nuclear recoils like those expected from WIMPs"

Group led by Juan Collar @ U. Chicago

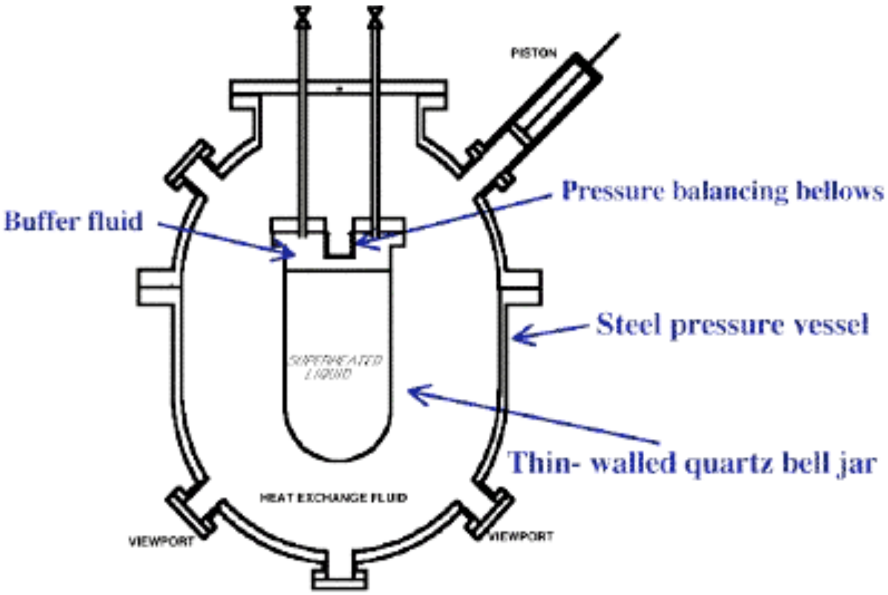


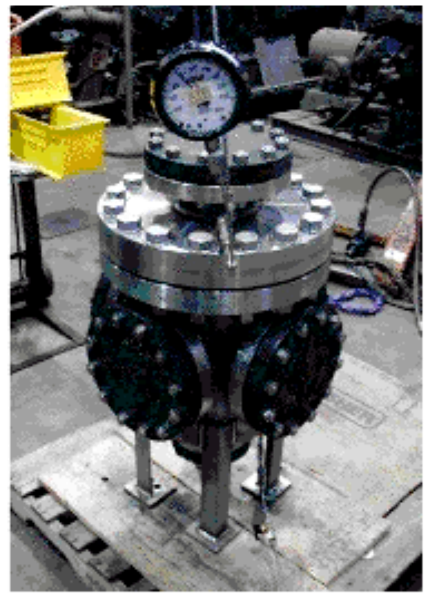


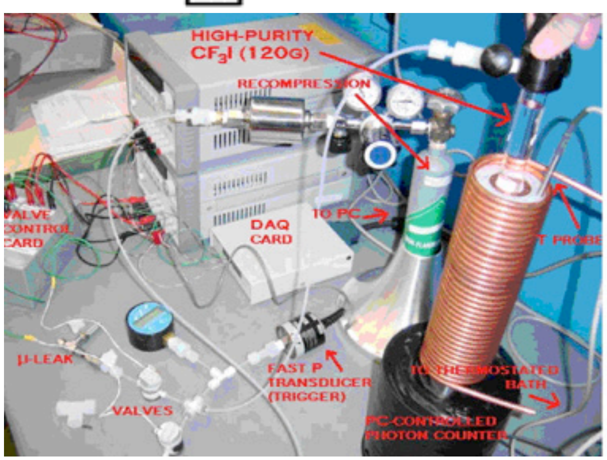
Use heavy "refrigerant" fluids like CF3Br, CF3I and C3F8

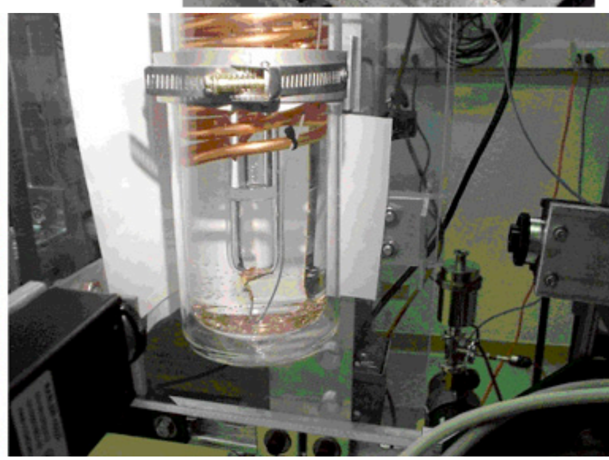
COUPP detector prototype

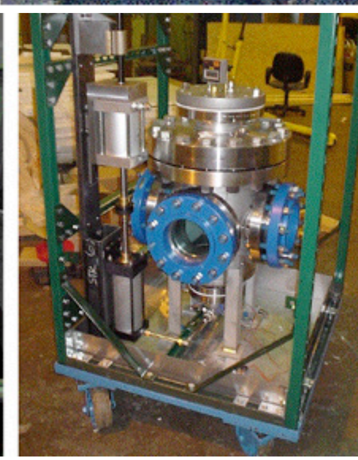
Chicagoland Observatory for Underground Particle Physics, COUPP
Ultimate goal: deploy a large bubble chamber dark matter search in the Soudan Underground Laboratory (MN). 1 Liter CF_3I prototype developed at Fermilab



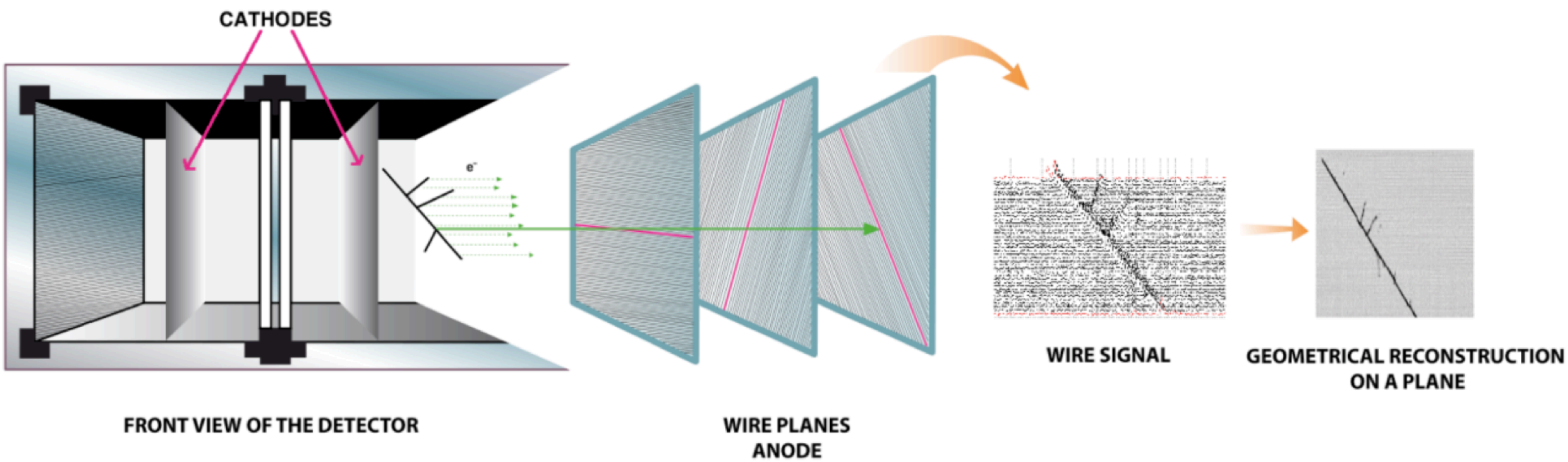




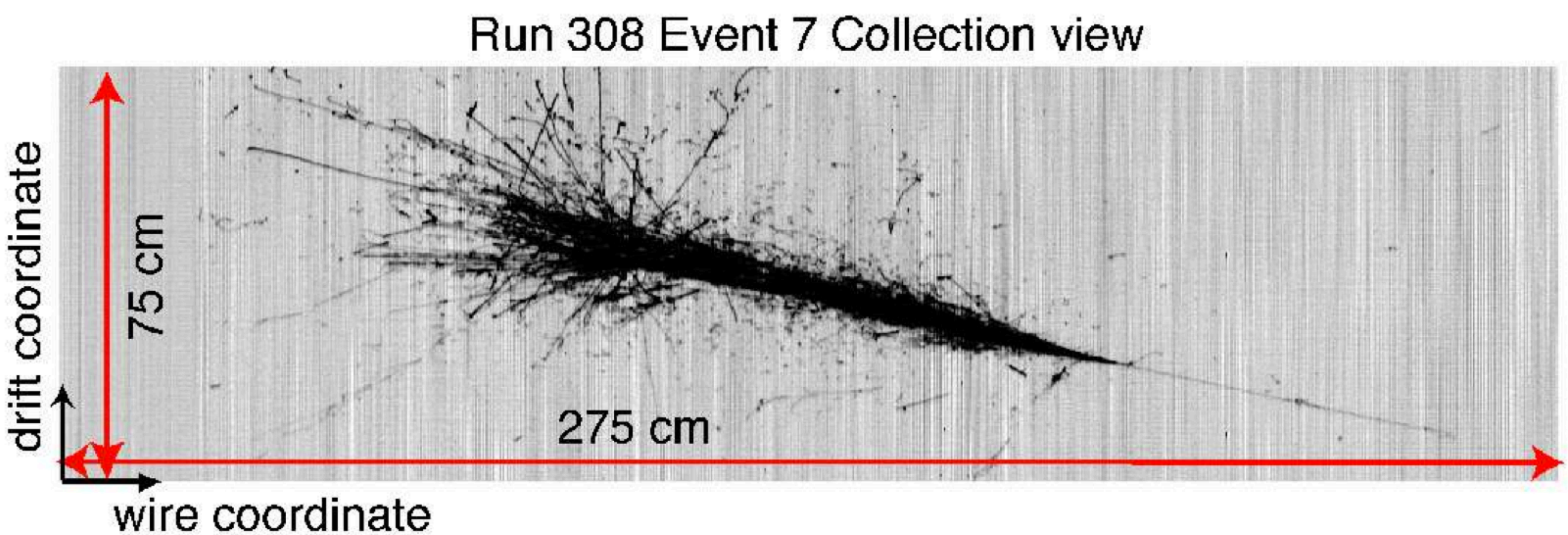




Liquid Argon Time Projection Chambers



We've already discussed gas TPC's. Ar gives high density target with excellent resolution, even for high-multiplicity events



Liquid Argon TPCs

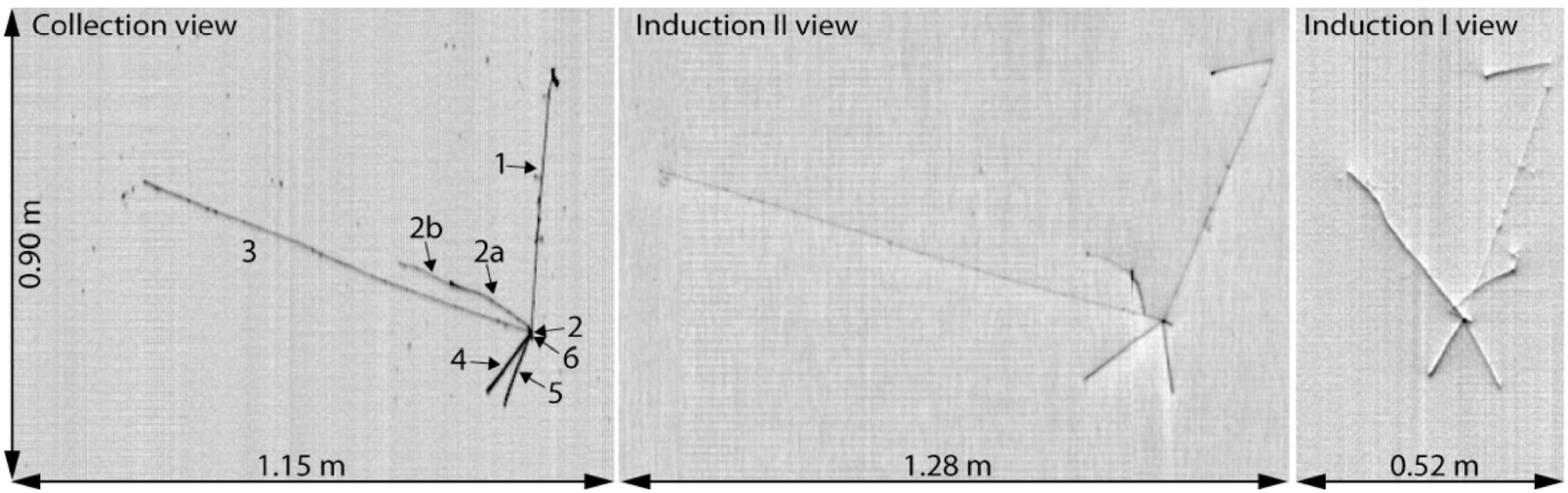
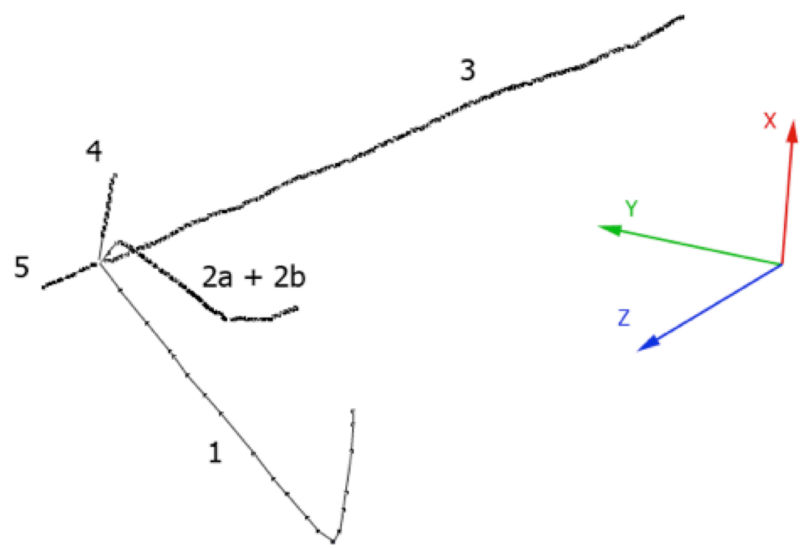
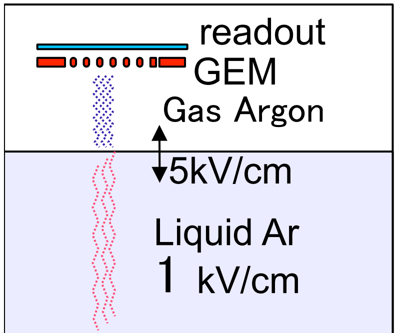


Figure 7. Example of low energy neutrino interaction. Three different 2D views are shown.



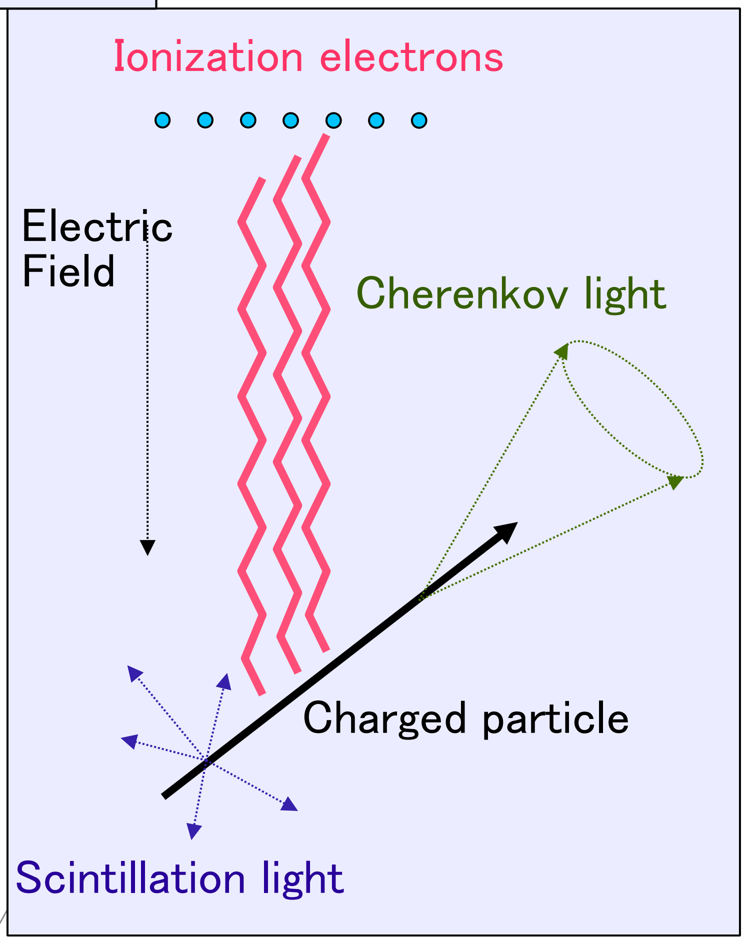
Concept of the LAr TPC



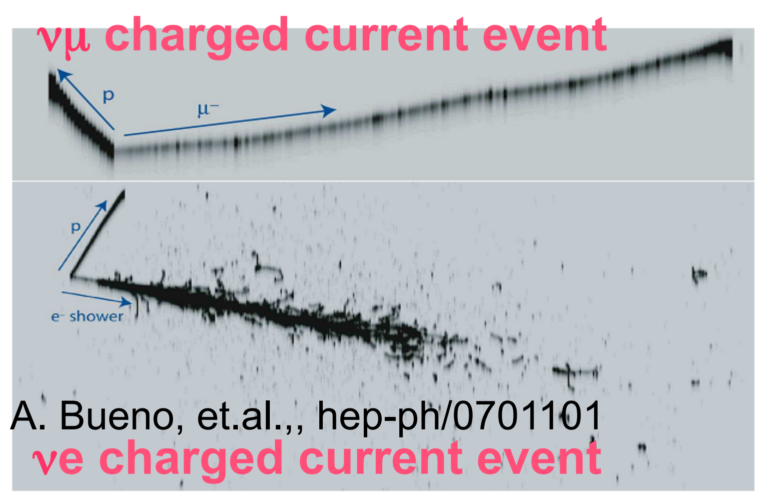
Double phase

(Slides from talk by T. Maruyama at NuFact conference)

- Ionization selection signal
  - ~5x10^{4}e/cm MIP
  - 3D track reconstruction as a TPC
  - drift velocity is ~mm/μs with ~kV/cm electric field
  - LAr purity affects the attenuation of the drift electrons.
  - No amplification inside LAr
  - Diffusion of the drift electrons is about 3mm after 20m drift

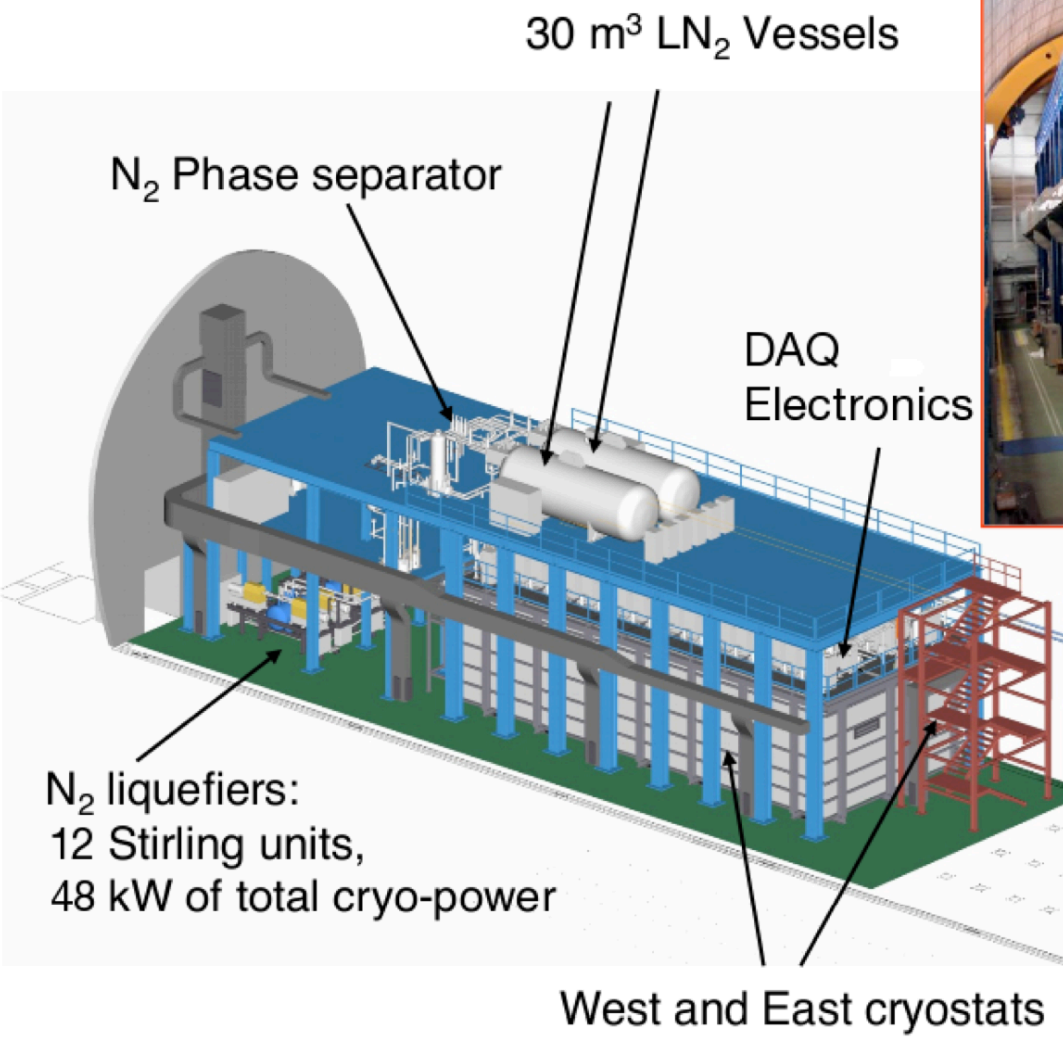


Closed dewar



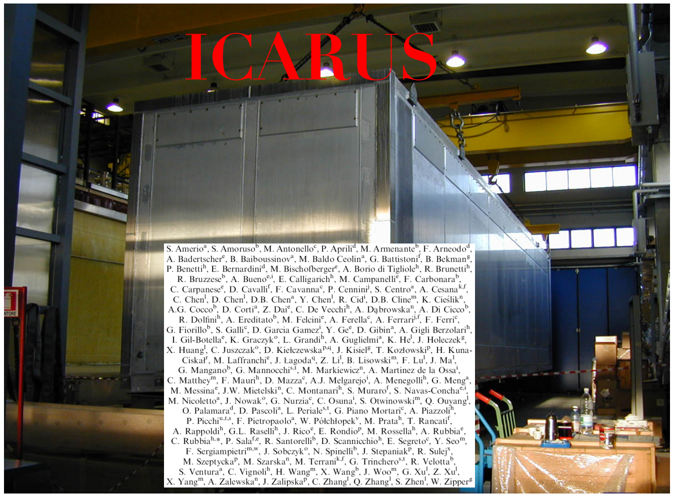
Liquid Argon TPCs in Gran Sasso Tunnel Lab

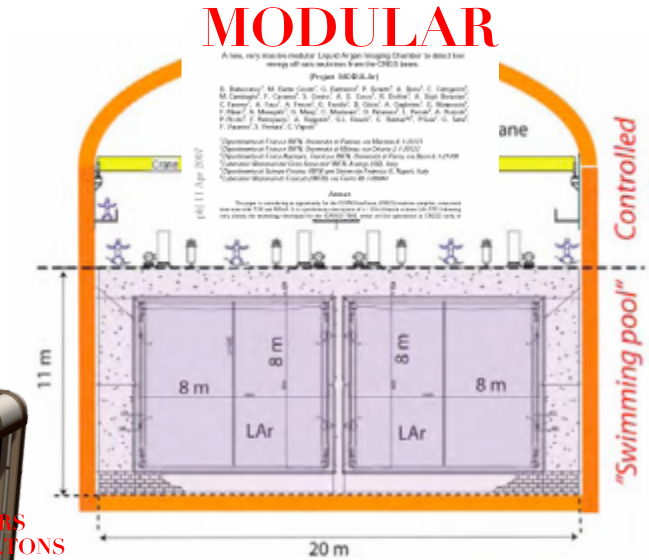
Far detectors for CERN neutrino beam
Prototypes for future giant L-Ar's

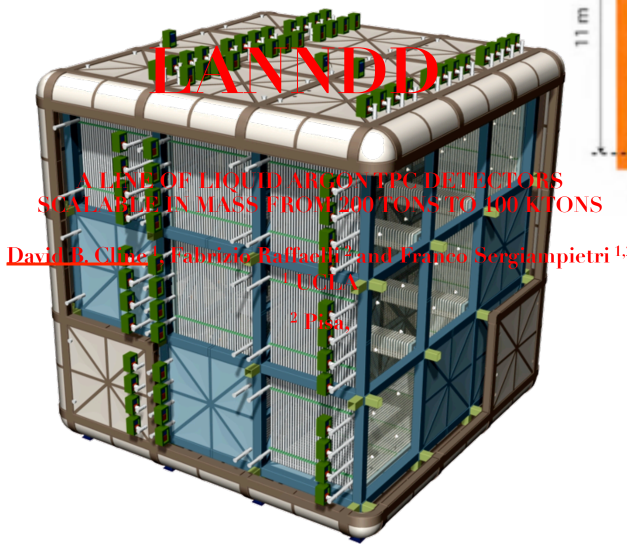


Pros and Cons of Water Cherenkov and Liquid Argon Huge detector

	Water Cherenkov	Liquid Argon
Pros	• matured technique • 50 kton detector has been working for more than 10 years • Easier to build huge and massive detector	• Possible to have excellent tracking performance, and it has directly impact to νe appearance or proton decays search.
Cons	• Cherenkov threshold is high for Kaons, protons, massive particles. • electrons / pi0 separation is relatively bad compared to LAr TPC	• There are lots of R&D items to attack to achieve 100 kton level detector.


ICARUS


MODULAR
Crane
ane
Controlled access
"Swimming pool"
11 m
8 m
8 m
8 m
8 m
LAr
LAr
20 m

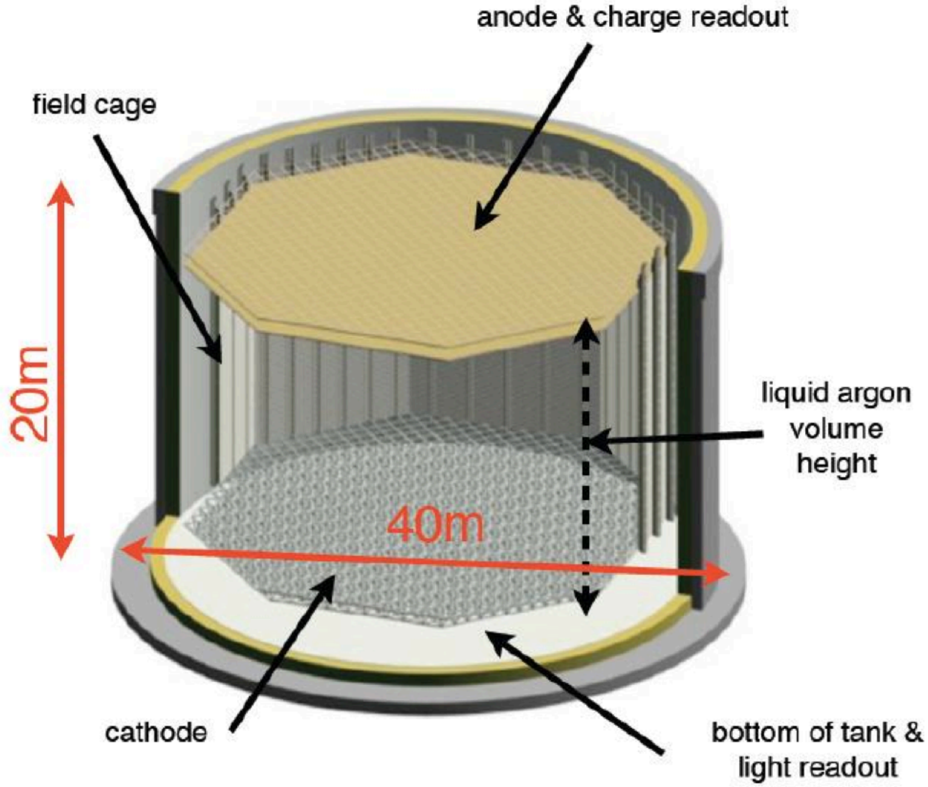

LANNDD
A LINE OF LIQUID ARGON TPC DETECTORS
SCALABLE IN MASS FROM 200 TONS TO 100 KTONS
David B. Cline [1], Fabrizio Raffaelli [2] and Franco Sergiampietri [1,2]
[1] UCLA
[2] Pisa

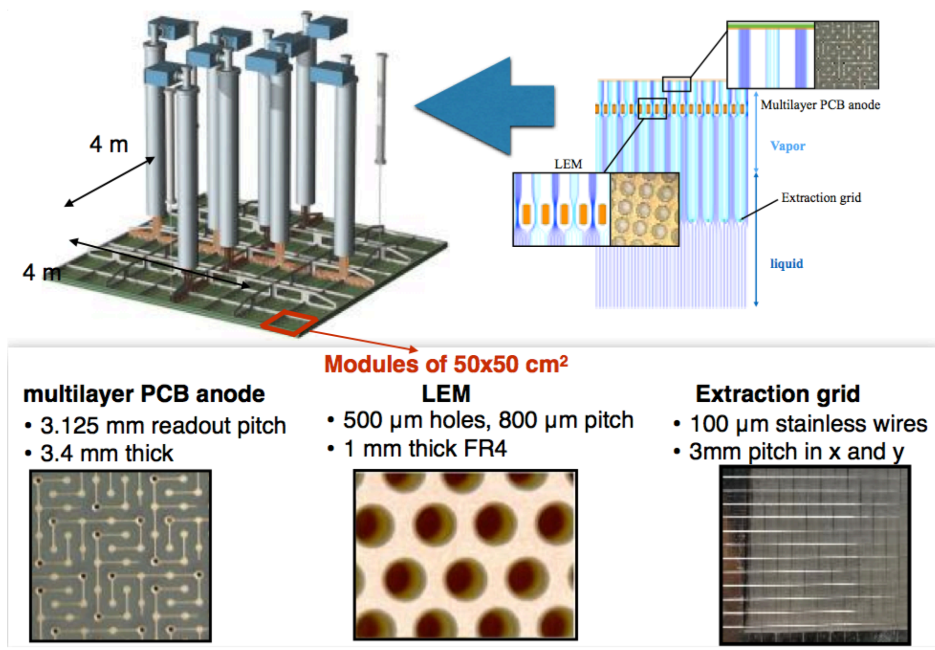

FLARE
Bartoszek Eng. - Duke - Indiana - Fermilab -
LSU - MSU -Osaka - Pisa - Pittsburgh - Princeton -
Silesia - South Carolina - Texas A&M -
Tufts - UCLA - Warsaw University -
INS Warsaw - Washington - York-Toronto


GLACIER
ETHZ, Bern U., Granada U., INP Krakow, INR Moscow, IPN Lyon, Sheffield U., Southampton U., US Katowice, UPS Warszawa, UW Warszawa, UW Wroclaw

20 kT LAr TPC @ Fermilab

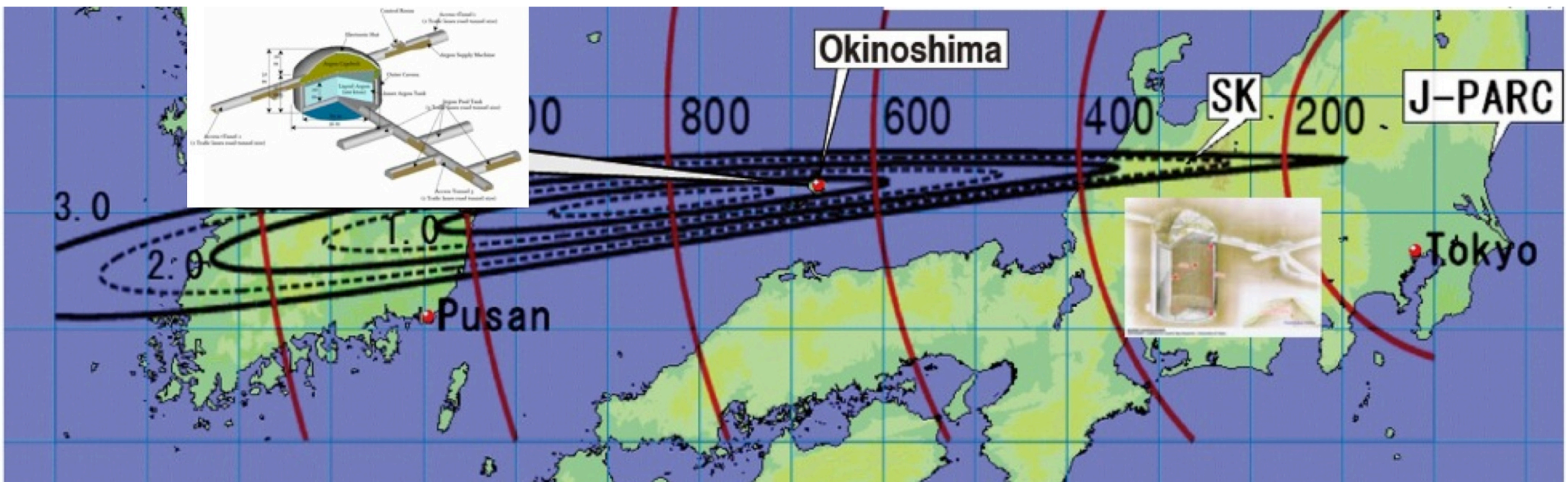
Proposed for LBNE project
neutrino beam aimed at Homestake Gold Mine





Large L-Ar chamber for T2K

Bottom edge of the T2K neutrino beam emerges in South Korea
Conveniently located mine in Okinoshima
Build a detector similar to Glacier (A. Rubbio proposed similar Lar detector for T2K 2km intermediate detector, which was never built)



Spark and Streamer Chambers

(historical item!)

Predecessor of proportional chambers – pre-digital!

- Wide gap (10s of cm) filled with He-Ne or other inert-gas mixture
- Track leaves ionization trail
- Pulse with very high voltage (10kV/cm)
- Operate just short of geiger breakdown, when streamers form from individual electron cascades along track
- Photograph streamers before breakdown occurs, reconstruct tracks from multiple views

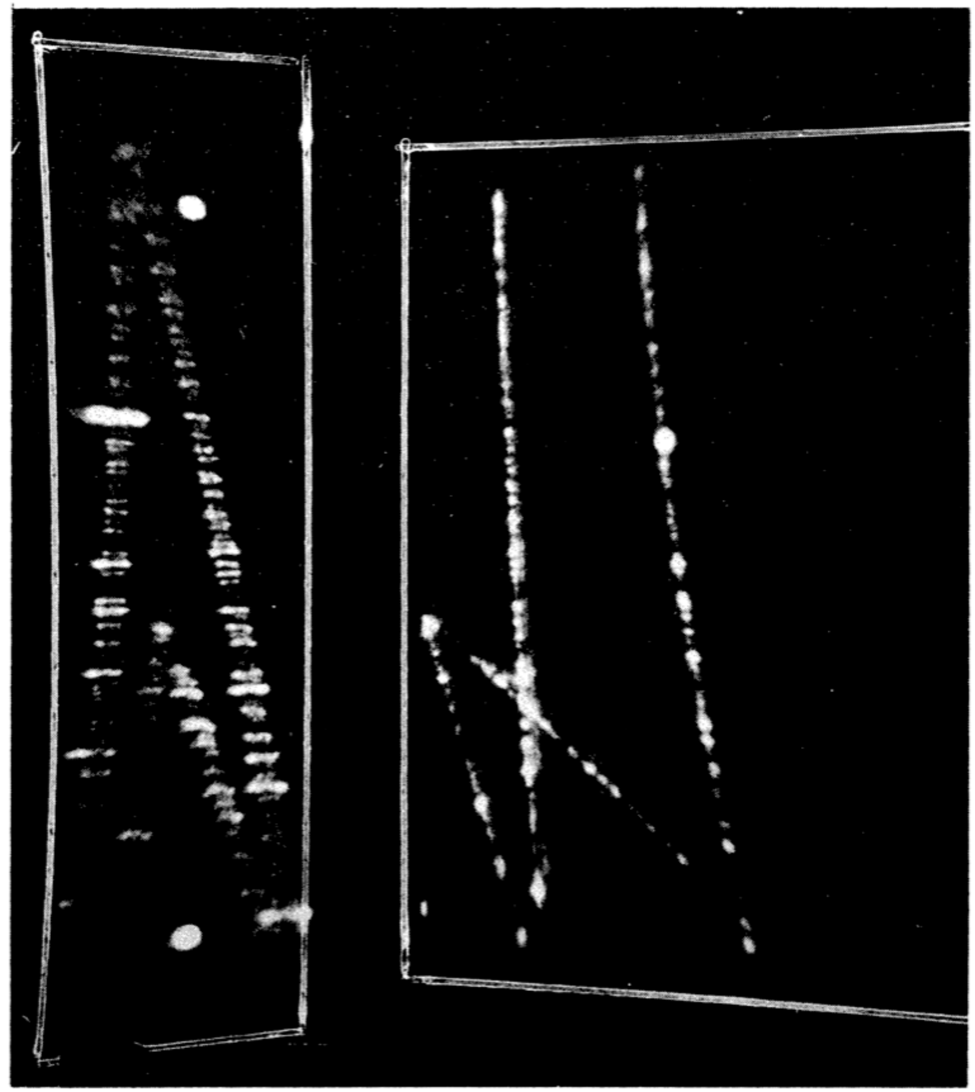


Fig.16 4.5 mm Streamers at f:11

Spark and Streamer Chambers

Marx Generator: charge capacitors in parallel, discharge in series by providing spark gaps to bridge them

Need pressurized, inert-gas filled container to suppress breakdowns

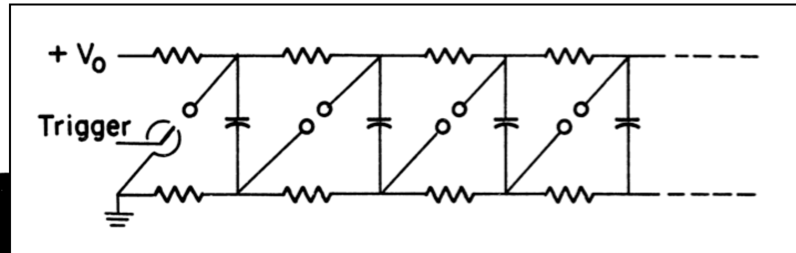


Fig.20 Marx Circuit for Generating a Negative Pulse

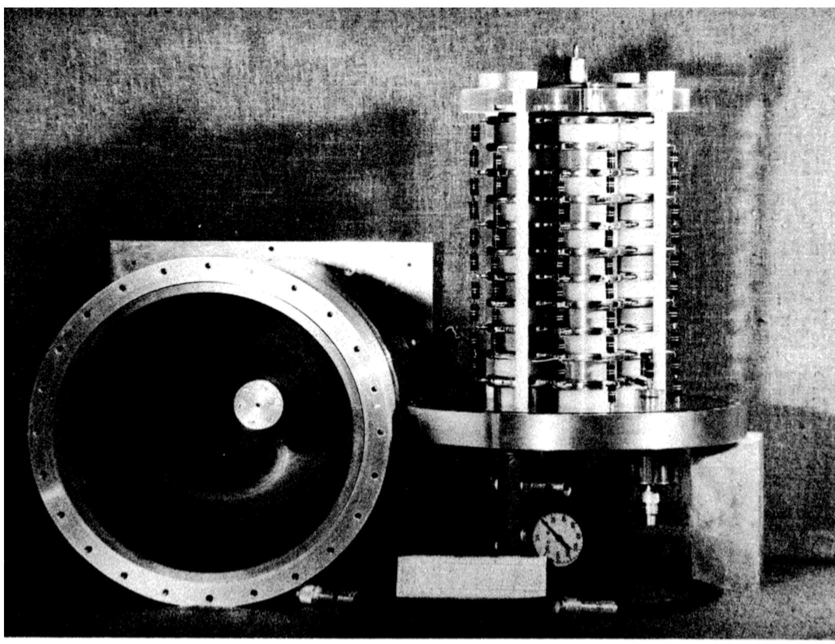


Fig.28 Side View of Model C Marx Generator

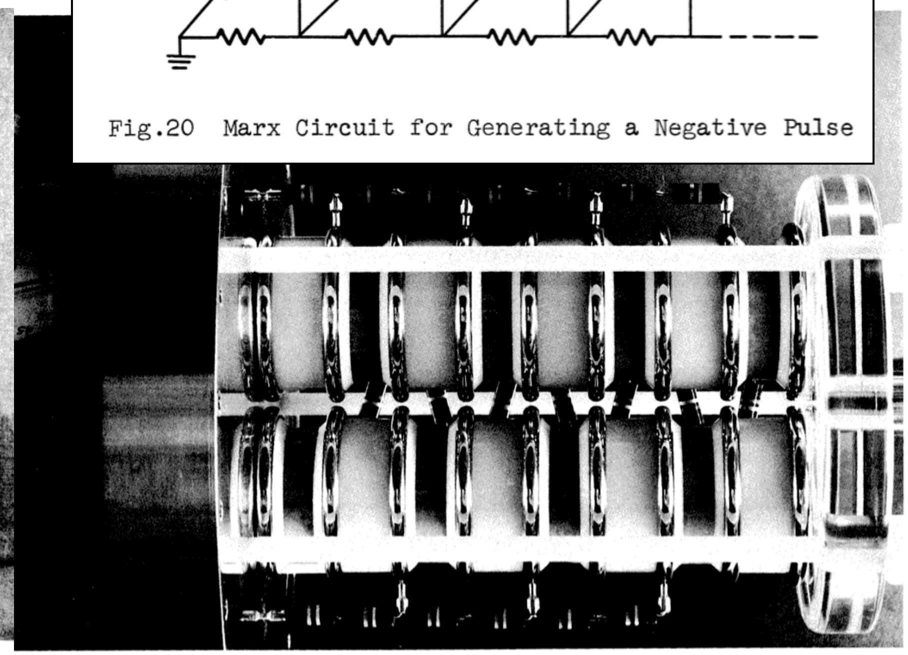


Fig.23 Side Ciew of Model B Marx Generator

Wide-Gap Tracking Spark Chambers

If tracks do not make large angles with beam direction, can avoid streamer chamber problems with robust, reliable visual spark chambers

Use multiple gaps of ~ 10 cm to provide faithful visualization of tracks

Efficiency drops if number of tracks is large (> 10)

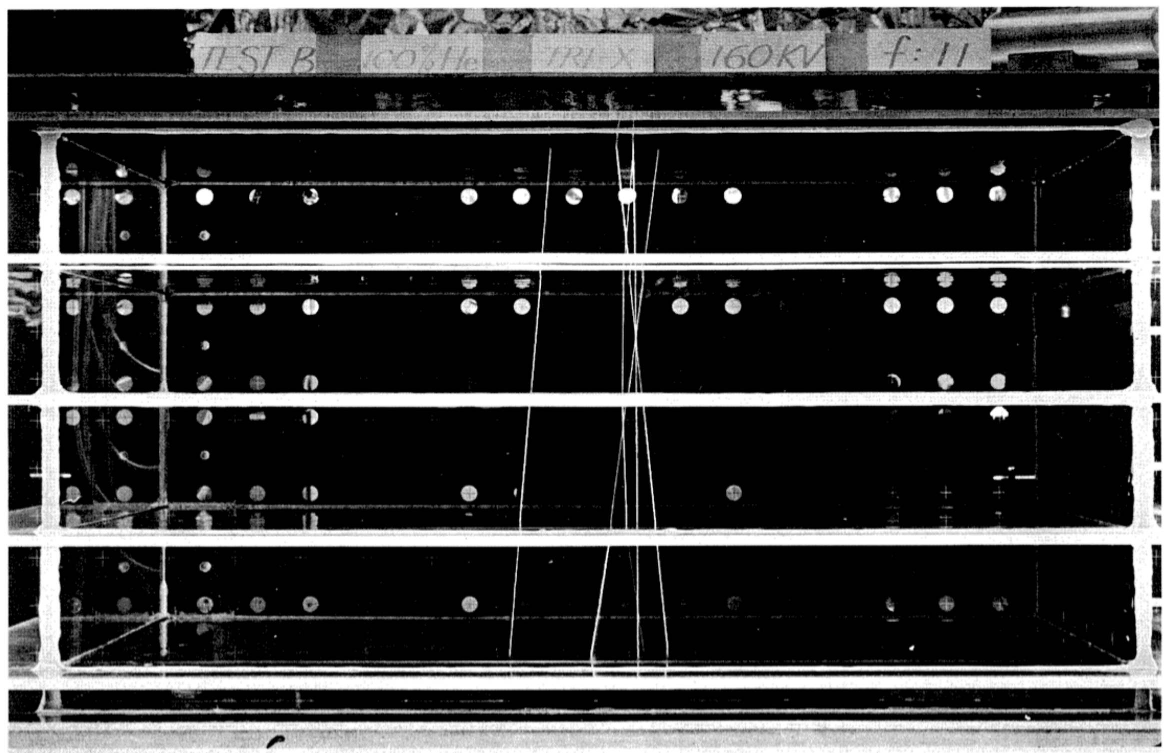
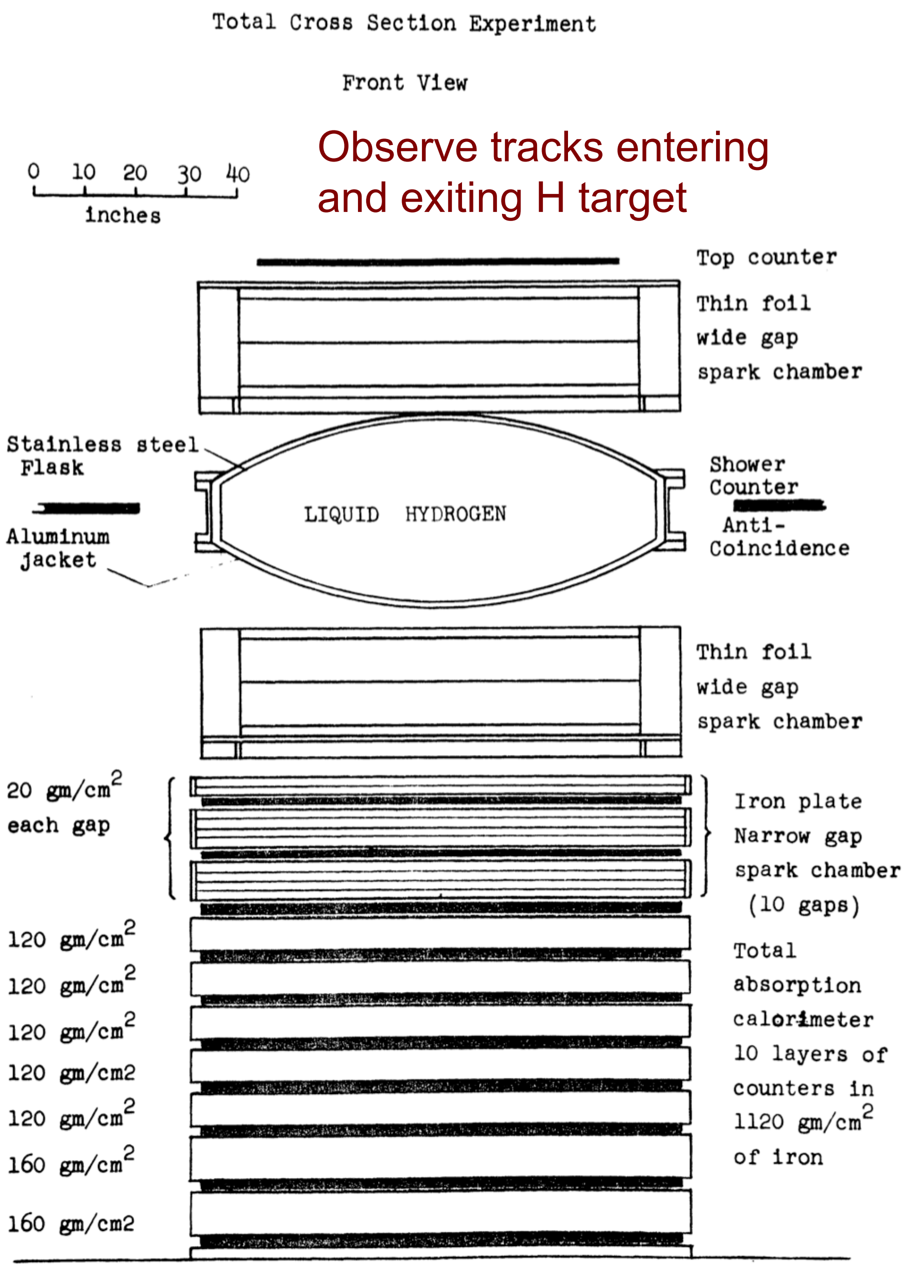


Fig.56 Spark Characteristics at 160 kV

Example of detector using spark chambers



Echo Lake (CO) experiment, c. 1970
Goal: measure total p-p cross section 100 to 1000 GeV, using cosmic ray protons
Need to go to high altitude to get even a few primary cosmic ray protons

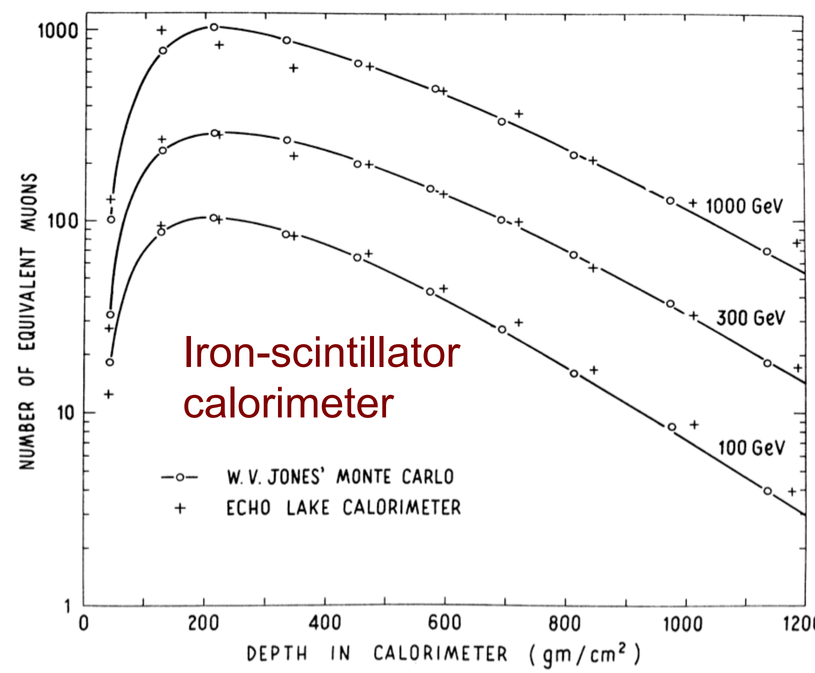


Fig. 65 Comparison of the Average Shower Curves with the Monte Carlo Results of W.V. Jones