







IceCube Summer Student Program Report 2025

Tananan Anansubying
Department of Physics, Chulalongkorn University

Report	IceCube Summer Student Program 2025
Name	Tananan Anansubying
Date	1 June 2025 - 31 July 2025

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1 IceCube Summer Student Program

The IceCube Summer Student Program is a collaborative initiative between Thailand and the IceCube Neutrino Observatory. The program runs for eight weeks, providing opportunities for Thai undergraduate and graduate students to engage in projects relevant to IceCube neutrino research at the Wisconsin IceCube Particle Astrophysics Center (WIPAC), University of Wisconsin–Madison, USA. Each year, two Thai students are selected through an interview process conducted by a selection committee, with the final candidates endorsed by Her Royal Highness Princess Maha Chakri Sirindhorn. Financial support is provided by the Information Technology Foundation under the initiative of Her Royal Highness, in partnership with WIPAC.



Figure 1: Her Royal Highness Princess Maha Chakri Sirindhorn together with the Thailand IceCube Committee and the selected students of the IceCube Summer Student Program 2025.

In 2025, WIPAC awarded scholarships to two Thai students to participate in the IceCube Summer Student Program in the United States. The scholarship covered living expenses and accommodation at the University of Wisconsin–Madison, while travel costs, visas, and additional expenses were supported by the Information Technology Foundation under the initiative of Her Royal Highness Princess Maha Chakri Sirindhorn.

To be eligible, applicants were required to be in their third or fourth year of undergraduate study, or enrolled in graduate studies (Master's or Ph.D.) in a related field, with prior academic experience in at least one of the following areas: (1) Cosmic Rays, (2) High-Energy Astrophysics or High-Energy Physics, (3) Computational Astrophysics or Computational Physics, and (4) Observational Astrophysics.

That year, the two Thai students selected for the program were Mr. Tananan Anansubying from Chulalongkorn University and Mr. Thammarat Yawisit from King Mongkut's Institute of Technology Ladkrabang. Both were chosen through a national selection process and formally endorsed by Her Royal Highness Princess Maha Chakri Sirindhorn.

2 IceCube summer school 2025 (IceCube Bootcamp)

The 2025 IceCube Summer School, formerly known as Bootcamp, will be held at 222 West Washington Ave in Madison, WI from June 2 - 6, 2025. It is organized annually by WIPAC as an intensive workshop covering various topics related to IceCube, such as the IceCube neutrino detector, multi-messenger astronomy, physics, statistics, and data analysis from the IceCube Neutrino Observatory at the South Pole. Additionally, participants will gain hands-on experience in data analysis, and software programs. The schedule is as follows:



Figure 2: Participants of IceCube Summer School 2025.



Figure 3: Thai participants in IceCube Summer School 2025 with Paras Koundal

Report	IceCube Summer Student Program 2025
Name	Tananan Anansubying
Date	1 June 2025 - 31 July 2025

2 June 2025

09:00 - 09:10	Introduction: Welcome and Introduction
09:10 - 09:50	Physics: IceCube Science
09:10 - 10:30	Detector and Calibration: IceCube Detector
10:30 - 11:00	Coffee Break
11:00 - 11:40	Physics: Neutrino Physics
11:40 - 13:00	Lunch Time
13:00 - 13:40	Physics: Cosmic rays
13:40 - 14:20	Physics: BSM physics with IceCube (including dark matter)
14:20 - 14:50	Coffee Break
14:50 - 15:50	Workshop: intro to Python

3 June 2025

09:00 - 09:40	Detector and Calibration: Winterover: Life at the South Pole
10:20 - 10:50	Physics: Cosmic ray anisotropy
10:20 - 10:50	Coffee Break
10:50 - 11:30	Physics: Diffuse neutrinos - from TeV to EeV
10:30 - 11:00	Coffee Break
11:00 - 11:40	Physics: Neutrino Physics
11:30 - 13:00	Lunch Time
13:00 - 13:40	Detector and Calibration: Detector Physics
13:40 - 14:20	Software and computing: Github talk
14:20 - 14:50	Coffee Break
14:50 - 15:50	Workshop: JupyterHub, NPX, Grid, Github
15:50 - 17:50	Social event

4 June 2025

09:00 - 09:40	Physics: Multimessenger
10:20 - 10:50	Physics: Astrophysics of compact objects
10:20 - 10:50	Coffee Break
10:50 - 11:30	Physics: SNe progenitors as sources of GeV-PeV neutrinos
10:30 - 11:00	Coffee Break
11:00 - 11:40	Group photo
11:30 - 13:00	Lunch Time
13:00 - 13:40	Physics: Neutrinos in Radio Waves
13:40 - 14:20	Software and computing: Icetray talk
14:20 - 14:50	Coffee Break
14:50 - 15:50	Workshop: I3 File Tools and SteamShovel
15:50 - 17:50	Social event

Report	IceCube Summer Student Program 2025
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5 June 2025

09:00 - 09:40	Data and Analysis: IceCube Event Selections
9:40 - 10:20	Data and Analysis: IceCube Analyses
10:20 - 10:50	Coffee Break
10:50 - 11:30	Detector and Calibration: Icecube upgrade talk
11:30 - 13:00	Lunch Time
13:00 - 14:30	Workshop: Machine Learning and Neural Networks, and exercise
14:30 - 15:00	Coffee Break
15:00 - 15:40	Detector and Calibration: charge collection, digitization, and processing/filtering at the Pole

6 June 2025

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14:30 - 15:00	Coffee Break
15:00 - 15:40	Detector and Calibration: charge collection, digitization, and processing/filtering at the Pole
17:00 - 19:00	Social event: Terrace hangout (TBD)

3 IceCube Neutrino Observatory

IceCube Neutrino Observatory is a cubic-kilometer neutrino telescope at the geographic South Pole built to detect astrophysical neutrinos with energies ~ 100 GeV. Such detections provide a unique probe of the origin of cosmic rays and the particle-acceleration mechanisms operating in extreme environments e.g., shock acceleration in supernova remnants (SNRs), active galactic nuclei (AGN), and gamma-ray bursts (GRBs). Unlike photons, neutrinos traverse dense, energetic regions essentially unimpeded, offering direct access to the physics inside them; however, this very weak interaction necessitates an exceptionally large instrumented volume.

In IceCube, a neutrino interaction in the glacial ice produces a charged lepton (for example, a muon from a charged-current ν_μ interaction) that emits Cherenkov light along its path. That light is recorded by an array of 5,160 Digital Optical Modules (DOMs) mounted on 86 vertical strings between depths of approximately 1.45–2.45 km within exceptionally clear Antarctic ice. Each DOM is a pressure resistant glass sphere housing a 25 cm photomultiplier tube (PMT) and on board waveform digitization electronics.

A denser infill region, *DeepCore*, consists of six strings equipped with higher-quantum-efficiency DOMs to enhance sensitivity to lower-energy neutrinos (below ~ 100 GeV). Complementing the in-ice detector, IceTop is a surface array used to observe extensive air showers from cosmic rays and to aid background rejection.

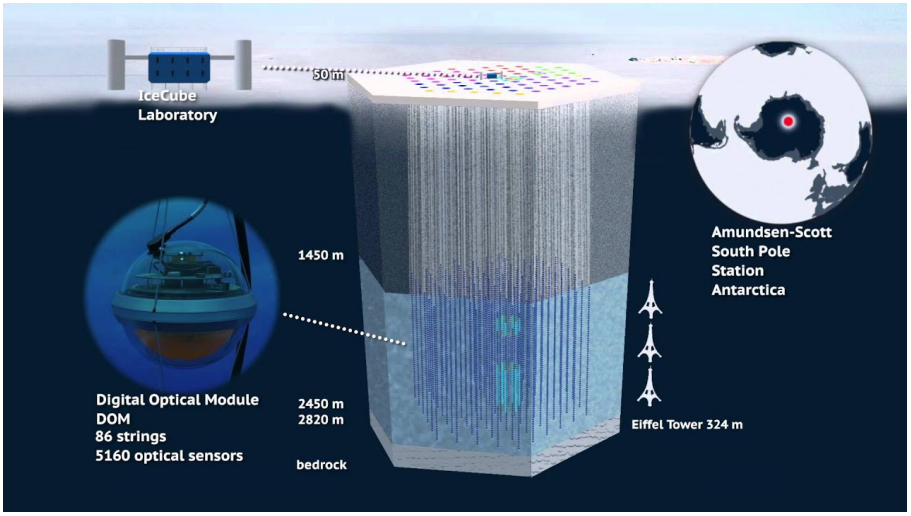


Figure 4: IceCube Neutrino Observatory

3.1 The primary goal of IceCube

The primary objective of IceCube is to detect astrophysical neutrinos. At TeV energies these neutrinos interact in the ice mainly through deep inelastic scattering, mediated by the exchange of a W boson for charged-current interactions or a Z boson for Neutral current(NC) interactions. Charged current(NN) interactions of muon neutrinos produce muons that traverse the detector and leave a clear track pattern in the signals recorded by the optical modules. Neutral-current interactions, as well as charged-current

interactions of electron and tau neutrinos at energies below the PeV scale, generate electromagnetic and hadronic showers that appear as cascade patterns of light.

Track events provide excellent directional information, with angular precision typically between 0.1° and 1°. Because the muon can travel far, the interaction vertex may lie outside the instrumented volume, which effectively enlarges the detection volume; however, the stochastic nature of muon energy losses limits the energy resolution. In contrast, cascades offer good calorimetric energy resolution, around fifteen percent, but poorer pointing due to their nearly spherical light distribution, with angular resolution of order ten degrees above 100 TeV.

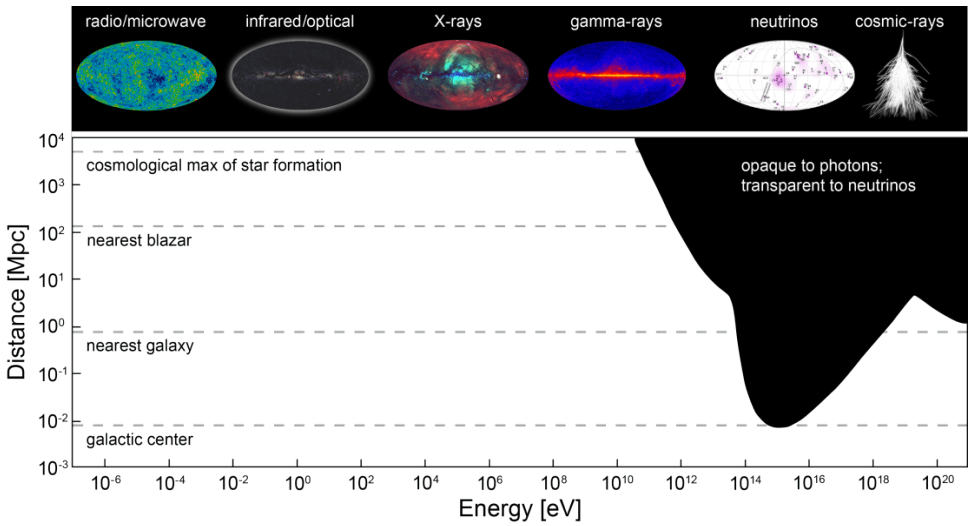


Figure 5: High energy photons are attenuated and charged cosmic rays lose direction, while neutrinos travel nearly unimpeded across dense regions and cosmological distances. IceCube observes this neutrino window from TeV to PeV energies (with DeepCore reaching to tens of GeV), allowing access to sources that are beyond the photon horizon. [reference: IceCube Research]

The dominant backgrounds for a neutrino telescope are atmospheric muons and atmospheric neutrinos created when cosmic rays strike nuclei in the upper atmosphere. Atmospheric muons mostly come from the decay of charged pions and kaons, while atmospheric neutrinos arise from the same channels and, at lower energies near the GeV scale, from muon decay. Muons can penetrate the overlying ice and reach the detector from above, whereas the Earth serves as an efficient shield for upgoing muons. Neutrinos, being weakly interacting, can pass through the Earth, which makes atmospheric and astrophysical neutrinos indistinguishable on an event-by-event basis.

IceCube reduces these backgrounds with two complementary selections. First, it keeps only high quality throughgoing tracks that come from below the horizon, which removes most downgoing atmospheric muons. Second, it identifies starting events whose first light is observed inside the instrumented volume, using the outer detector as a veto. This starting event selection eliminates throughgoing atmospheric muons and, for nearly vertical downgoing directions, also suppresses atmospheric neutrinos because they are commonly accompanied by muons from the same air shower.

4 IceCube simulation

Neutrino interactions in IceCube are rare and the detector is embedded deep in Antarctic ice, which makes controlled test-beam calibration impossible. Simulation is therefore the only way to connect a physics model (fluxes, cross sections, propagation through the Earth) to the signals recorded by the optical modules. It lets us predict detector acceptance, efficiencies, resolutions, and backgrounds under realistic conditions, and it provides the truth information needed to develop and benchmark reconstruction and selection methods. In short, without accurate simulation we cannot translate a measured rate of light pulses into neutrino fluxes and source properties.

4.1 End-to-end simulation chain

The full chain starts with event generation, continues with particle and photon propagation in the ice, then models the detector response and on-line triggering. In IceCube production this involves dedicated components for generation (CORSIKA, NuGen, GENIE, LeptonInjector, MuonGun), propagation (PROPOSAL and GEANT4 via CLSim), photon transport (PPC or CLSim), detector electronics (DOMLauncher), and trigger simulation, with noise and coincident backgrounds added where appropriate.

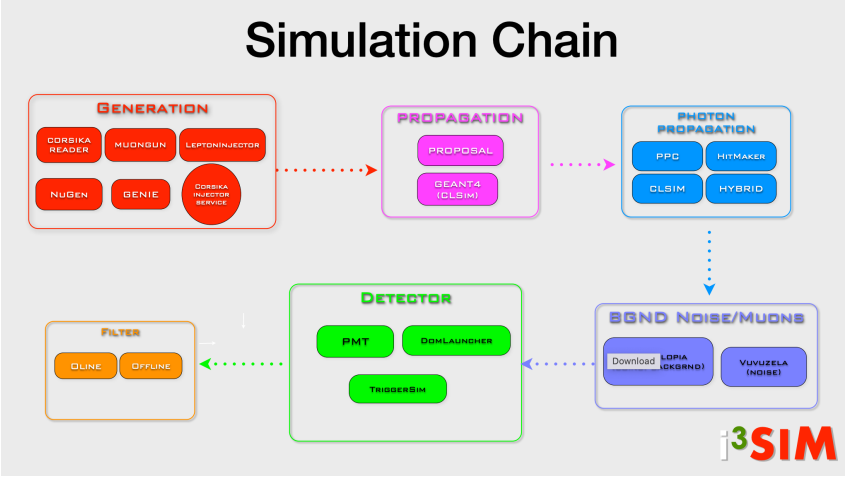


Figure 6: Simulation workflow in ICECUBE

Step 1: Generation [red panel]

Purpose: create primary particles that will produce light in or near the detector.

We use: CORSIKA Reader or Corsika Injector Service for precomputed air-shower files; MuonGun for a fast sampler of single muons and muon bundles at depth; NuGen and LeptonInjector for astrophysical or atmospheric neutrinos including Earth crossing; GENIE for detailed low-energy neutrino interactions.

Inputs: cosmic-ray or neutrino flux models, primary energy and direction ranges, interaction models.

Outputs: truth trees of particles with four-vectors and vertices, ready for transport.

Step 2: Propagation in ice [magenta panel]

Purpose: transport muons and taus through glacial ice with correct stochastic losses and decays. We use: PROPOSAL for lepton transport including ionization, bremsstrahlung, pair production, photo-nuclear interactions, decay; GEANT4 (via CLSim when needed) for specialized low-energy or hadronic detail. Inputs: generated particle lists from Step 1, ice density profile, cross-section and energy-loss parameterizations, cut settings for step recording. Outputs: sequences of energy-loss points and secondary cascades that act as photon sources.

Step 3: Photon propagation [blue panel]

Purpose: carry Cherenkov photons from tracks and cascades to the DOMs through layered, scattering ice. We use: PPC or CLSim for photon transport with depth-dependent absorption and scattering; Hybrid mode to mix fast tables with GPU tracking where needed; HitMaker to convert photon arrivals at DOMs into expected photoelectrons given PMT angular acceptance, glass and gel effects, and hole-ice corrections. Inputs: energy-loss vertices from Step 2, an ice model (e.g., SPICE family), DOM geometry and efficiency maps. Outputs: time-of-arrival and charge expectations per DOM, expressed as photoelectron series.

Step 4: Backgrounds and noise [purple panel]

Purpose: reproduce the data-taking environment. We use: PolyPlopia to overlay independent air showers in the same readout window to model coincidences; Vuvuzela to add uncorrelated dark noise and correlated late/after-pulse structures that match data rates. Inputs: PE series from Step 3, Poisson rates for coincident showers, DOM noise parameterization. Outputs: PE streams that look like those observed in real data.

Step 5: Detector response and triggering [green panel]

Purpose: simulate DOM electronics and apply the actual triggers. We use: a PMT response model and DOMLauncher to convert photoelectrons to waveforms with transit-time spread, gain, saturation, digitizers and local-coincidence logic, clock phase and timing jitter; TriggerSim to apply the in-ice trigger menu such as SMT8, string or cluster topology triggers, slow-particle and volume triggers. Inputs: PE streams from Step 4, detector configuration and run conditions. Outputs: triggered events with full digitized waveforms and DAQ frames suitable for reconstruction.

Step 6: Filtering and analysis outputs [orange panel]

Purpose: match the online and offline selections used on data and produce compact analysis files. We use: the Online filter set to emulate real-time selections and the Offline filter set to build analysis-level datasets; standard reconstruction chains are usually run at this stage so that each event carries both truth labels and reconstructions. Inputs: triggered events from Step 5. Outputs: skimmed datasets with per-event weights, truth, reconstructions and systematics bookkeeping.

5 Summer Student Project

This summer project explores a data-driven surrogate for atmospheric muons at the South Pole: *Preliminary Study on Surface Muon Generation for IceCube Using Generative AI (Normalizing Flows).* The goal is to learn a conditional density for key surface and near-surface muon observables (energy, zenith, multiplicity, lateral distance, bundle properties) under realistic conditions such as composition, primary energy, and season. The trained model will emulate the expensive stage of air-shower generation and provide fast, re-weightable samples that can be passed to the standard propagation and detector simulation chain. Validation focuses on rate and shape comparisons against CORSIKA productions and on end-to-end agreement after propagation and triggering.

5.1 CORSIKA Simulation

What CORSIKA does. CORSIKA is the standard Monte Carlo for extensive air showers initiated by cosmic-ray primaries. It tracks hadronic and electromagnetic cascades through a stratified atmosphere and delivers the secondary particle content at a chosen observation level near the ground. For IceCube and IceTop it provides the spectrum and composition of atmospheric muons and the particle fields at the South Pole surface that seed both in-ice backgrounds and surface-array signals.

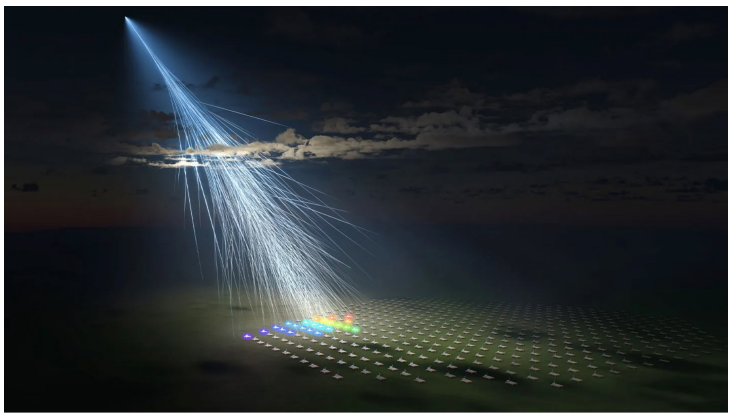


Figure 7: Cosmic-ray induced air shower as simulated by CORSIKA, showing particle cascades propagating through the atmosphere and striking the IceCube/IceTop detector array.

How CORSIKA connects to the IceCube chain. The surface muons and hadrons produced by CORSIKA become inputs to lepton propagation in ice with *PROPOSAL*. The resulting stochastic energy losses and cascades generate Cherenkov photons that are transported with *CLSim* or *PPC* to the Digital Optical Modules. Electronics and trigger responses are then simulated with *DOMLauncher* and *TriggerSim*, and standard online and offline filters are applied.

Why this matters for the project. CORSIKA sets the ground truth for atmospheric muon backgrounds and for coincident air showers that accompany atmospheric neutrinos. It is accurate but computationally heavy. The Normalizing-Flow generator developed in this project aims to reproduce the key CORSIKA distributions at the South Pole surface with orders-of-magnitude speed-up, while remaining compatible

with the downstream IceCube propagation and detector simulation.

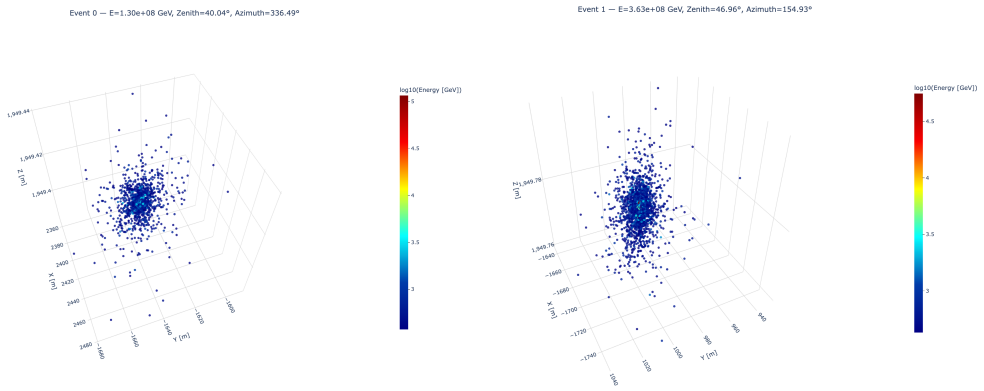


Figure 8: Muon at surface in 3D visualize

5.2 Normalizing Flows

Normalizing flows (NF) are generative models that describe a complicated data distribution by pushing samples from a simple base distribution through a sequence of invertible and differentiable maps. Let $z \sim p_Z(z)$ be easy to sample, for example a standard normal. The model learns a bijection T_θ so that $x = T_\theta(z)$ reproduces the statistics of the data. The direction $z \to x$ is used to generate new events, while the inverse $x \to z$ allows us to assign exact probabilities to observations.

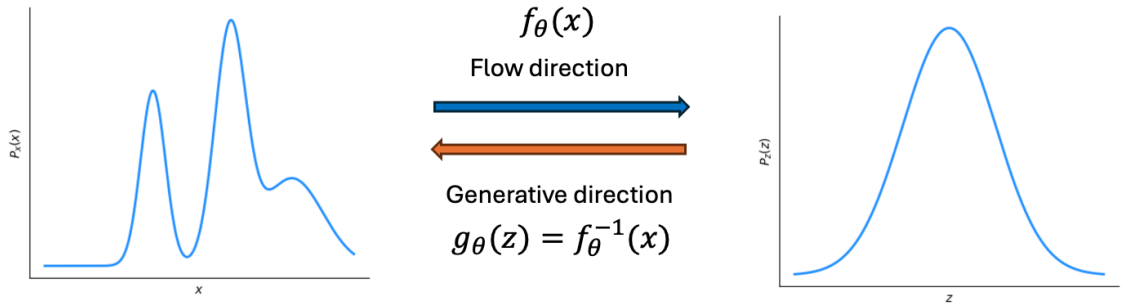


Figure 9: Normalizing flow directions. Right: base density $P_z(z)$. Left: data density $P_x(x)$. Training maps $x \to z$ with f_θ to compute exact likelihoods; sampling draws $z \sim P_z$ and uses f_θ^{-1} to obtain x.

5.2.1 Change of variables

For an invertible map the model density follows directly from probability conservation,

$$p_\theta(x) = p_Z\big(T_\theta^{-1}(x)\big)\left|\det J_{T_\theta^{-1}}(x)\right|, \tag{1}$$

where $J_{T_\theta^{-1}}(x) = \partial T_\theta^{-1}(x)/\partial x$ is the Jacobian matrix. Equation (1) states that the probability mass at x equals the base density evaluated at its preimage, scaled by the local volume change of the inverse map. This is the reason NF layers must be bijective and differentiable. Bijectivity ensures that every x has a unique preimage, so the density is well defined, and differentiability provides the Jacobian that measures

how volumes are stretched or compressed.

Taking logarithms gives a numerically stable form,

$$\log p_\theta(x) = \log p_Z\big(T_\theta^{-1}(x)\big) + \log\Big|\det J_{T_\theta^{-1}}(x)\Big|. \tag{2}$$

5.2.2 Composition of layers

In practice the map is built as a composition of K simple bijections T_k with tractable Jacobians, $T_\theta = T_K \circ \cdots \circ T_1$. Defining $u_1 = x$ and $u_{k+1} = T_k^{-1}(u_k)$ leads to

$$\log p_\theta(x) = \log p_Z(u_{K+1}) + \sum_{k=1}^{K} \log\Big|\det J_{T_k^{-1}}(u_k)\Big|. \tag{3}$$

Stacking layers increases expressivity while keeping the likelihood computable, because each layer contributes an additive log Jacobian term.

5.2.3 Maximum likelihood training

Given a dataset $\{x^{(i)}\}_{i=1}^N$ we fit the parameters by maximizing the total log likelihood,

$$\max_\theta \sum_{i=1}^{N} \log p_\theta\big(x^{(i)}\big) \quad \Longleftrightarrow \quad \min_\theta \ \mathrm{NLL}(\theta) = -\sum_{i=1}^{N} \log p_\theta\big(x^{(i)}\big). \tag{4}$$

This objective moves the model density toward the empirical distribution and provides calibrated probabilities for evaluation.

5.2.4 Conditional flows

When external information c is available we use a conditional map

$$x = f_\theta(z; c), \qquad p_\theta(x \mid c) = p_Z\big(f_\theta^{-1}(x; c)\big)\,\Big|\det J_{f_\theta^{-1}}(x; c)\Big|. \tag{5}$$

Conditioning lets the same flow represent different regimes while preserving exact likelihoods.

5.2.5 Implementation view

Generation applies the forward maps

$$u_k = T_k\big(u_{k-1};\, \theta_k(c)\big), \qquad u_0 = z, \quad u_K = x, \tag{6}$$

whereas likelihood evaluation applies the inverses

$$u_{k-1} = T_k^{-1}\big(u_k;\, \theta_k(c)\big), \qquad u_K = x, \quad u_0 = z. \tag{7}$$

This split explains again why invertibility is essential. Without the inverse we could not evaluate the density in Equations (1)–(3).

5.2.6 Transformer and conditioner

Each layer uses a transformer τ that is strictly monotone in its input, which guarantees invertibility, and a conditioner that supplies the parameters of the transform. With h_i denoting the parameters,

$$u_i' = \tau(u_i; h_i), \qquad h_i = c_i\big(u;\, \theta_i(c)\big). \tag{8}$$

Two common choices are:

Affine transformer

$$\tau(u; h) = \alpha \odot u + \beta, \qquad \log\big|\det J_\tau\big| = \sum_j \log|\alpha_j|. \tag{9}$$

This layer is simple and stable and its Jacobian is immediate.

Monotone spline transformer For a one dimensional rational quadratic spline $s(u; h)$ with positive derivative,

$$u' = s(u; h), \qquad \log\big|\det J_\tau\big| = \sum_j \log s_j'(u; h), \tag{10}$$

which gives flexible warping while keeping an analytic Jacobian.

5.2.7 Autoregressive layers

Autoregressive layers transform each coordinate using only earlier coordinates, which yields a triangular Jacobian and therefore a determinant that is cheap to compute. A standard parameterization is

$$z_i = \frac{x_i - \mu_i(x_{<i}, c)}{\sigma_i(x_{<i}, c)}, \qquad \log\big|\det J\big| = -\sum_{i=1}^{d} \log \sigma_i(x_{<i}, c). \tag{11}$$

Sampling then proceeds sequentially with $x_i = \mu_i(x_{<i}, c) + \sigma_i(x_{<i}, c)\, z_i$ and $z \sim \mathcal{N}(0, I)$. The triangular structure keeps the computational cost essentially linear in dimension.

5.2.8 The ideal of this project

Normalizing flows require maps that are bijective for well defined densities and differentiable for Jacobians. By composing such maps we obtain models that admit exact likelihoods, can be trained by maximum likelihood, and can be conditioned on physics inputs, while still generating new events efficiently. These properties match the needs of our IceCube application.

5.3 Data preparation and feature visualization

Figure 10 presents one dimensional summaries of the variables used in the first flow model. These plots are inspected for range, skew, and outliers before any preprocessing. We then normalize each continuous

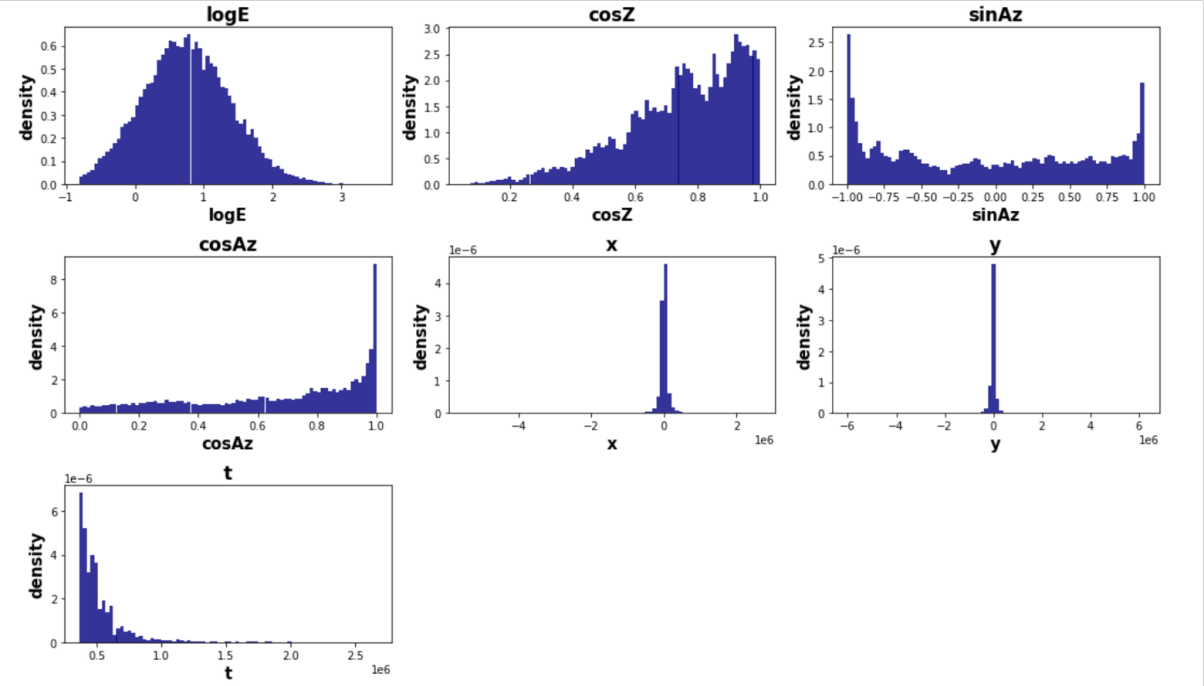


Figure 10: Feature visualization for the first NF experiment. Shown are the marginals of $\log_{10} E$ [GeV], $\cos Z$, $\sin$ Az, $\cos$ Az, surface coordinates x, y [cm], and time t [ns]. Directional variables $(\cos Z,\ \cos \text{Az},\ \sin \text{Az})$ are used as conditioning inputs; the model generates $(x,\ y,\ \log_{10} E,\ t)$ as targets. All continuous features are standardized to zero mean and unit variance and, where needed, rescaled; azimuth uses sine and cosine to encode periodicity.

feature. Standardization to zero mean and unit variance is applied,

$$\tilde{v} = \frac{v - \mu_v}{\sigma_v},$$

and a simple min–max scaling is used when a bounded input is preferred,

$$\hat{v} = \frac{\tilde{v} - \min(\tilde{v})}{\max(\tilde{v}) - \min(\tilde{v})}.$$

Energy is modeled as $\log_{10} E$ to reduce skew. Azimuth is encoded with sin and cos to respect periodicity. The coordinates x and y are centered on a detector reference and scaled with the same factor.

Model inputs and learning objective. The conditioning vector is $c = (\cos Z,\ \cos \text{Az},\ \sin \text{Az})$ which summarizes direction. The target vector is $x = (X,\ Y,\ \log_{10} E,\ t)$. The model learns the conditional density $p_\theta(x \mid c)$ so that, for any chosen direction, it can generate surface bundles that follow the same statistics as the reference Monte Carlo. Only muon information is used in this initial study.

5.4 Results of the NF model

The conditional flow reproduces the main shapes of the test dataset. For $\log_{10} E$, x, and y the model follows the bulk of the distributions and the ratio panels sit close to one over wide ranges; the reported KS values around 0.07–0.11 indicate moderate but acceptable differences for a first pass. The time variable t is more difficult: the model concentrates too much probability near the mode and underestimates the long tail, which is reflected in a large KS and Wasserstein distance. Training and validation losses decrease quickly and reach a stable plateau, so the model is not overfitting and the selected checkpoint corresponds to the minimum validation loss. Next steps are to refine the conditioning inputs and increase capacity in the final spline layers, and to test alternative transforms for t to better capture the long tail.

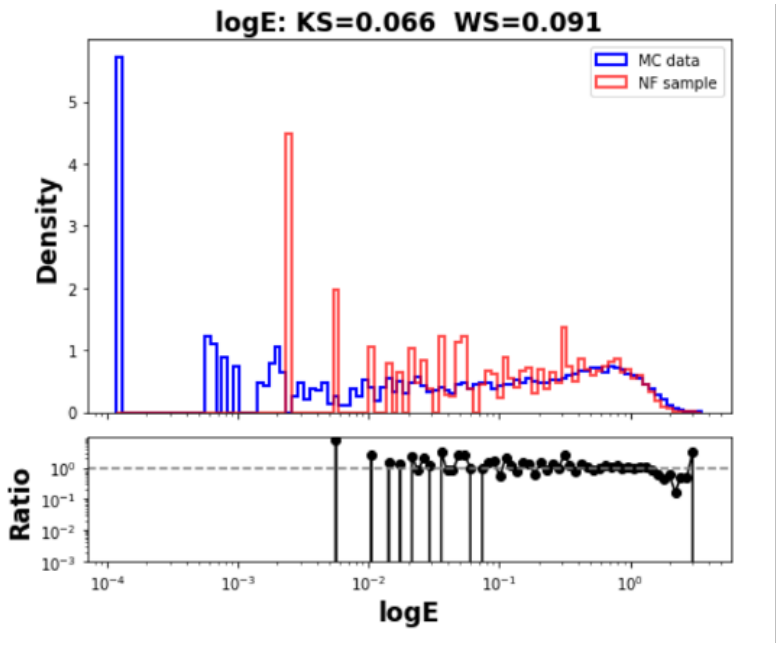


Figure 11: Overlay of MC data (blue) and NF samples (red) for $\log_{10} E$. The title reports the KS and WS metrics. The lower panel shows the bin–by–bin ratio NF/MC on a log scale; the dashed line at 1 indicates perfect agreement.

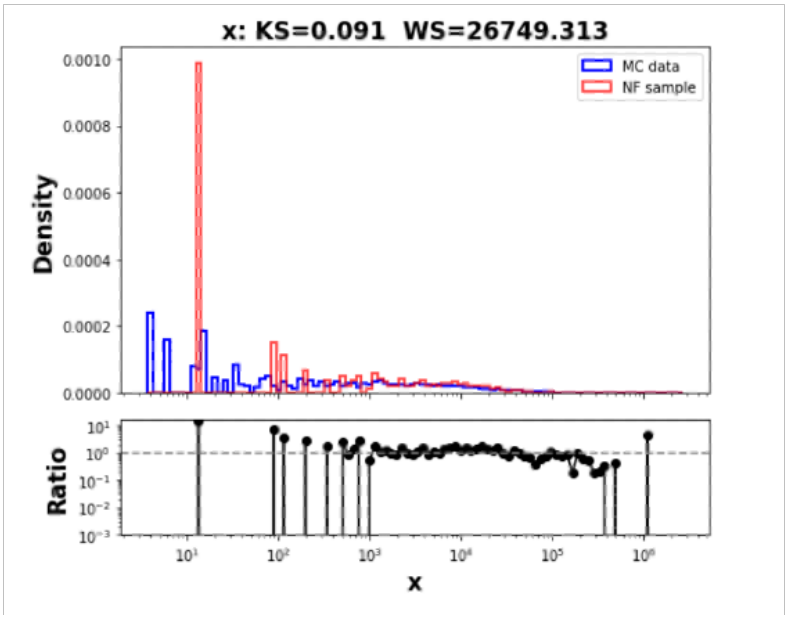


Figure 12: Comparison of the x coordinate at the surface: MC (blue) versus NF (red). Ratio panel shows NF/MC per bin; values near 1 denote good agreement while spikes flag regions with low statistics.

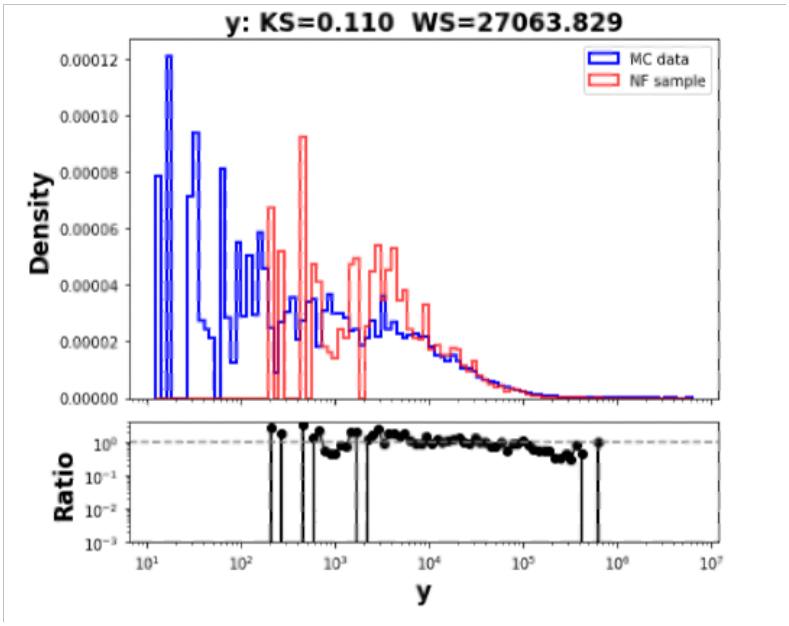


Figure 13: Comparison of the y coordinate: MC (blue) versus NF (red), with KS and WS shown in the title. The lower panel displays the NF/MC ratio on a log scale.

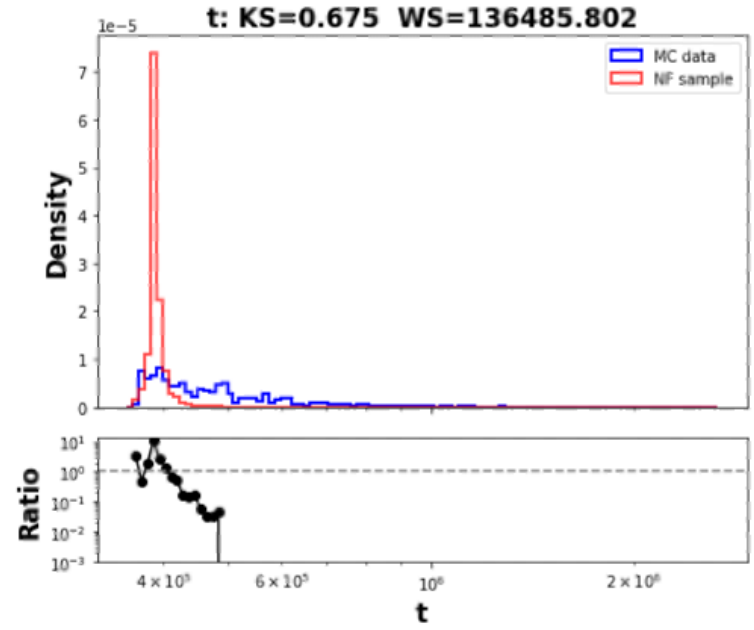


Figure 14: Distribution of time t [ns] for MC (blue) and NF (red). The heavy tail in data makes t challenging; the ratio panel highlights the deviation at large t.

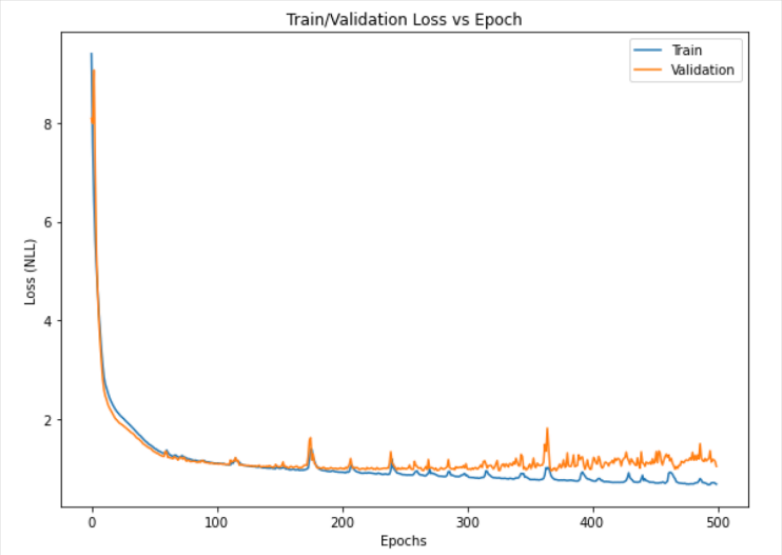


Figure 15: Training and validation negative log likelihood versus epoch. Rapid improvement at early epochs followed by a broad plateau; the selected model is the checkpoint with the lowest validation loss.

6 Two month in USA (Land of freedom)

I touched down in the U.S. on June 1, a little dazed about how to get from O'Hare in Chicago up to Madison, Wisconsin. I had a small carry on packed with adapters, way too many Thai snacks and instant noodles, and an embarrassing amount of optimism. Madison quickly became home for two months, a college town wrapped in nature: lakes, bike paths, and that molten gold sunset at the Memorial Union Terrace. Since it was my first time in the U.S., everything felt a bit surreal: wide roads with many lanes, the endless chorus of small talk ("How's it going?"), strangers holding doors like it is a local sport, and at times people shouting across the street like background radio. And the plot twist was the weather: summer was cold, which hit hard because I had packed only light clothes.

6.1 Work life

Weekdays had a steady rhythm: bus or brisk walks to WIPAC, a hello wave to the front desk, then headphones on and code up. My days alternated between training conditional Normalizing Flows, plotting diagnostics, and learning when to stop telling myself "just one more run." Coffee breaks often turned into micro seminars; whiteboards filled with arrows from cosmic ray primaries to muon multiplicity; Slack pings became PR reviews and "aha!" moments when a loss curve finally stabilized. Weekly check ins with my mentor kept me both accountable and curious, balancing time between debugging and imagining what the model could unlock for IceCube.

6.2 Food and little rituals

Food and little rituals. If Wisconsin had a welcome committee, it would probably greet you with cheese curds that squeak, frozen custard, and the Capitol farmers market on Saturdays, bursting with colors and the smell of basil, bread, and flowers. On quiet evenings I cooked Thai comfort food in my little kitchen, making basil stir fry and improvised tom yum, then swapped recipes with lab mates who bravely tried my spicy experiments. I also picked up local wisdom: the science of tipping, the art of saying "have a good one," and the revelation that drip coffee is basically a religion here. People are crazy about anything organic: organic fruit, organic vegetables, even organic soap. But when it comes to actual food, the taste is... well, let's just say I missed chili, fish sauce, and the concept of flavor.

6.3 Culture and moments

I arrived around the Fourth of July, which is Independence Day in the United States. I went to watch the fireworks alone by the lakeshore, hoping to soak in the atmosphere, but the lake smelled fishy and the air was heavy with smoke from wildfires. I also caught sight of the season's first fireflies, tiny lights in the dark that felt magical. The weather changed all the time: cold, hot, rainy, and stormy, sometimes all in one day, and it made me sick more than once. Still, I loved that at night the stars came out clear and beautiful. I even witnessed people protesting against Trump, something unusual and full of energy that I had never seen back in Thailand. Strange things seemed to happen all the time, making every week feel unpredictable. The only downside was that there were not many malls to go shopping, which was tough

for someone who loves shopping, lol.

6.4 What changed.

In two months I learned a lot of small but important things. I had to organize my day so I would not waste time, ask questions that actually made sense, and accept that a training run can still be useful even if it is not perfect. By the end I had more notes in my notebook, felt lighter walking back from the lab, and realized that science is not only about numbers and data. It is also about people who share jokes, eat snacks together in the afternoon, and get excited over plots on a screen.

I also had to explain my work to people who were not from physics at all. That meant saying clearly what I was trying to do, what evidence I had, and why it mattered—without hiding behind difficult words. Outside the lab I had to manage my time and money. Eating out every day was too expensive, so I learned to plan groceries, cook simple meals in big pots, and follow a weekly budget. I also had to plan for buses, laundry, and meeting times. Sometimes things overlapped or went wrong, so I kept checklists and left extra time just in case. It was not perfect, but it made life in the lab more fun and less stressful.

7 My Journey Diary (Life in Madison, WI)

7.1 Week 1

Week 1 was the toughest. The trip from Bangkok to Madison took about 26 hours door to door, and I landed still figuring out how to get from O'Hare to campus. The very next morning *IceCube Summer School* started and ran for a full week. Mornings were lectures on the detector, simulation, and reconstruction; afternoons were hands on tutorials. It was exciting but also a blur because of jet lag, and I even caught a mild case of food poisoning while adjusting to American food, so rice, crackers, and instant noodles saved the day.



Figure 16: My room in Phillip Hall, a dorm at UW Madison. It is a double room with large windows, a desk, drawers, and a small fridge.



Figure 17: This is my meal in first week

Madison is the capital of Wisconsin. The city sits between two big lakes, Mendota and Monona. The Memorial Union Terrace is a friendly place to relax, listen to live music, and enjoy beer, cheese curds.



Figure 18: Memorial Union Terrace at sunset. Live music on the Terrace Stage, sailboats on Lake Mendota, and people relaxing with friends.



Figure 19: A home cooked Indian meal my friend made for me.

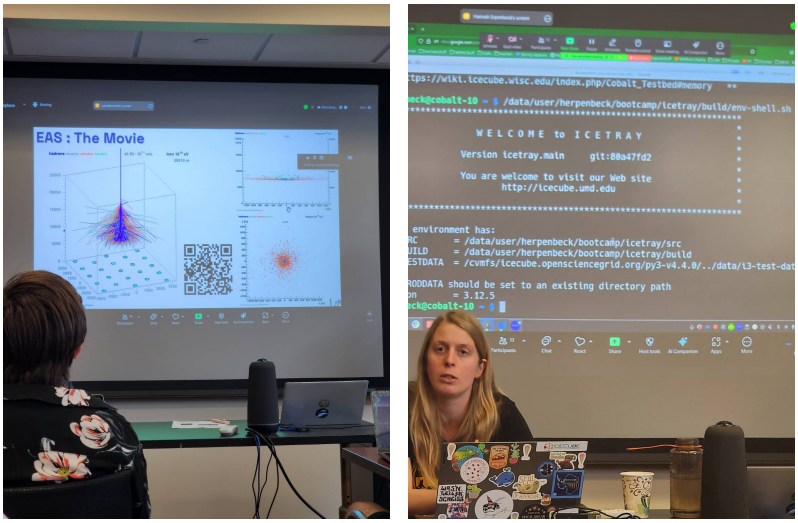


Figure 20: Some of the IceCube Summer School lecture

7.2 Week 2

This week the project finally started. Prof. Albrecht Karle introduced me to Prof. Lu Lu and Dr. Tianlu Yuan so we could discuss the plan for the next two months. We agreed on the topic *Preliminary Study on Surface Muon Generation for IceCube Using Generative AI (Normalizing Flows)* and set simple milestones: prepare and visualize the data, build a first NF model, compare to Monte Carlo, and write a short report.

I set up the working environment, organized the datasets, and produced the first plots for $\log_{10} E$, direction, position, and time. I also prepared the standardization and scaling steps that will feed the model.

A special moment this week was the visit of the President of Chiang Mai University to WIPAC. I had a

brief chance to present what I learned in Week 1 and to outline the plan for the project. It was a good motivation to make steady progress.



Figure 21: The visit of the President of Chiang Mai University to WIPAC.



Figure 22: Picture of me with Prof. Albrecht Karle (on the right)

7.3 Week 3

This week I mostly stayed on WIPAC and worked. I cleaned up the code, fixed bugs, and ran frequency tests of the model. I also did more EDA to decide which features should go into the next version of the flow. Most of the time went into trying ideas, checking plots, and rewriting parts that did not behave.

After work I went straight back to the dorm to cook and to pack lunch for the next day. My simple routine worked well: steak with soft scrambled eggs for lunch almost every day. For groceries I bought in larger amounts at the supermarket because it was cheaper.

7.4 Week 4

This was a quiet week for travel, but a steady week of meetings and small steps forward. My weekly rhythm is now clear: on Monday I meet with Prof. Lu Lu's group to discuss progress and plans; on Tuesday there is the open "X Meeting" where students and researchers share ideas or practice talks; on Wednesday we join the "A Team" analysis meeting; and on Thursday we have Journal Club where someone reviews a paper for the group.

This Wednesday I gave my first short update. I presented the exploratory data analysis of cosmic ray showers and highlighted the physics meaning behind the main features, such as the energy distribution, zenith dependence, and lateral spread. I received useful comments on which variables to condition on and how to clean the data and transform skewed variables. It was a good first experience presenting to the group.

7.5 Week 5

This week I trained the first NF model on IceCube data to see if the idea works. It did. Even with a simple architecture the samples looked reasonable and the loss curves were stable. I produced the first comparison plots and wrote notes on preprocessing, conditioning, and open issues for the next round. The workload grew a lot once the model was running, so I spent many hours cleaning code, running small sweeps, and sending regular updates to the PhD student at WIPAC.

Outside of work I explored a few malls and went to see the July 4 fireworks. I watched from the lakeshore where it was quite dark, so I did not see much, but it was still fun to sit by the water with the crowd. One evening I also had a brief run in with someone on the street who shouted at me; it was surprising but ended quickly. Overall it was a busy and memorable week.

7.6 Week 6

This week I spent more time outside the lab. I visited the *Quantum Computing Lab* at UW Madison thanks to TL, who introduced me to a Thai researcher there. I saw the control room, the readout electronics, and the dilution refrigerator used for quantum devices. We talked about noise, measurement time, and calibration methods, which felt close to my work in simulation and statistics.

I also took a trip to *Yerkes Observatory* near Chicago and watched the main telescope move on its lift

system. It was a nice mix of history and engineering. I met several new friends, including a Harvard undergraduate with Thai roots.

Over the weekend I went to *Devil's Lake State Park*. The hike was tiring but the views were worth it. I packed my own food and ate lunch while sitting on the rocks. Because of the trips I worked a bit less, but I still cleaned some code, checked small tests on preprocessing and the time variable t, and wrote down plans for the next round of model updates.



Figure 23: Devil's Lake State Park

7.7 Week 7

Most people at WIPAC were away at ICRC 2025 in Switzerland, so the building felt very quiet. Before they left, Prof. Albrecht Karle invited TL and me for dinner, his friend had brought moose meat, so we cooked Thai *larb* with moose. It was a fun (and delicious) first.

On the research side I focused on tightening the current flow model: small hyperparameter sweeps,



Figure 24: moose larb at Albrecht Karle's house

learning rate and batch size scans, better preprocessing for t, and calibration checks using KS and Wasserstein on the test set. In parallel I started a second model aimed at the real task: predicting surface muon features from primary particle inputs (energy, mass group, and direction). This is challenging because of limited statistics, the wide dynamic range, and the need to keep the physics constraints, but early tests look promising and working on it is genuinely fun.

7.8 Week 8

My last week in the U.S. was mostly for exploring and enjoying the city. Everyone returned from ICRC, so WIPAC felt lively again. On Monday I gave my project talk to the group. I was nervous, but it went well and people were kind with questions and feedback. That evening Prof. Lu invited me to dinner at her home with Tianlu and TL, and I met her very energetic child.



Figure 25: visit lulu house before came back to Bangkok

Tuesday was my final day at WIPAC. I said goodbye, handed out small gifts, and took a few photos with the group. On Wednesday I traveled to Chicago to wait for my flight on Thursday. It became a free day in the city, so I walked from morning until late at night and did some shopping. My bags were full, my feet were tired, and my heart was happy.

8 Appendix

8.1 Presentation Slide

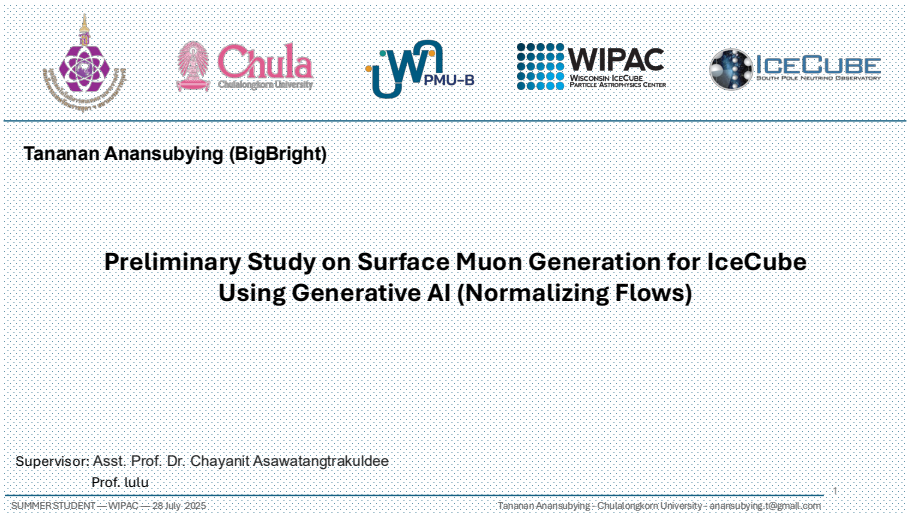


Figure 26: slide 1

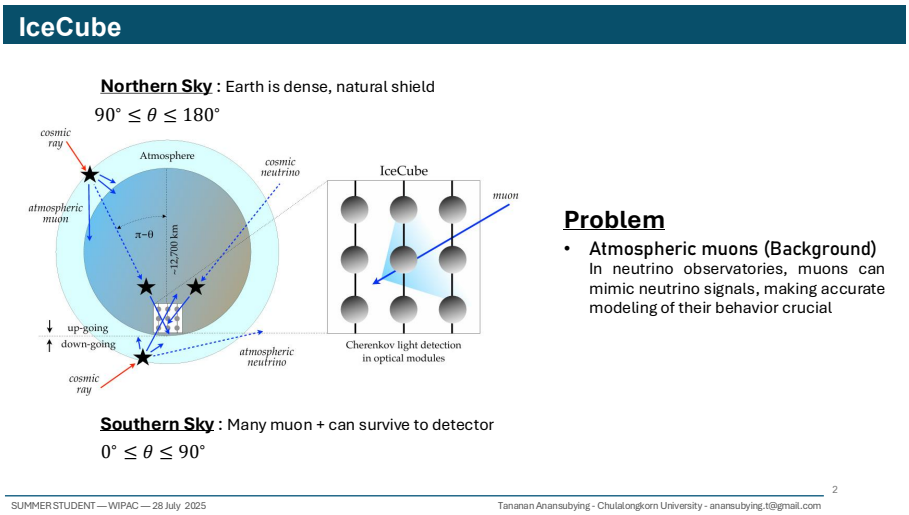


Figure 27: slide 2

IceCube simulation

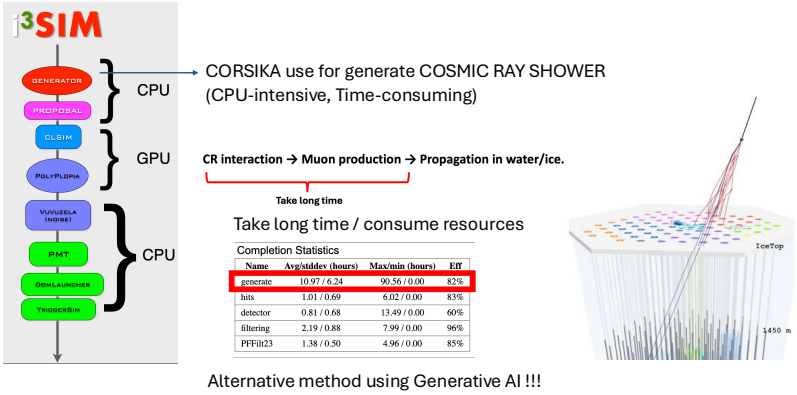
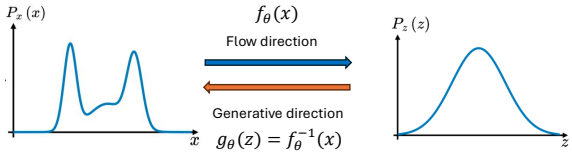


Figure 28: slide 3

Overview Normalizing Flows

Normalizing Flows is a generative AI model. It used to build probabilistic models of data. It starts from a simple known distribution, such as a Gaussian distribution, and applies a series of invertible transformations to convert this simple distribution into a more complex one that resembles the real data distribution.



Change of Variables Formula : $p_X(x) = p_Z(f^{-1}(x)) \cdot \left|\det\left(\frac{\partial f^{-1}}{\partial x}\right)\right|$

Figure 29: slide 4

Overview Normalizing Flows

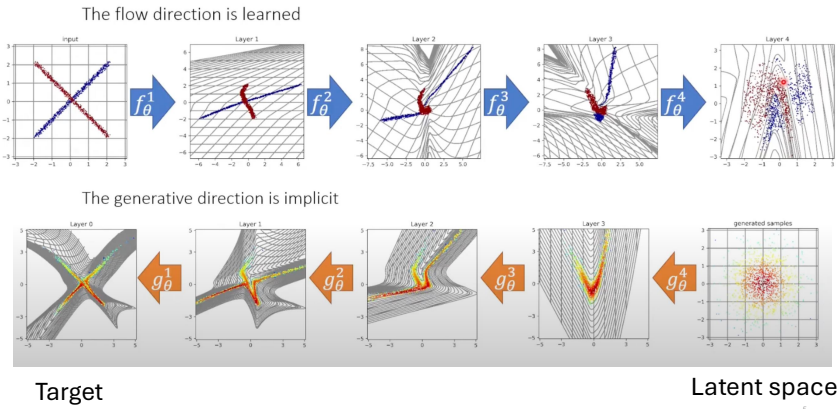


Figure 30: slide 5

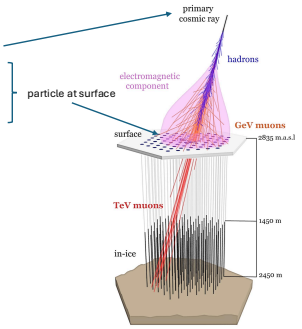
Data sample

Use 23123 iceprod data : 1e8 to 1e11 GeV

23123 juancarlos (simprod) PROCESSING

IC86.2023 CORSIKA-in-ice 5-component model Sibyll2.3d with weighted spectrum of E^-2.0, using Spice ftp-v3, 1e8 to 1e11 GeV, 1000 showers per file, oversize 3, hole ice MSU parameterization (p1=0.35, p2=0), 15,000 total files.

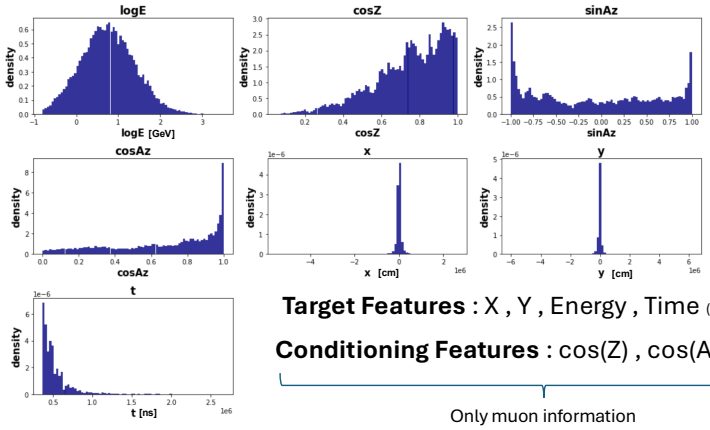
	x	y	z	zenith	azimuth	energy	event_number	run_number	depth	pdg	time
0	48768.358609	-127183.700073	110526.151590	0.890291	5.078155	2.220132e+08	0	12302001	0	2212	-573659.751943
1	803.212501	-1970.144791	1949.724924	0.889250	5.078713	2.769353e+02	0	12302001	1	14	1826.748057
2	801.192671	-1938.430103	1949.734901	0.889237	5.077880	5.514249e+02	0	12302001	1	-13	1933.373057
3	801.430203	-1937.791776	1949.735066	0.892255	5.077995	2.005800e+03	0	12302001	1	-14	1912.935557
4	777.972970	-1932.384019	1949.739613	0.890402	5.079386	5.773798e+02	0	12302001	1	-13	1969.810557
...	...	...	...	...	...	...	...	...	...	...	...
102538956	-4376.535685	-6815.169348	1944.934166	1.399330	4.140813	1.102693e+03	707	12302021	1	-14	-18182.988332
102538957	-4403.507033	-6944.677591	1944.775806	1.399115	4.140369	8.061774e+02	707	12302021	1	14	-18588.488332
102538958	-4307.286267	-6833.469021	1944.961745	1.399443	4.140218	9.514279e+02	707	12302021	1	14	-18115.113332
102538959	-4260.599539	-6704.677997	1945.129893	1.399604	4.140488	3.532422e+02	707	12302021	1	14	-17672.613332
102538960	-4320.564148	-6713.558973	1945.080182	1.399529	4.140868	5.225926e+02	707	12302021	1	-14	-17803.238332



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Figure 31: slide 6

First try NF with IceCube data



Target Features : X , Y , Energy , Time (want to be output)

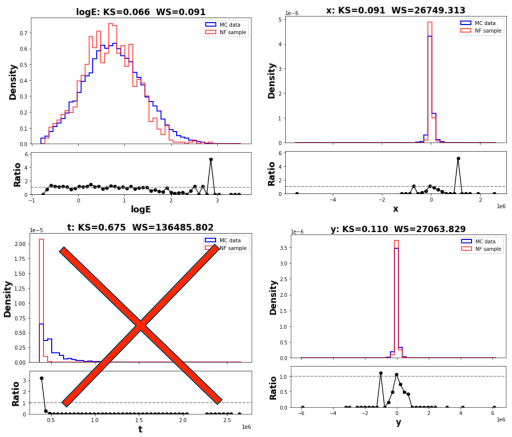
Conditioning Features : cos(Z) , cos(Az) , sin(Az)

Only muon information

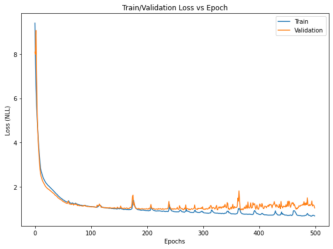
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Figure 32: slide 7

Is this model good ???



Comparison between the MC real data and NF sample



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Figure 33: slide 8

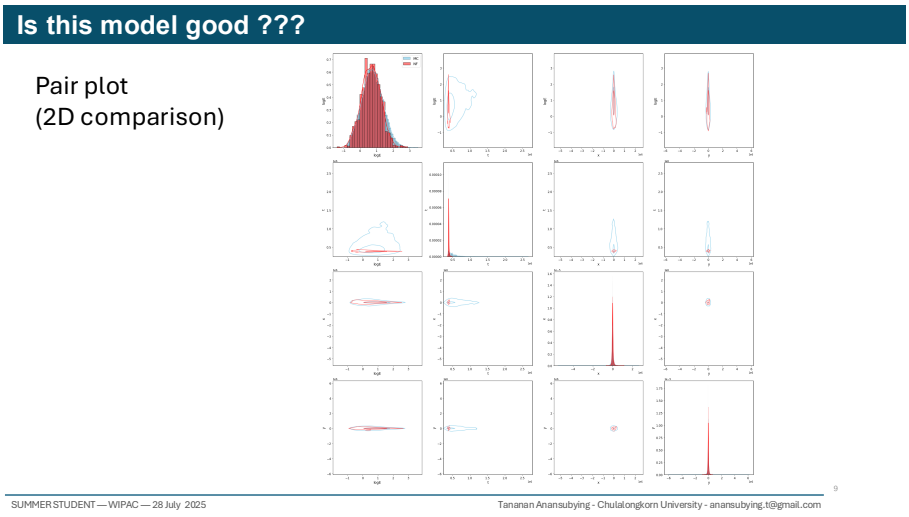


Figure 34: slide 9