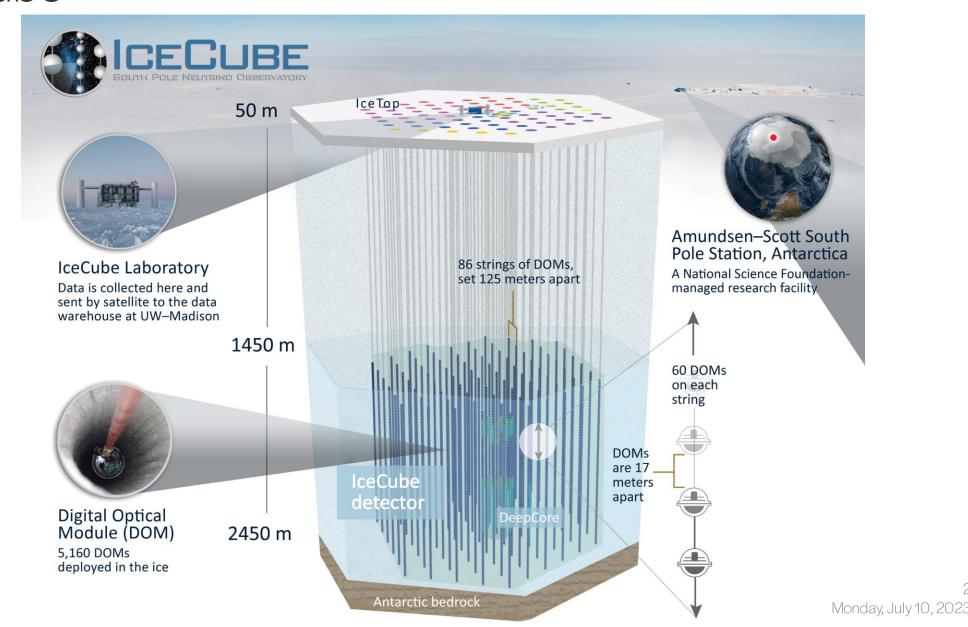


IceCube

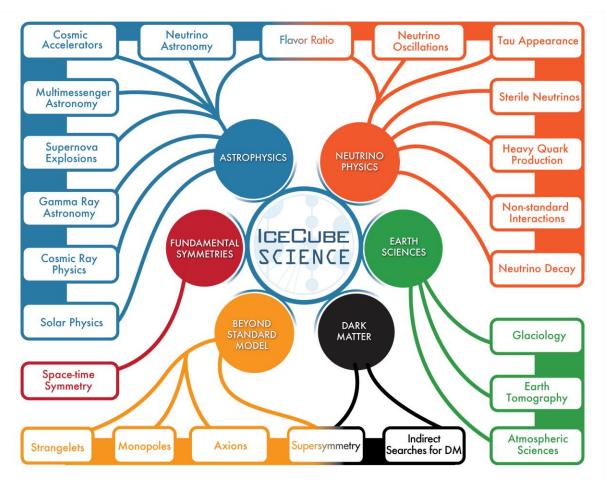








IceCube Science



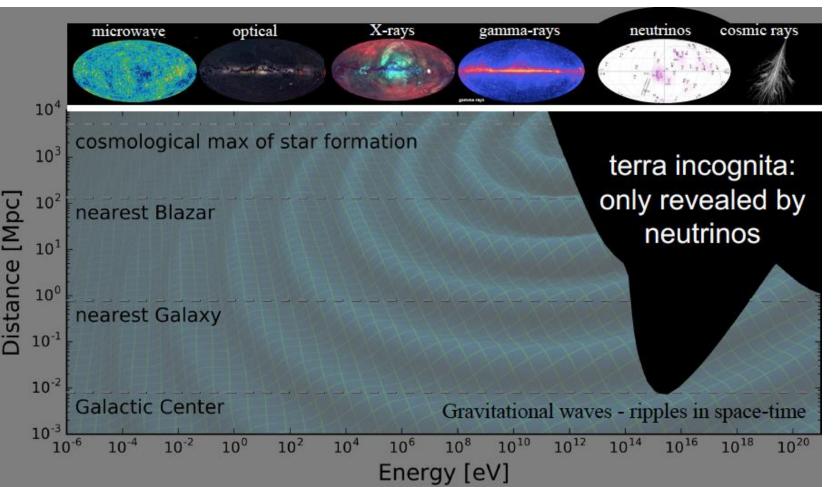
- Novel instrument in multiple fields
- Broad science abilities across 9+ orders of magnitude
 - MeV neutrinos: Core-Collapse Supernovae
 - GeV TeV: Atmospheric neutrinos to study neutrino and BSM studies
 - > TeV: Neutrinos for VHE/UHE neutrino astronomy
- Lots of data that needs to be processed in different ways
- Lots of simulation that needs to be generated







IceCube Science – Why neutrinos?



- 20% of universe is dark to "traditional" astronomy, i.e. using electromagnetic waves/light
- Need a new set of "messengers" –

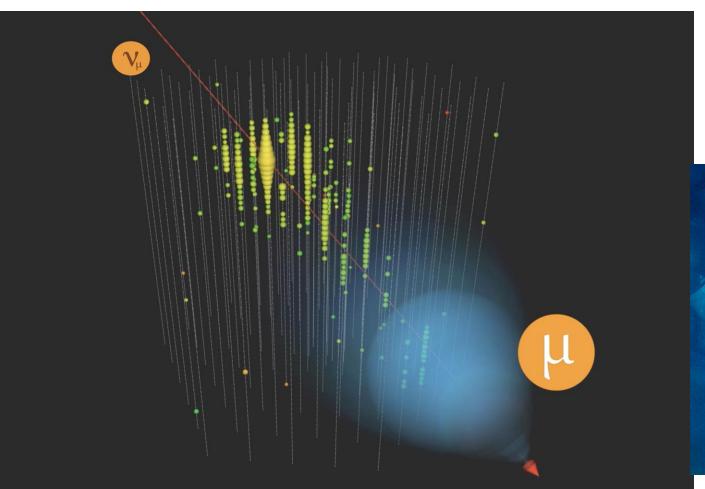
 Gravitational Waves and Neutrinos



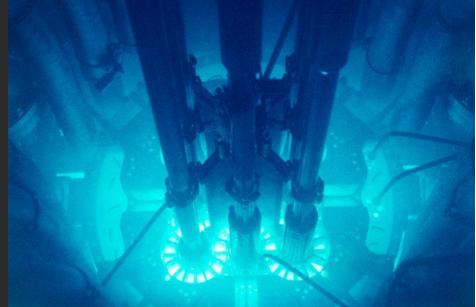




IceCube Science – How does it work?



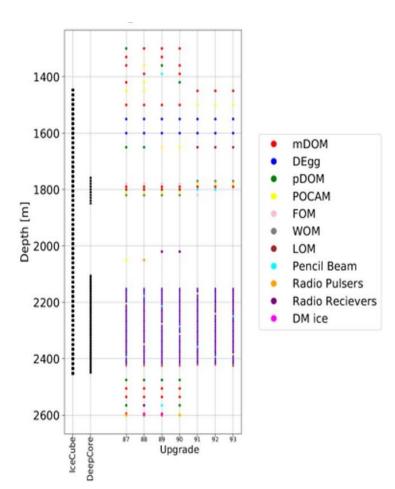
- Cherenkov light Sonic boom with light
- Cherenkov light appears when a charged particle travels through matter faster than light can

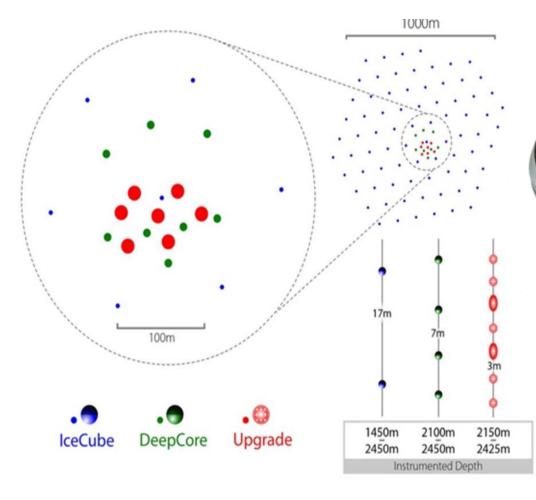






IceCube's Future – Upgrade





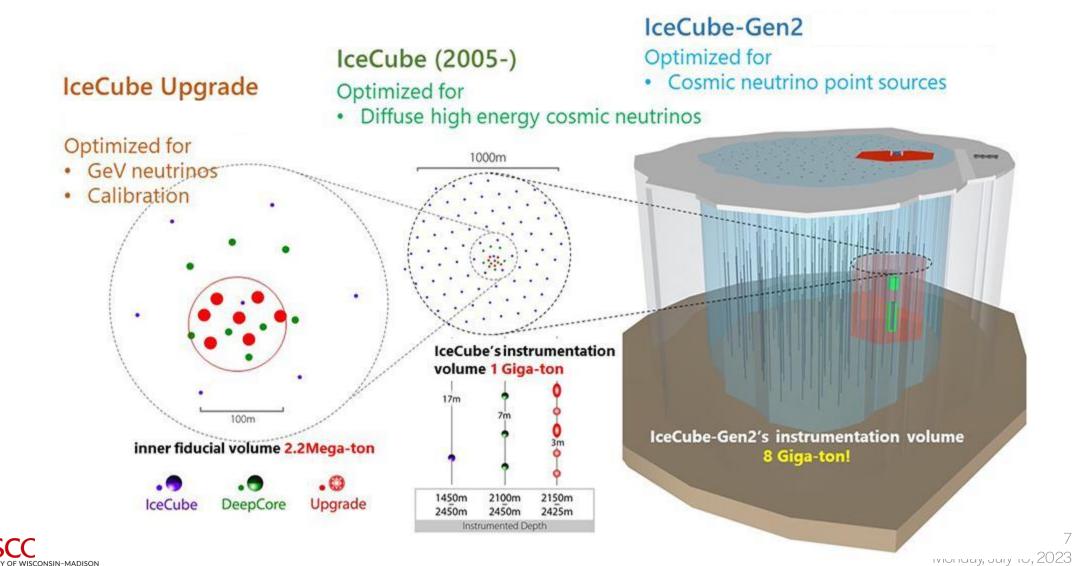




Co-Processor Meeting



IceCube's Future – Gen2





IceCube Events

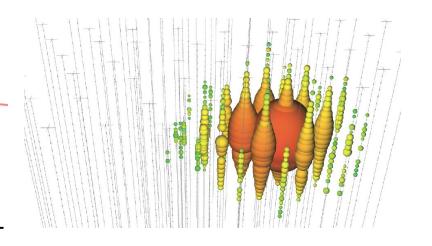
- Data is a three-dimensional movie or time-evolving point cloud of photon hits
- Different neutrino flavors produce different event topologies

Track - Muon Neutrino

Good Pointing, Poor Energy

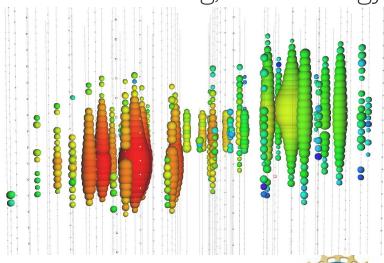
Cascade – Electron/Tau Neutrino, NC Interactions

Poor pointing, Good Energy*

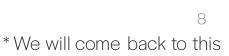


Double Bang – High Energy Tau Neutrino*

Good Pointing, Good Energy



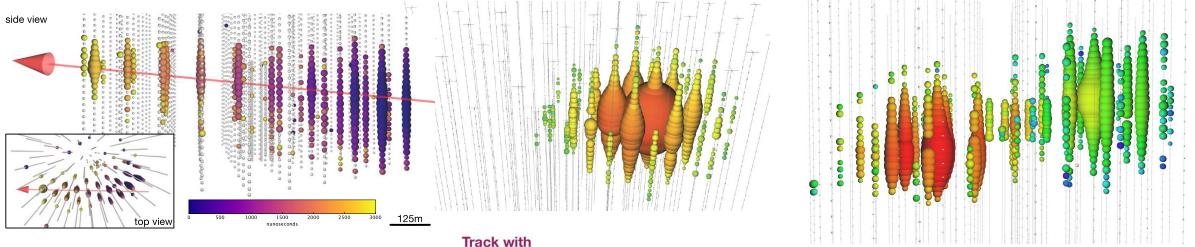


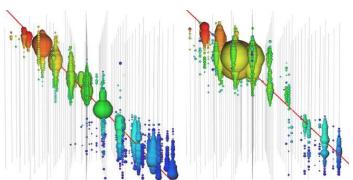




Applications – Particle ID and Classifcation

energy of 26 GeV





Cascade with energy of 30 GeV

- Same particles can "look" different
 - Lower energy = Less Information
 - Higher Energy
 - Cataphoric/Stochastic energy losses
 - Relativistic Boosting "delays" particle decays - High energy Tau
 - Different ice models
- Subtle differences can identify the particle

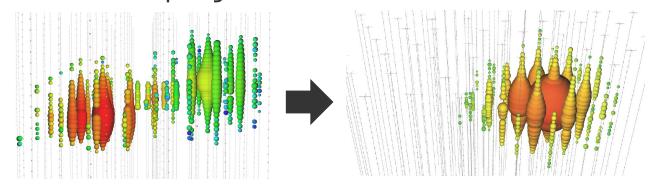






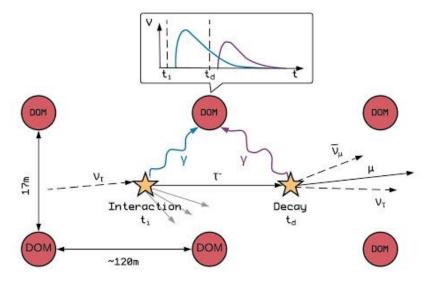


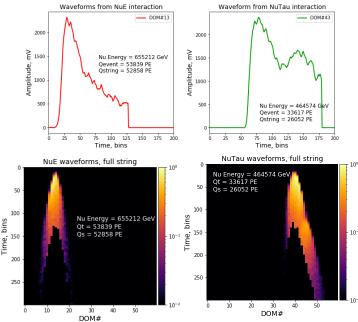
Astrophysical Tau Neutrino Search



- TeV O(1) PeV Tau neutrinos look like Electron neutrinos due to sparse instrumentation
- Differentiation by shape of waveform in a given module, i.e. two waveforms in the same module offset by a certain quantity
- Create an image (2D histogram) of the of the charge distribution in time along a string
- CNN used to find the subtle difference in waveform shapes

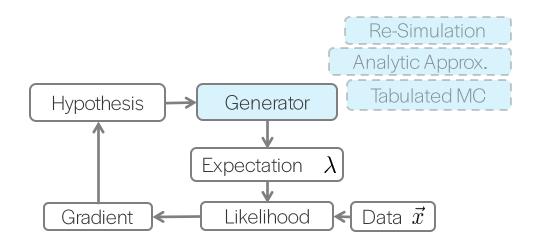








Combining Maximum Likelihood and NN



- Learn the PDF/likelihood
- Use Gradient Descent as a minimizer More information than traditional minimizers
- Still have the errors from the maximum likelihood, but can encode the details that tabulated light yield can't
- Doing this in MMA is a next step







Southern Sky Neutrino Point Source

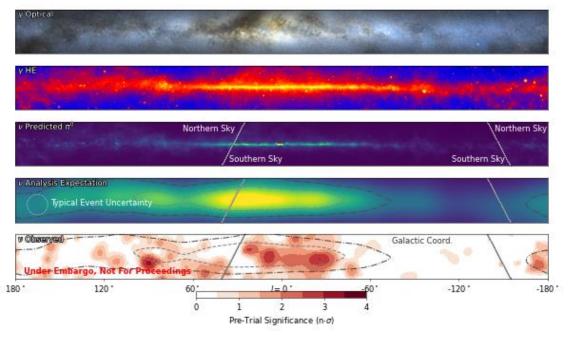
- Southern Hemisphere is astrophysically-speaking more interesting
 - More individual sources
 - More larger sources
- ...But there are issues for IceCube
 - Energy spectrum E^N, where N is -2ish, at >= TeV flux is tiny
 - No earth as a shield from atmospheric background for the Southern sky Extremely high background that looks exactly like the background
 - Estimating track-like event energy is difficult, so can't cut on energy
 - Flux of >= 10 PeV tau-like events (good pointing and energy) is extremely low
 - Cascade-like events have poor pointing resolution, but are the only realistic option







Southern Sky Neutrino Point Source



- Using Cascade events for "large" (e.g. Milky Way) or isolated sources a good option for Southern Sky point source search – Clear differentiation from background
- Maximum-Likelihood method for cascade pointing insufficient to find a source –
 Using BDT and CNN to find and reconstruct cascade events
- Third High Energy Neutrino Point Source! Galactic Plane







Kaggle Competition

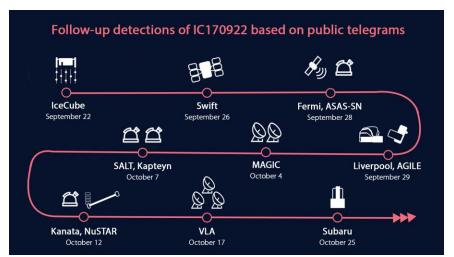
- Kaggle competition finished: https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice
 - Top 3 Results all use some form of attention:
 - https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice/discussion/402976
 - https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice/discussion/402882
 - https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice/discussion/402888
 - Better results than current state of the art!
 - Large Language Model technology gets best results
- Data is public!

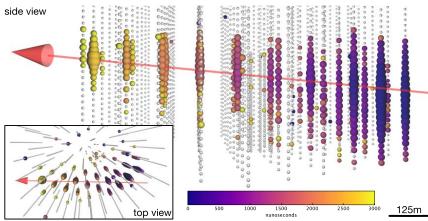






IceCube Science – Multi-Messenger Astrophysics





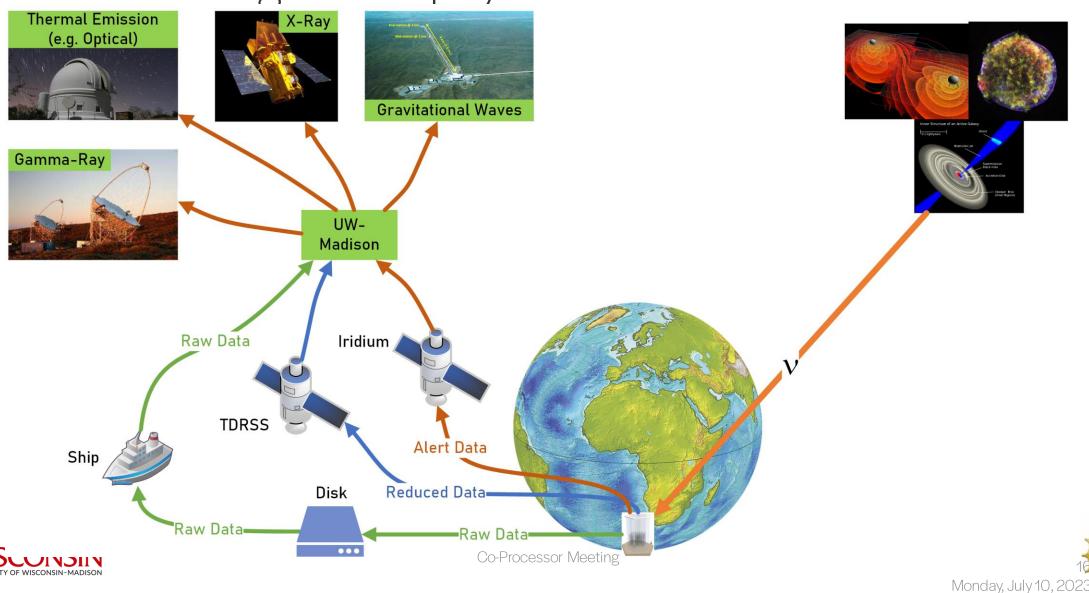
- Multi-Messenger Astrophysics (MMA)
 - Observing astrophysical phenomena with more than one "messenger" (gravitational waves, neutrinos, EM)
 - One of NSF's Big 10 Ideas
- IceCube detected an event that came from Blazar TXS 0506+056
 - Follow up observations by several observatories/telescopes showed signal
 - Back catalog showed access for this source
- Fast response to alerts requires significant cyberinfrastructure
- NS+NS merger would be ideal IceCube+LIGO observation
- Core collapse supernova would be ideal for IceCube+DUNE observation



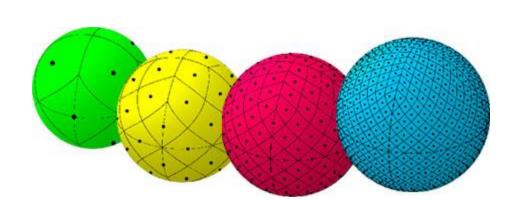


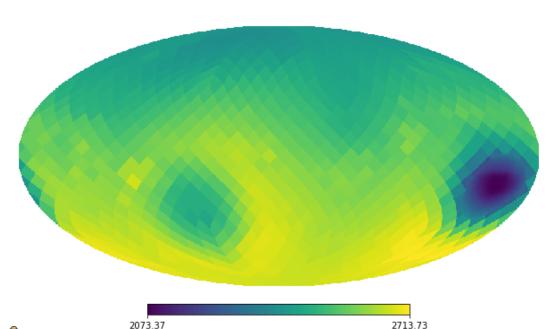


Multi-Messenger Astrophysics



Multi-Messenger Astrophysics – Reconstruction





- Most accurate (and with well understood errors) directional reconstruction comes by scanning across the sky
 - Split sky into constant surface area pieces
 - Test each directional hypothesis against likelihood
 - Create directional likelihood map
 - Gives most probable direction and error
- Each hypothesis calculation is independent – Easy to split up workload across O(1000[000]) or cores

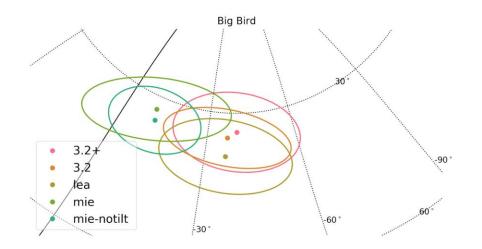


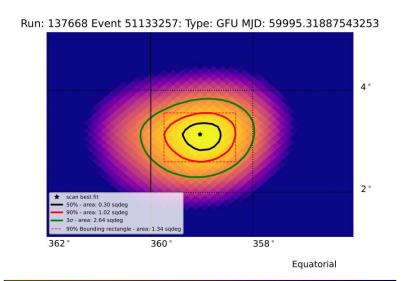




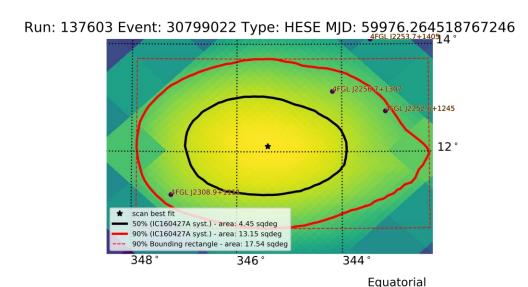
But... ML in MMA?

- What is the issue? Errors
 - Errors from ML are poorly understood Derived from simulation rather than statistically rigorous and "understandable" method
 - Is there a bias? Are we using the right systematics?
 - We know the simulation doesn't describe the detector 100%, so can ML?
 - Poor training data in, Poor results out
 - In some events multiple sources are within in 90% bounds





 $-2\Delta ln(L)$



 $-2\Delta \ln(L)$

150

200

250

100

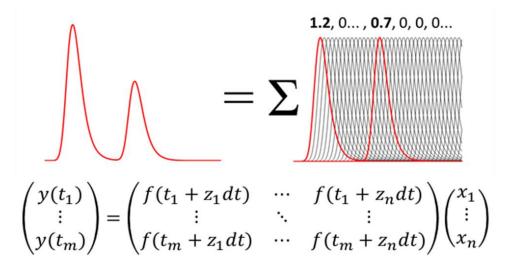
Madison "Virtual" Collaboration Meetine

50



Bottlenecks

- Most MMA sources are transient
 - Fast follow-up is essential
 - 2 non-transient sources: Galactic Plane and NGC 1068
- IceCube pipeline is ~30 seconds from data acquisition to preliminary result for IceCube-initiated events
 - Partner-initiated takes longer due to network limitations to South Pole
- Limited hardware/power overhead at the pole Accelerators and ML/Al can save power and speed up computation
- Biggest computing sink is waveform unfolding/deconvolution - 30-50% of CPU time (closer to 50% for MMA events)



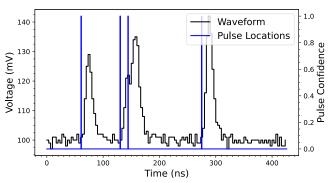




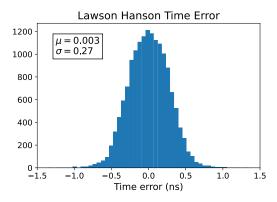
ML unfolding

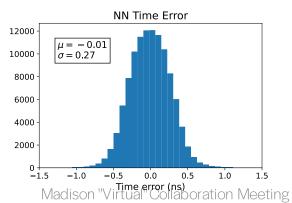
- Use an MLP to find pulses in PMT voltage waveforms
 - Scan over waveforms for more compact size
- Ability to find SPEs with a comparable performance to standard template fitting method
- Able to distinguish separate pulses 12 ns apart
 - Will be able to improve
- Eventually plan to implement on GPU and FPGA

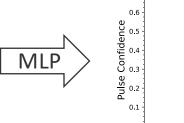


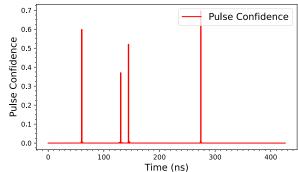


Performance with SPEs

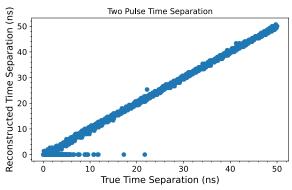


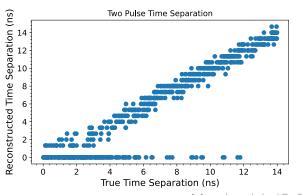






Two Pulse Performance



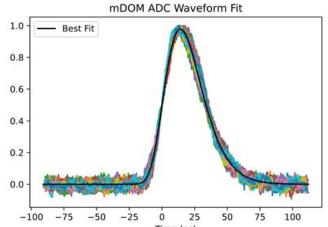




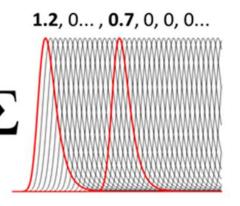




- Currently use the Lawson Hanson nonnegative least squares algorithm to fit SPE template functions to voltage waveforms
- Our current algorithm runs on CPU, could perhaps speed up the algorithm by running on GPU
- Plan on adapting current C++ code to be compatable with CUDA







$$\begin{pmatrix} y(t_1) \\ \vdots \\ y(t_m) \end{pmatrix} = \begin{pmatrix} f(t_1 + z_1 dt) & \cdots & f(t_1 + z_n dt) \\ \vdots & \ddots & \vdots \\ f(t_m + z_1 dt) & \cdots & f(t_m + z_n dt) \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$







Thank you!

Questions?

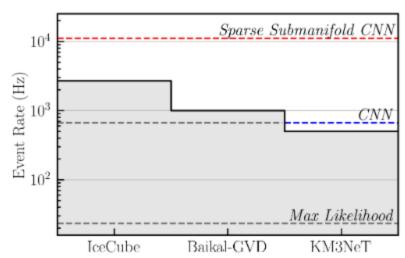


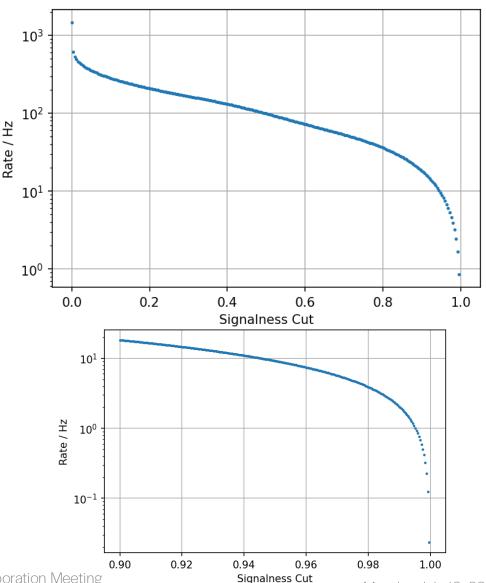




ML in MMA?

- Current pipeline takes ~30 seconds from data taken to alert
 - Biggest hurdle is extraction charge information from electronic readout
- Work on a single shot ML pipeline
 - From trigger to final selection in one step
 - Can we use this with even less information?
 - Can we accelerate the waveform unfolding?







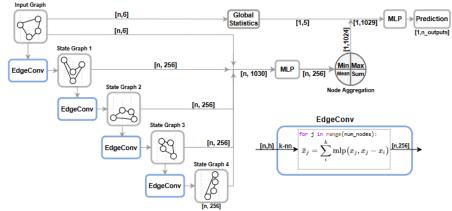


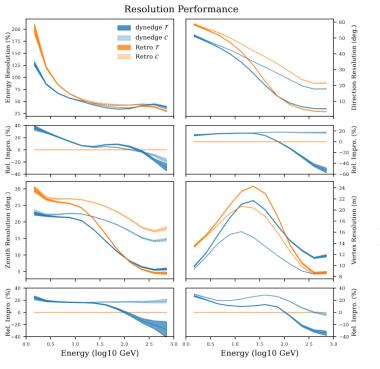


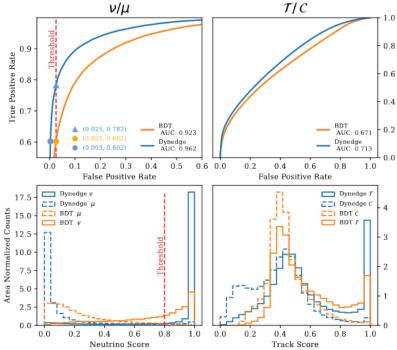


GNNs

- Neutrino Telescopes
 - Collection of individual detectors – Time-evolving 3D point cloud
 - GNNs a natural fit Nodes (Individual detectors) with a connection (geometry of telescope)
- GraphNet
 - GitHub, IceCube Paper
 - Effort among neutrino telescopes to create a GNN framework and pre-trained models for reconstruction, particle ID, etc.







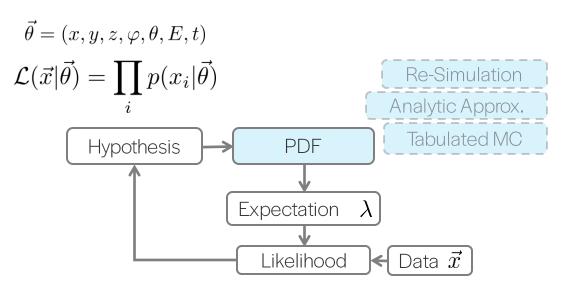


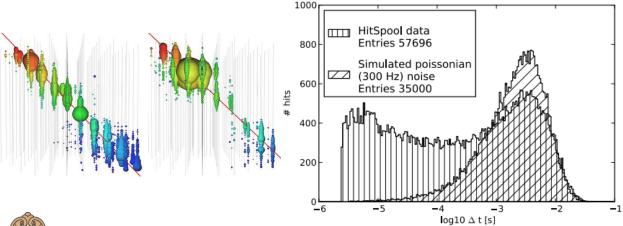


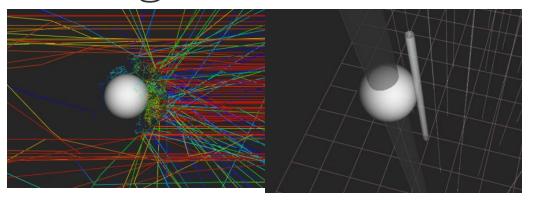




Maximum Likelihood – Short Comings







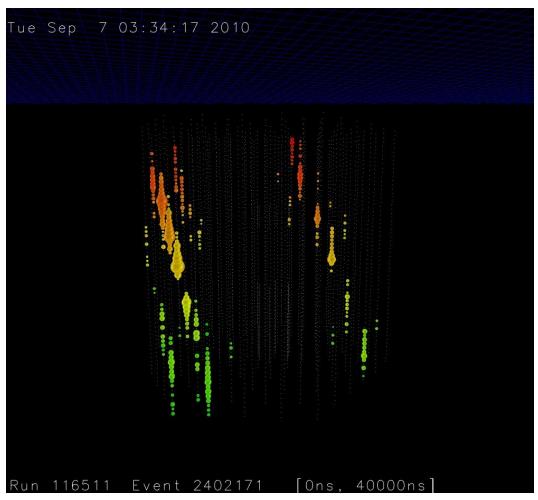
- Largest issue for reconstructions is the estimated light yield
 - At high energies Ice and catastrophic energy losses
 - At low energies Ice and non-poissian noise
 - Ice
 - Low energies Area close to individual detectors
 - High energies Bulk properties







Applications – Splitting



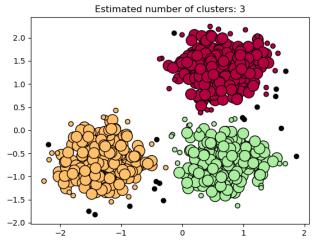
- Coincident events Two or more events in the same trigger window
- Semantic Segmentation Nets –
 Question how to differentiate objects of the same class







Applications – Splitting



Splitter computing speeds

IceHive
HiveSplitter
TriggerSplitter
OPTICS

10⁻³

10⁻⁵
10⁻⁴
10⁻³
10⁻²
10⁻¹
10⁻²
10⁻¹
10⁻²
10⁻¹
Time per event (s)

- Unsupervised clustering algorithms have proven either too slow or not as performant as existing algorithms
- There are advantage in noise identification with unsupervised learning – Needs to be revisited in new detector designs
- Looking at GNN-based clustering





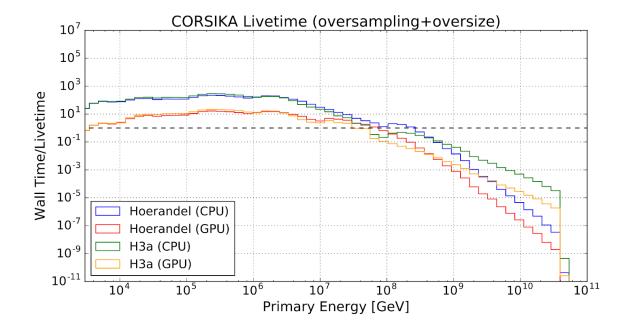
mDOM







Applications – Simulation

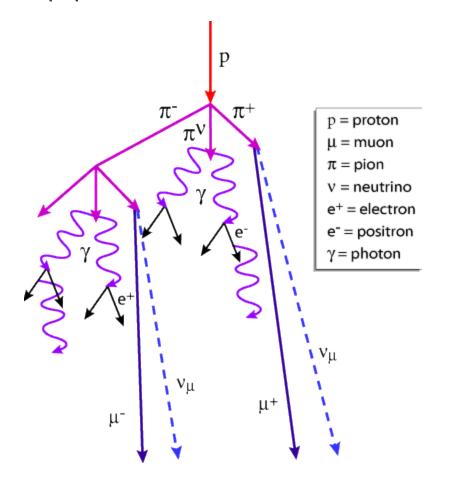


- Physics is the issue here
 - Lots of background
 - Lots of possible physics
- Enormous energy range and flux 3 kHz of muons across 9+ orders of magnitude in energy with running at 90+% uptime for 10+ years
- Desire is 100+ years of simulation
- Up to 500x the compute time compared to livetime
 - 2 seconds of detector runtime: CORSIKA Showers: 1M events CORSIKA Output: 92K events Photon Prop/Ray-tracing: 18K events Detector Sim output: 10K events Final output: 5897 events
 - Anywhere from 34-98% of CPU/GPU time is spend on first principal particle simulation





Applications – Simulation



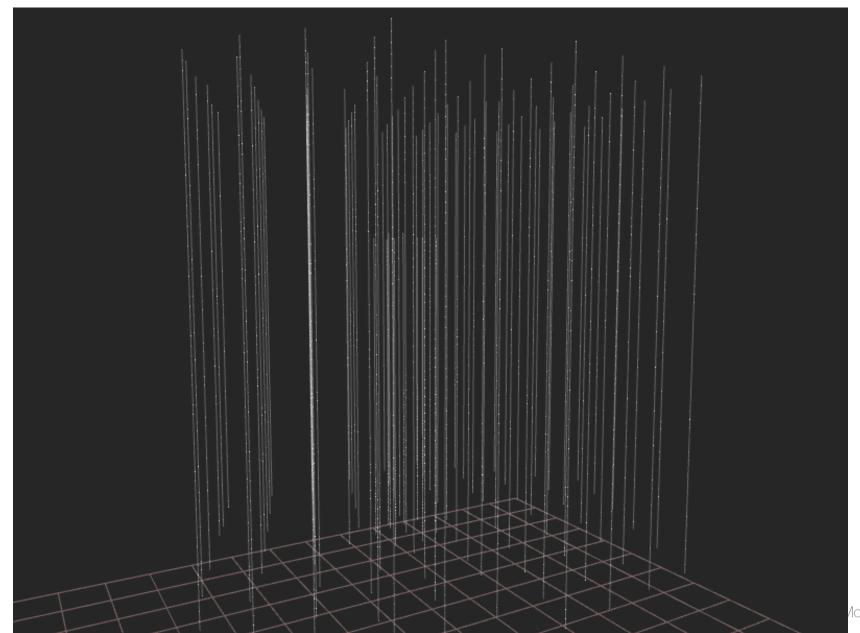
- First order simulations are good for deep dives
 - Not good if you need to generate lots of it
 - Edge cases important
- Existing parametrizations are lacking Missing "muon bundles" (groups of related particles)
- Potential CPU saving solutions use flawed assumptions – Local network connectivity needed





IceCube Events



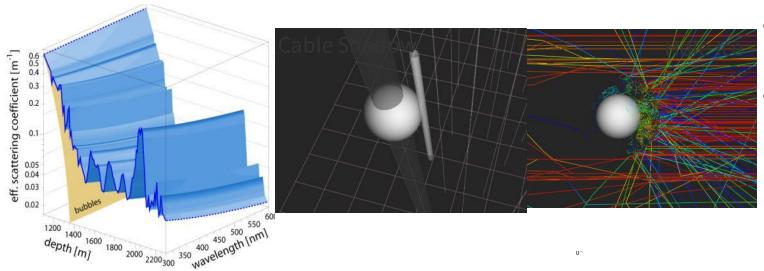


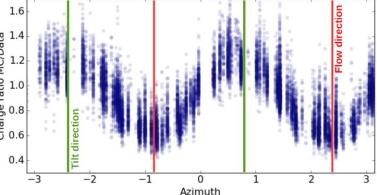


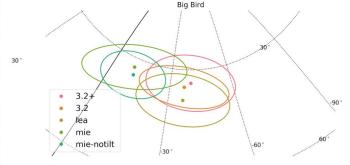


Ice Model









Cascade Events – Results with cascades and ML coming soon, stuck in journal

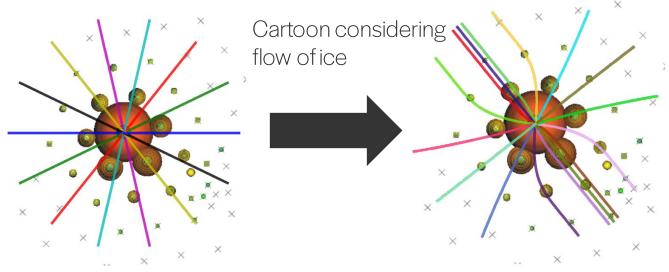
Co-Processor Meeting

- Natural medium Hard to calibrate properly
- Dropped a detector into a grey box
 - The ice is very clear, but...
 - Is it uniform?
 - How has construction changed the ice?
- Ray-Tracing with GPUs
 - Too complex for a parametrized approach
 - Needs brute force approach
- Drastic changes in reconstructed position with different ice model



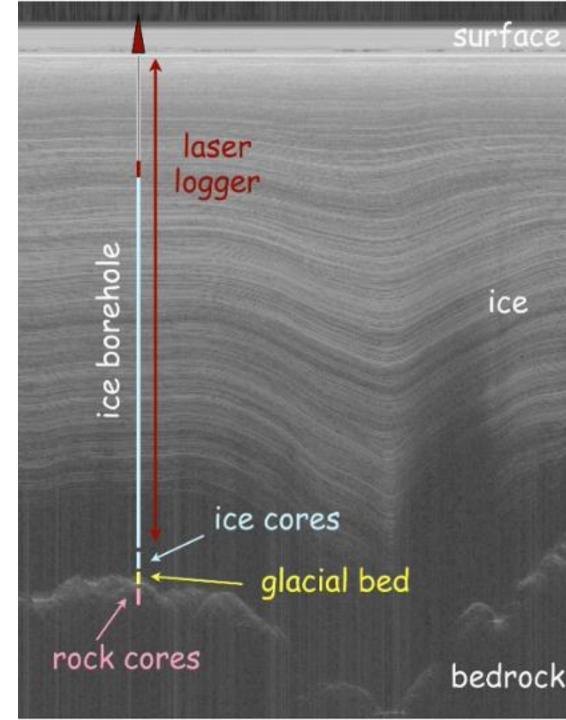


Ice Model



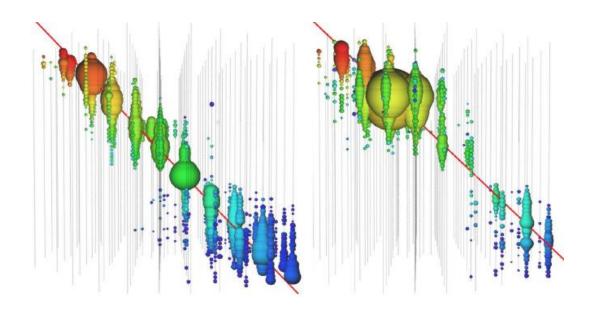
- New calibration data is available every year More data being data, new ice cores being taken, etc.
- Want to have most up-to-date information in detector
- "Fitting" the model is compute intensive Up to 400 GPU years
- Newer analyses want the most up-to-date simulation
- Ice model is the largest systematic effect in detector Adding new systematic effects
- The deeper we dig the more complicated it gets
 - Birefringence Ice Crystal Size
 - Layering of ice over millenia and moving across a changing bedrock







Classification



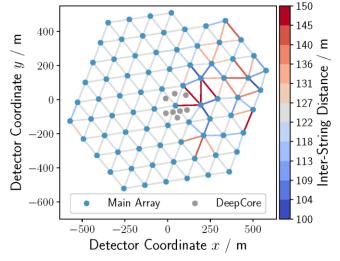
- CNN being added to "standard" processing to identify:
 - Through-going Tracks-Pass through entire detector
 - Stopping Track Enters the detector and stops in it
 - Starting Track Starts in the detector
 - Starting Cascade Starts in detector and doesn't exit
 - Skimming Enters and exits at the corners of the detector
- Graph Neural Nets
 - IceCube is a collection of points in space with a relationship
 - Graphs are a "natural" fit
 - First signs of impact Differentiation in events performs better than CNN
 - https://arxiv.org/abs/1809.06166





Convolutional Neural Networks

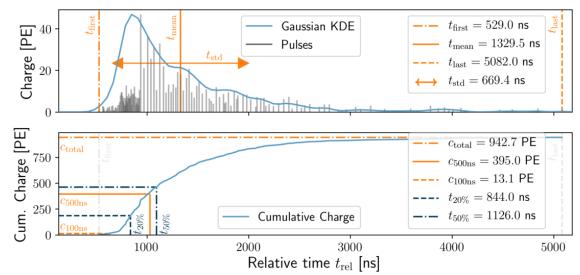




Main Array
 DeepCore
 Zero Padding
 2D Space
 1D Time
 Lower DeepCore
 Main Array
 3D Space
 1D Time

Main Array
3D Space
1D Time

- Convolutional Neural Networks Square Peg Round Hole Problem
- IceCube is not a CCD Irregular geometry
- Time evolution of events Contains information about detector, events, etc.

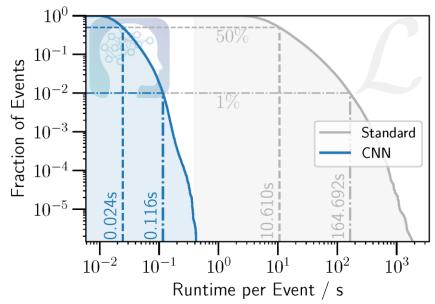


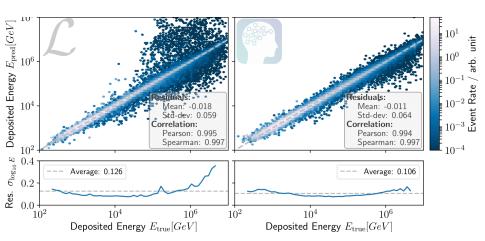


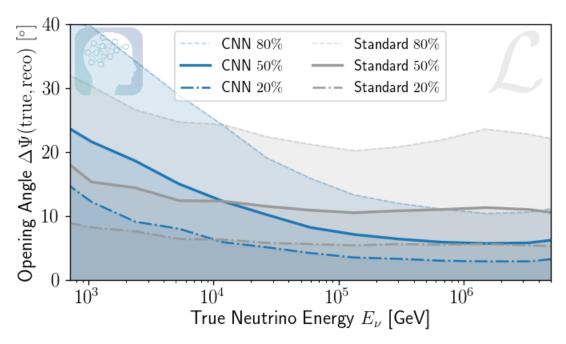




CNN Performance

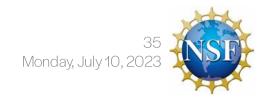






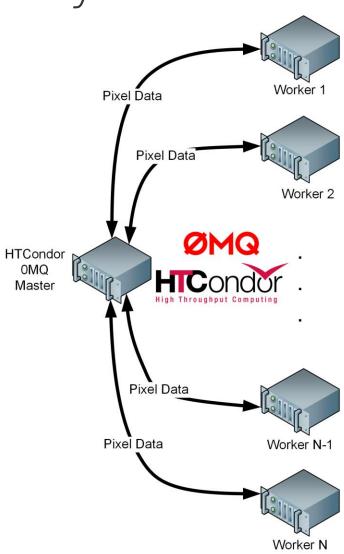
- Faster
- Better resolution







Today



- Manager-worker setup
- Worker resource requirements are the same
- Manager makes decision about next scan
- Data communication via ZeroMQ
 - Easy to use and setup
 - Scaling an issue
 - Issue with communicating over external network Firewall issues
 - Manager can't keep up > 2000 cores
- Using HTCondor for scheduling workers

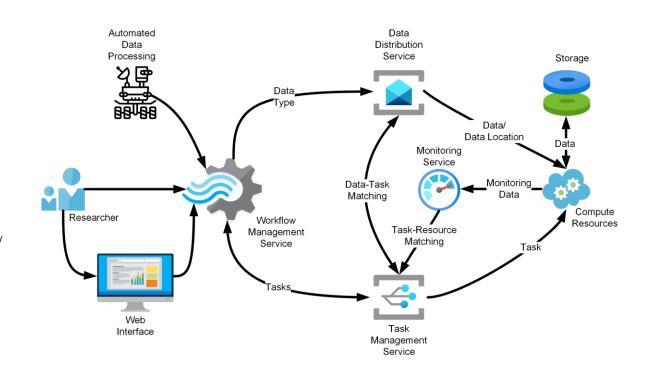




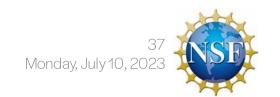


CSSI – Event Workflow Management Service

- Introduce Manager-Worker paradigm to dHTC workloads Map-Reduce for the Hadoop Afficinados
- Plain HTCondor not good for Manager-Worker
 - Schedule overhead dominates in execution time with small tasks
 - Use the right tool for the right job HTC ondor to aggregate resources and schedule workers
- Message Queues (MQ) have all the tooling needed to extend HTCondor
 - Handle many small data packages (messages) efficiently
 - Multi-user, multi-workflow separation
 - Persistence (if needed)
 - Offload to storage (only Apache Pulsar)
 - Monitoring
 - Off-shelf No first principal derivation

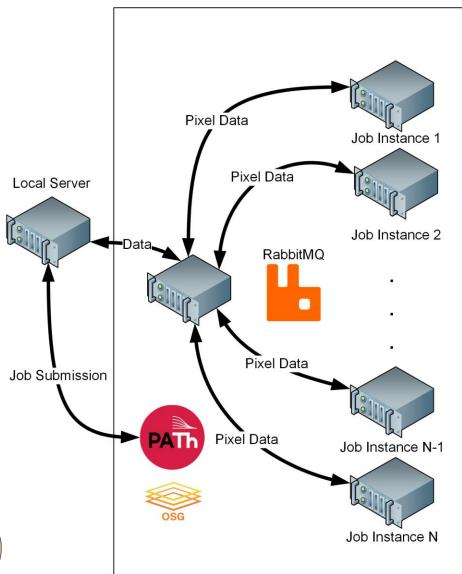








Tomorrow – Grid



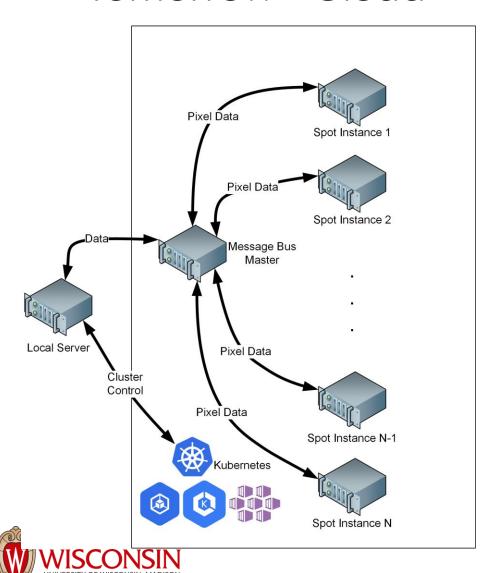
- Replacing OMQ with RabbitMQ Why?
 - Build for scaling
 - No network issues
- Why use the Grid?
 - More resources available Faster completion
 - Free!
- Need an RabbitMQ instance running continuously – PATh facility to the rescue!



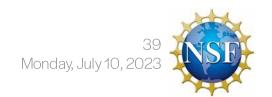




Tomorrow – Cloud



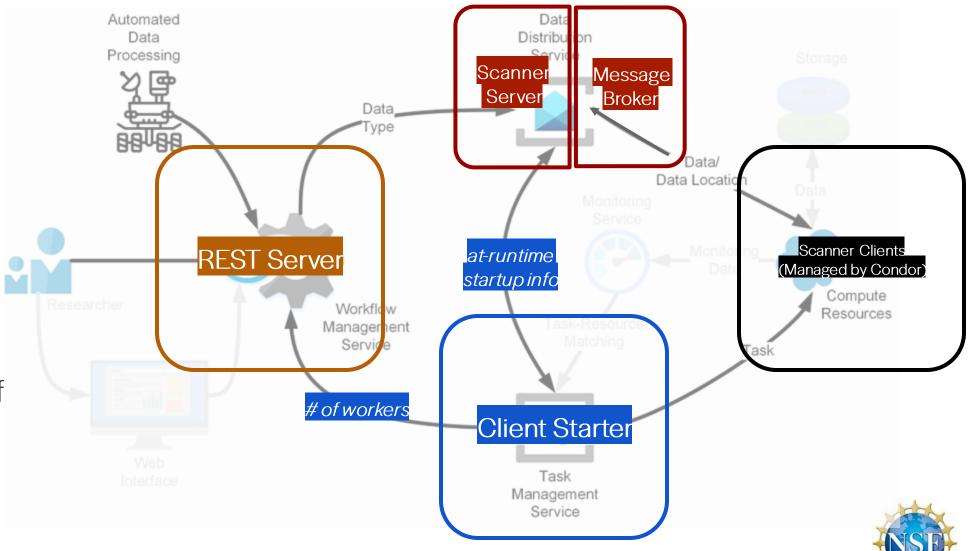
- Substituting Grid resources with Cloud resources
- Much larger pool of resources
- Readily available resources
- More control over resources
- Autoscaling cluster size (Kubernetes as a Service) makes things easier
- \$\$\$ Question about cost (~\$100-1500 per alert)





SkyDriver-Reconstruction-a-a-S

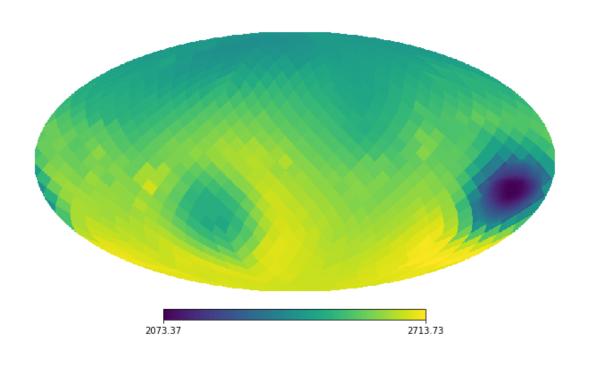
- Researchers
 submit an event to
 a service be
 reconstructed
 through a scan
- Researcher does not need to worry about the details of the scan







Applications – Reconstruction



- Determine
 - Direction
 - Energy
 - Position in detector
 - Type
- State of the Art:
 - Maximum likelihood technique Cannot support newest detector knowledge
 - CNN (>TeV) and GNN (O(10) GeV) reco
- Different type of events require different methods
 - Energy a factor At low energies events "stops" in detector
 - Lots of physics is "known"

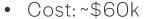


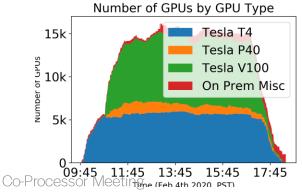


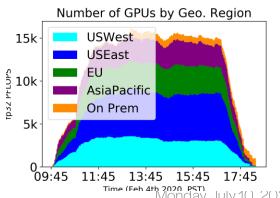


GPU Cloudburst Experiments

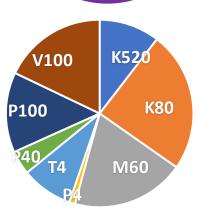
- Original Goal: Create an ExaFLOP compute pool in the cloud (80,000 NVIDIA V100) and address review panel recommendations
- Cloud provider(s) do not have those resources available We were promised they do
 - Pre-allocated resources
 - Single cloud provider does not have those resources
- First Experiment On Nov 16 2019 we bought all GPU capacity that was for sale in Amazon Web Services, Microsoft Azure, and Google Cloud Platform worldwide Creating The Largest GPU Cloud Pool in History
 - 51k NVIDIA GPUs in the Cloud
 - 380 Petaflops for 2 hours (90% of DOE's Summit, No. 1 in Top 500)
 - Distributed across, US, EU, and Asia-Pacific
 - Cost: \$50-150k (under NDA)
- Second Experiment More realistic test
 - Most cost-efficient GPUs for 8 hours
 - Achieve 1 ExaFLOP-hour of compute
 - Distributed across, US, EU, and Asia-Pacific







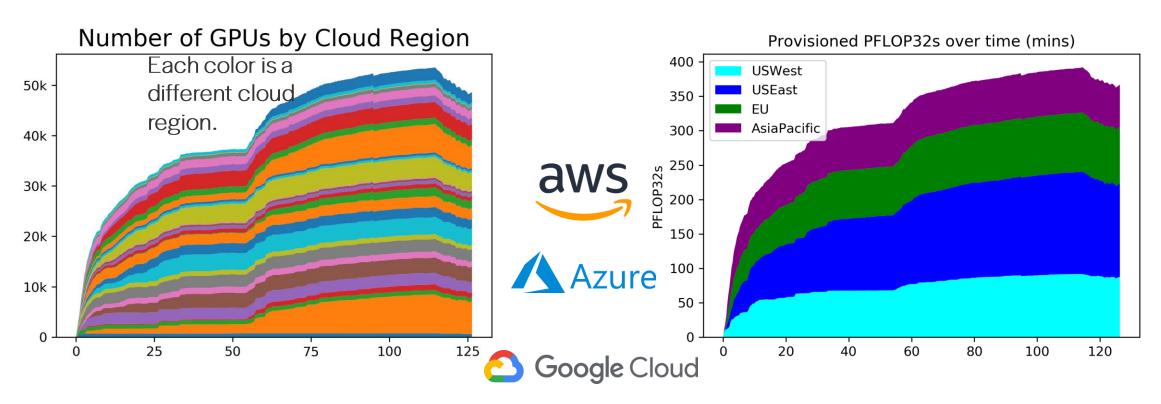








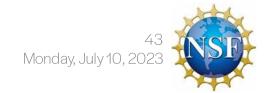
GPU Cloudburst – 1st Experiment



Peaked at 51,500 GPUs

Total of 28 Regions in use.

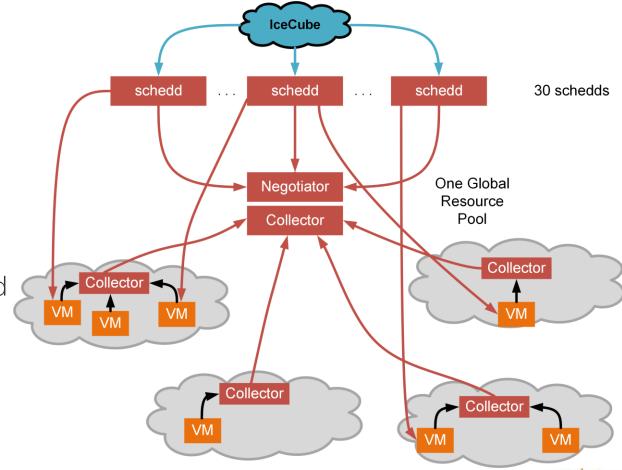






GPU Cloudburst Technology

- Multi-collector HTCondor setup Already well-established
- Collector in each cloud region to reduce load on start-up – No idea where resources would be
- Workload is computing heavy compared to typical IceCube load – Reduce potential networking cost
- 1st Demo: In and output data stored in cloud
- 2nd Demo: Input came from UW, output stored in cloud, dedicated network links – Saturated UW SciDMZ network (100G)
- 3rd Demo: Week-long cloud usage, output and input at UW





https://arxiv.org/abs/2002.06667 https://arxiv.org/abs/2004.09492 https://arxiv.org/abs/2104.06913 https://arxiv.org/abs/2107.03963



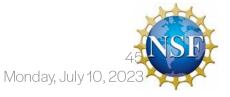




IceCube Computing – 30,000 Foot View

- Classical Particle Physics Computing
 - Ingeniously parallelizable Grid Computing!
 - "Events" Time period of interest
 - Number of channels varies between events
 - Ideally would compute on a per event-basis
- Several caveats
 - No direct and continuous network link to experiment
 - Extreme conditions at experiment (-40 C is warm, desert)
 - Simulations require "specialized" hardware (GPUs)
 - In-house developed and specialized software required
 - Large energy range cause scheduling difficulties Predict resource needs, run time, etc.

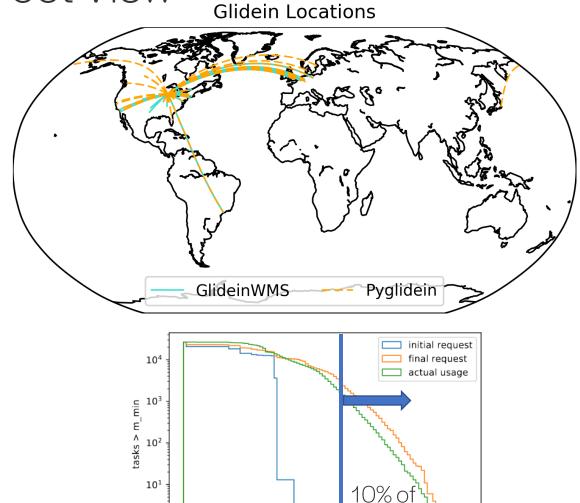






IceCube Computing – 10,000 Foot View

- Global heterogeneous resources pool
- Mostly shared and opportunistic resources
- Atypical resources requirements and software stack
 - Accelerators (GPUs)
 - Broad physics reach with high uptime-Lots to simulate
 - "Analysis" software is produced in-house
 - "Standard" packages, e.g. GEANT4, don't support everything or don't exist
 - Niche dependencies, e.g. CORSIKA (air showers)
- Significant changes of requirements over the course of experiment Accelerators, Multimessenger Astrophysics, alerting, etc.



workload

Monday, July 10, 202

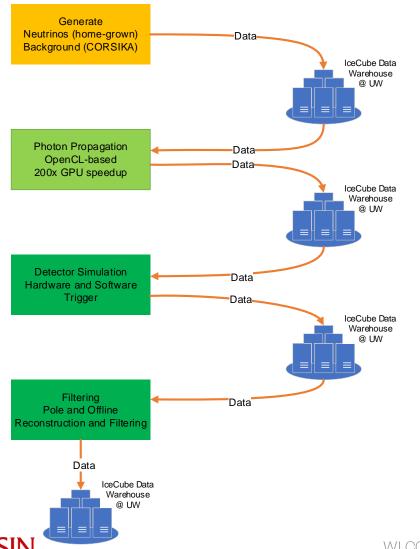
101

Memory m min (GB)





IceCube Grid – Simulation Workflow

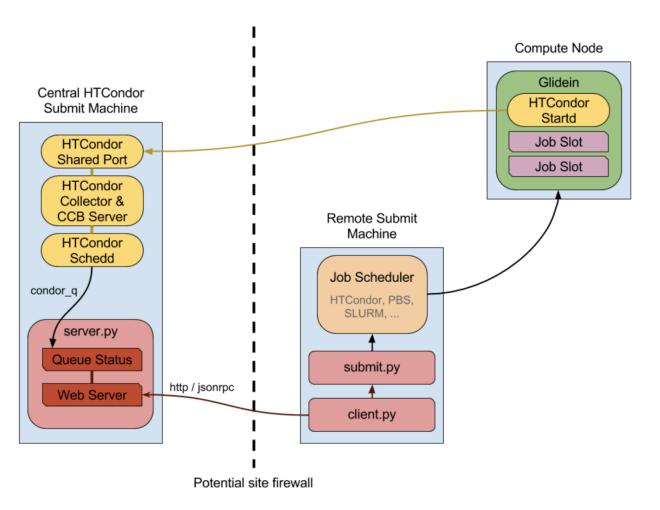


- Fairly straightforward particle physics-like workflow
- Big constraint is lack of dedicated resources
 - No data aware scheduling
 - Lots of data movement Lots of time wasted to move data
- Different steps can have drastically different requirements





IceCube Grid – PyGlidein - I



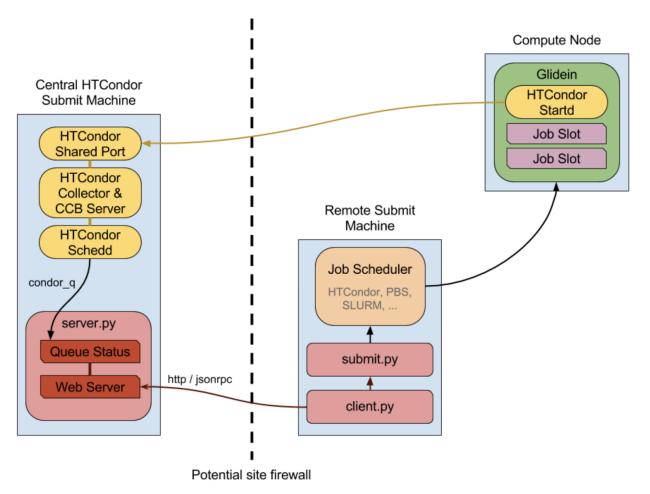
- Separate job submission from workflow management
- Lightweight design as possible
- Only difference between sites is a config file
- Why separate system?
 - Performance issues Maximum ~3500 jobs
 - Experts needed for deployment, operation, and monitoring
 - Individual users could not use distributed resources







IceCube Grid – PyGlidein - II



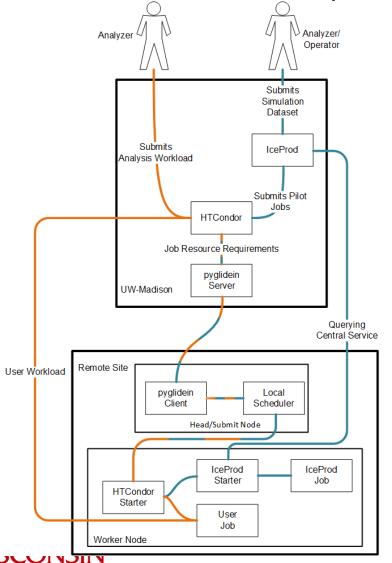
- Exposed the job resource requirements - CPU, Memory, Disk, GPU - via HTTP
- Remote client queries for job requirements and submit HTCondor startd jobs accordingly within local resource constraints
- When **HTCondor startd** executes connects back to central pool
- Multiple jobs are submitted per single job in pool – Assuming other jobs will be able to use slots, otherwise dies within set amount of time







IceCube Grid – PyGlidein - III



- User perspective
 - HTCondor + Data Management
 - "Just an HTCondor pool"
- Operator perspective
 - Little overhead to add cluster to pool
 - Fairly easy to monitor, e.g. condor_status
 - No need for a CE-Use SSH or cron for submission
 - Local container support
- Future improvements
 - Code needs clean-up Organic growth to support multiple schedulers
 - User container support

