Trusting dark matter results

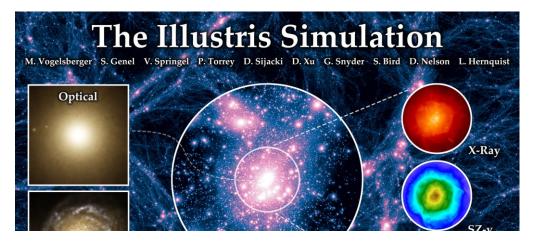
THREE SHORT STORIES ABOUT INCREASING TRUST IN THE DIFFICULT REALM OF DARK MATTER ANALYSIS

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Dark Matter

A simulated universe with a weaklyinteracting, 40 GeV particle ~0.5 MeV/ c^2 mass density looks a lot like our universe.

http://www.illustrisproject.org/movies/illustris_movie_rot_sub_f rame.mp4

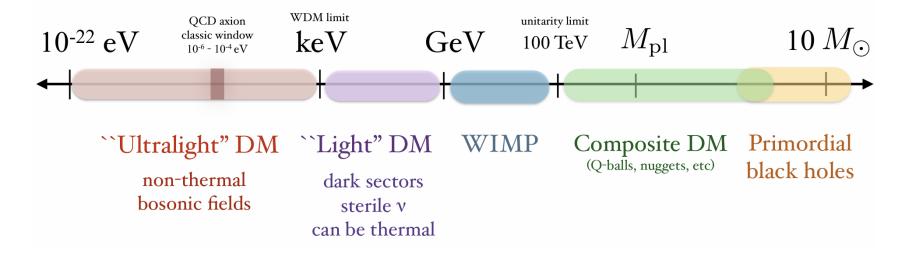




Dark Matter

Mass scale of dark matter

(not to scale)



There are many dark matter candidates: fun for detector designing, difficult to blind analysis Image from <u>1904.07915 (arxiv.org)</u>



Story 1. How can we mitigate bias in our analyses?

We don't know what to expect for a dark matter signal. We do know the models rarely involve peaks :(

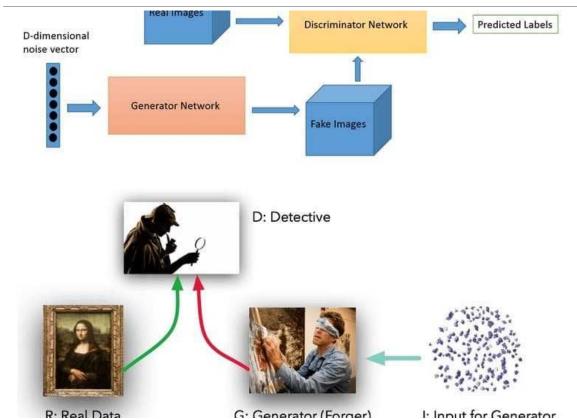
Several dark matter collaborations (SuperCDMS, LUX) have used "salting" to blind their data

See Maria-Elena Monzani's excellent talk at <u>PHYSTAT-2019-</u> <u>Monzani.pdf (cern.ch)</u> for additional details

Create "fake" signal data and insert it into the data stream. You should recover the injected signal when you analyze. This is a way to build trust in the analysis.

- This is great! We can create salt for all our signal models!
- >The problem is that creating salt takes a long time

Story 1. How can we mitigate bias in our analyses?

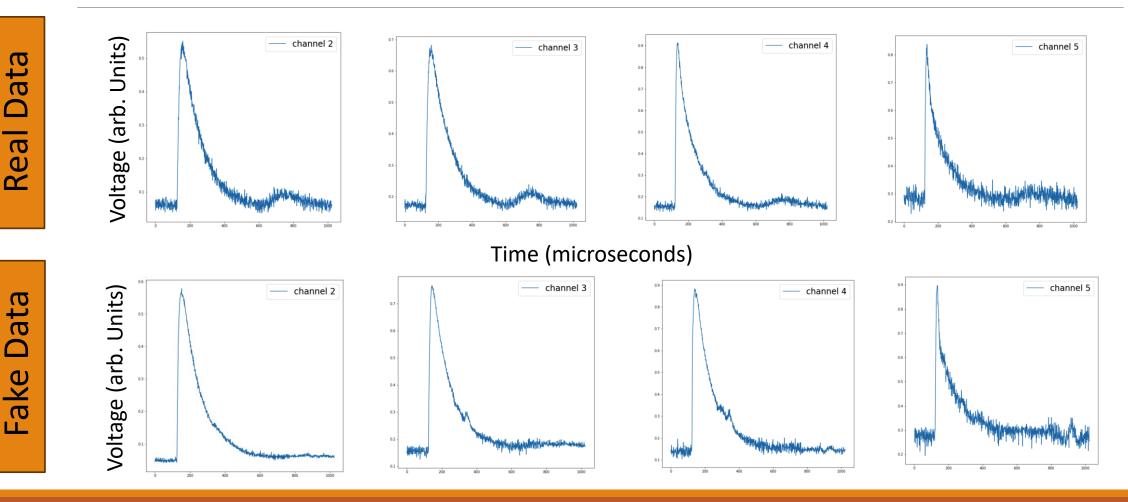


Generative Adversarial Networks (GANs) are specifically built to create fake data.

We're working on using GANs to create raw data that's useful as salt.

From <u>Decrypt Generative Adversarial Networks (GAN) | AI Summer (theaisummer.com)</u>, with elements from <u>Generative Adversarial Networks for beginners – O'Reilly (oreilly.com)</u>

Story 1. How can we mitigate bias in our analyses?

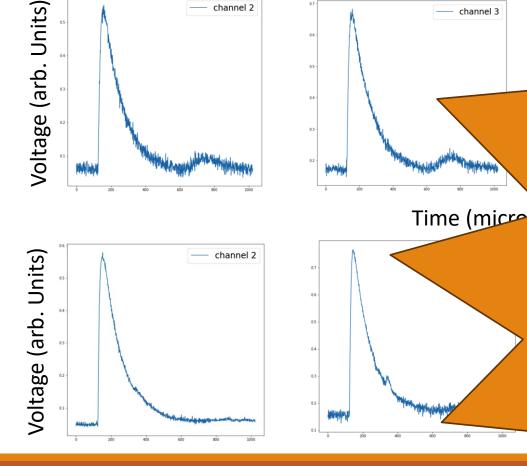


Story 1. How can we mitigate bias in 🗹 analyses?

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This work uses **TimeGAN** extensively and we're currently testing the fake data as salt for SuperCDMS. If you're interested in using this library (soon available through pip) we'd love to talk!

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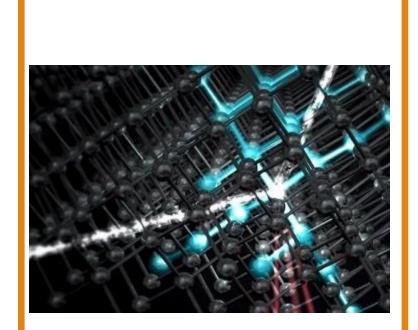
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Story 2. What are our detectors telling us?

SUBTEXT: DATA AND ANALYSIS PRESERVATION CAN HAVE SIGNIFICANT SCIENTIFIC VALUE.

WE ARE USING DATA MORE THAN 10 YEARS OLD TO UNDERSTAND GERMANIUM RESPONSE TO DEPOSITED ENERGY!



A particle deposits energy by interacting with a nucleus, and that energy turns into vibration (phonons) and charge (ionization). To reconstruct the energy, we need the expected ratio (yield). The fraction that goes into phonons itself has a variance, labeled "F" in the figure. Imagine we see an event at 3.5 e/h pairs. How do we interpret this? With increasingly high resolutions, understanding energy response is increasingly important.

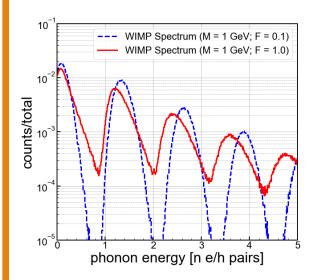
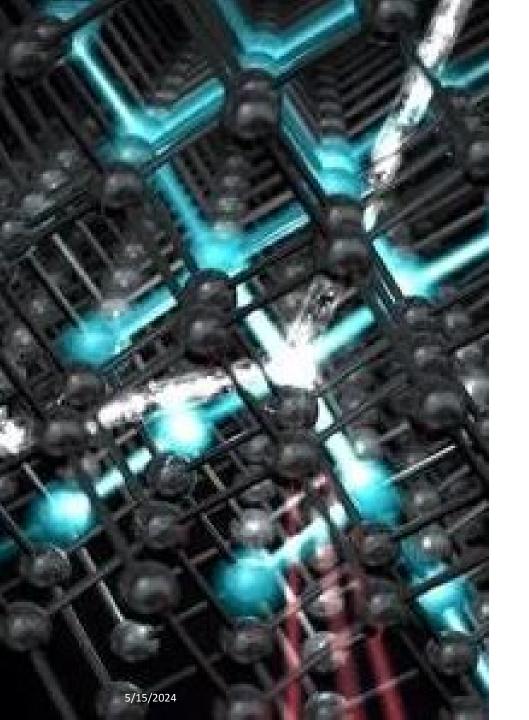


Figure from Anthony Villano

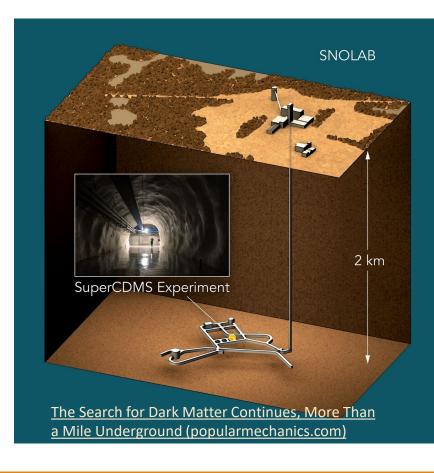


Story 3. How can we constrain our backgrounds?

Some of our backgrounds are specific to our experiment.

But other backgrounds are shared by everyone at an underground facility. If I see a germanium nucleus recoil, is it a neutron or something more interesting?

Luckily, there are many detectors near our dark matter detector: SNOLAB experiment posters | SNOLAB



DEAP-3600 SENSEI **NEWS-G** DEAP-3600 uses a vessel of SENSEI is sensitive to low-mass liquid argon to look for dark dark matter using CCD (charge couple device) technology to search for rare particle events Detection with CCDs Detection with gas Detection with light matter by sensing the ultravio light produced when the grage atoms are excited by particle interactions. When a particle interacts with the CCDs, there is a small energy change which is The light is detected by sensor that surround the vessel and analyzed to determine what captured by its millions of pixe SENSEI can count every electron within a pixel which leads to type of particle caused it. accurate measurements and no oockground noise The spherical acrylic vessel in the centre of DEAP had to be CCDs are commonly found in hipped to the lab in three separate pieces because it was too big to fit in the mine cage in diaital cameras, but the ones i Dark matter SNO+ HALO **PICO** SNO+ uses a liquid scintillata to detect neutrinos. When a PICO uses a bubble chambe Detection with light neutrino hits the detector, it Detection with lead filled with fluid which is superheated to look for dark creates charged particles that Detection with bubbles cause the scintillator to give off light which is detected by matter. When a particle teracts, the fluid boils and thousands of sensors creates a bubble surrounding the vesse Bubbles are captured with This detector will be sensitive cameras and microphones, and tudying them can tell scientis neutrinoless double beta decay anti-neutrinos, solar neutrino about which particle caused it and supernova neutrinos The fluid is a refrigerant so ever Combining information from these detectors can help "veto" dark matter – if they see something when we see something, it's not dark matter. If we're up for a tough project, combining data could provide additional constraints

on shared environmental backgrounds.

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NEWS-G uses a spherical

copper vessel filled with a

noble gas to search for dark

matter. When a particle enter

the sphere it ionizes some of the gas, creating electron

The sensor in the middle of the

sphere is kept at a high voltag to attract the electrons, which

creates a charge that can be

The pieces of the detector made

in Europe had to be shipped to

SNOLAB by sea because a fligh

HALO is a dedicated super

and helium detectors which

Part of SNEWS (the sup early-warning system), HALO

produce neutr

detector that uses lead block

when neutrinos hit the lead and

and other detectors around the

upernovae so they can view

world alert astronomers to

them with telescope

NSDF-SLAC

Stanford Linear Accelerator Center (SLAC) Super Cryogenic Dark Matter Search (SuperCDMS) Sudbury Neutrino Observatory Lab (SNOLAB) National Science Data Fabric (NSDF)

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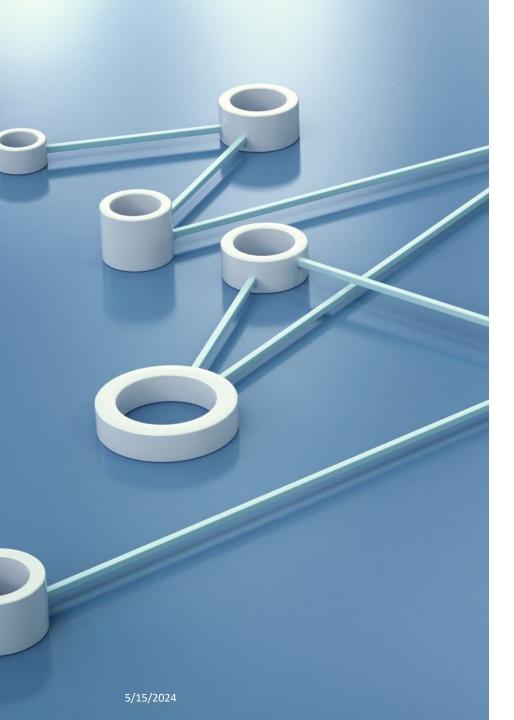




Describing data formats to get a common interface

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ONDD project is borative t to improve to custom data sets. ort for small, andard, binary ets already with openprojects like and DFDL. The D project aims similar support -scale files.



In conclusion

Preserving data can lead to better science, particularly as we develop new detectors and analysis methods. Also we need to train our students!

Sharing data across collaborations is becoming technically feasible and offers new ways to constrain backgrounds.

Please contact me if you're interested in collaborating!