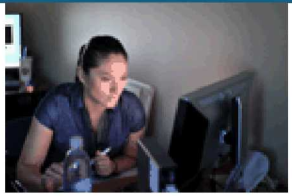
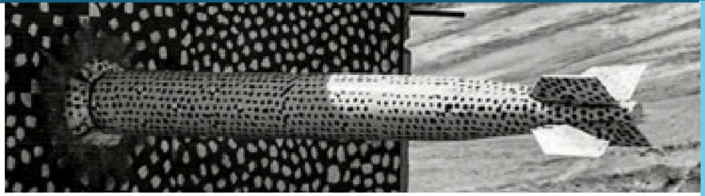
SAND2019-10641PE

Deep Learning for Shock Physics





PRESENTED BY

Emily Donahue (BS ’15) & Peter Yeh (BS ’11)

Code acceleration for fragment flight

Sandia is tasked with characterizing challenging-to-model environments

Predicting fragment flight from cased munitions is an important problem for range safety

However, explosions are difficult to characterize in fine detail

We need this finely detailed analysis to make statistical arguments about fragment distribution and kinetic energy

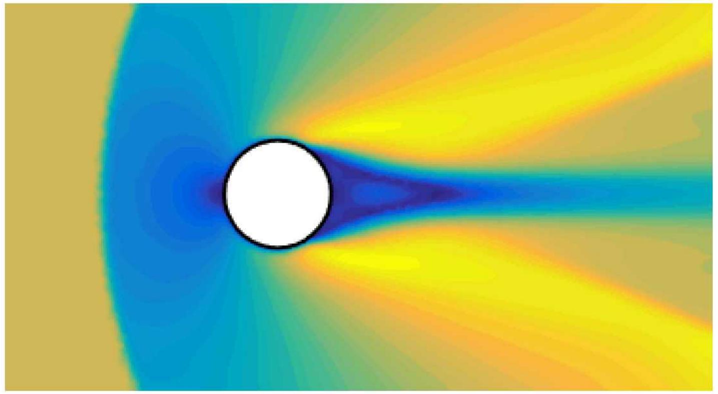
Predicting fragment flight

Current methods assume single drag coefficient

Real fragments are non-ideal

- Explosive fragments fly at supersonic speeds
- Fragment-air interaction leads to tumbling and chaotic motion
- Fragment geometry is complicated

Goal is to characterize a range of drag coefficients for real fragments



Pressure field of a circular cylinder calculated by CFD

Real fragment geometry is more complicated

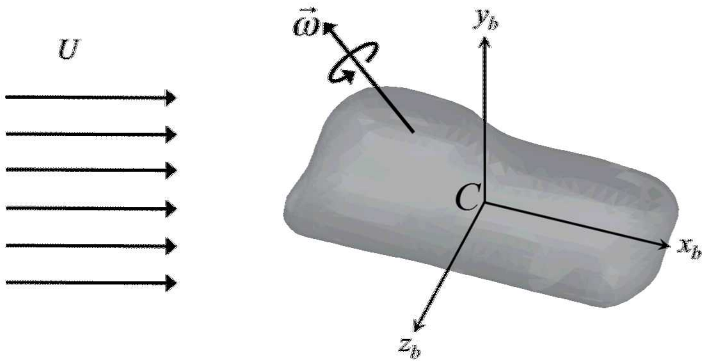
Sandia's HPC resources enable high fidelity physics simulations

We computed aerodynamic forces and moments sampling multiple orientations using CFD simulations

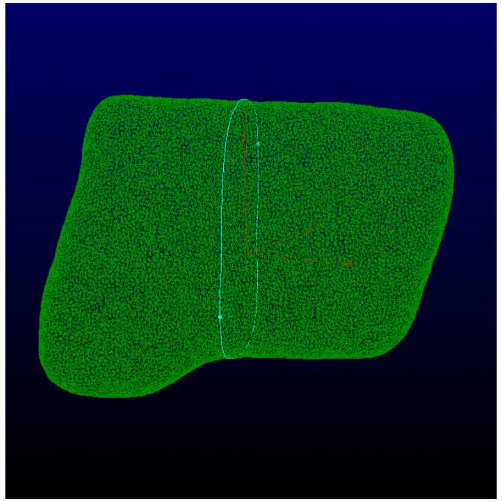
Characterizing a single fragment requires ~500 separate simulations, requiring thousands of cores on HPC

Is there a faster way?

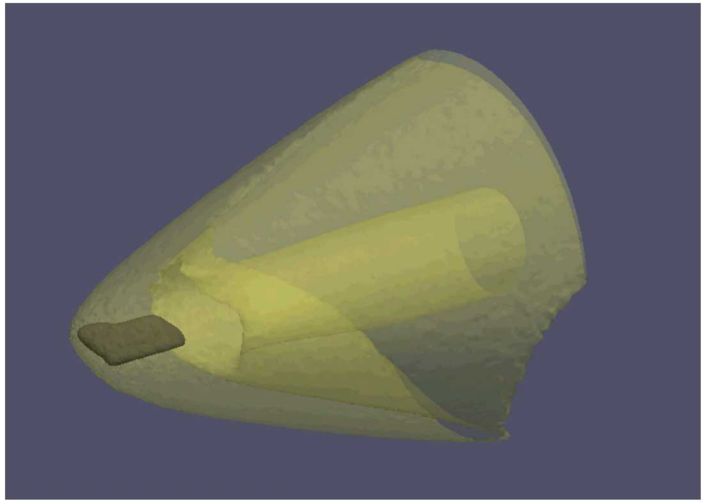
Astra, a new ARM-based supercomputer has achieved 1.76 PFlops



Problem Formulation



Mesh



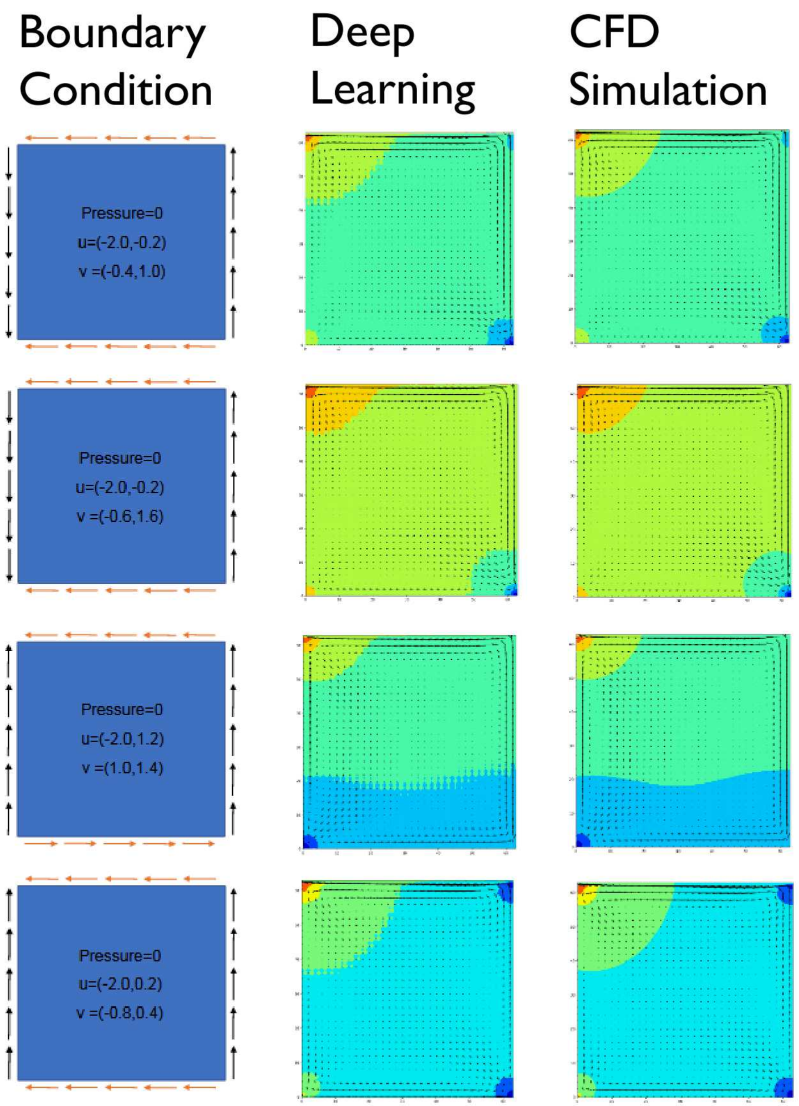
Solution

Deep learning can be used for physics code approximations

In 2017, researchers at Stanford showed that deep learning could be used to approximate CFD codes

Used conditional Generative Adversarial Networks (cGANs), adapted pix2pix algorithm

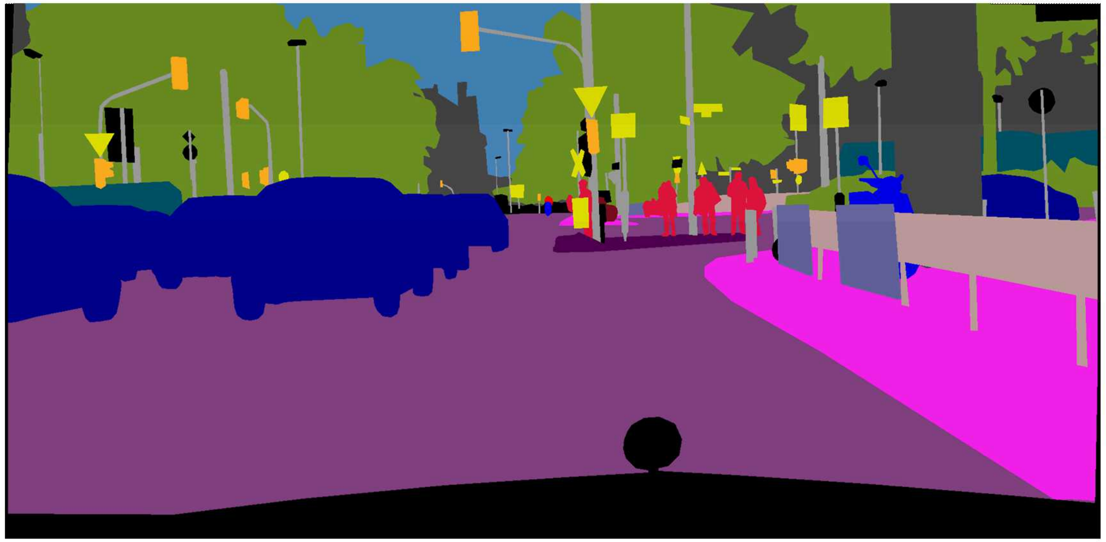
Achieved **orders of magnitude** speed-up in inference time



Farimani et al. 2017

Generative Adversarial Networks (GANs) learn to mimic complex systems with wide applicability

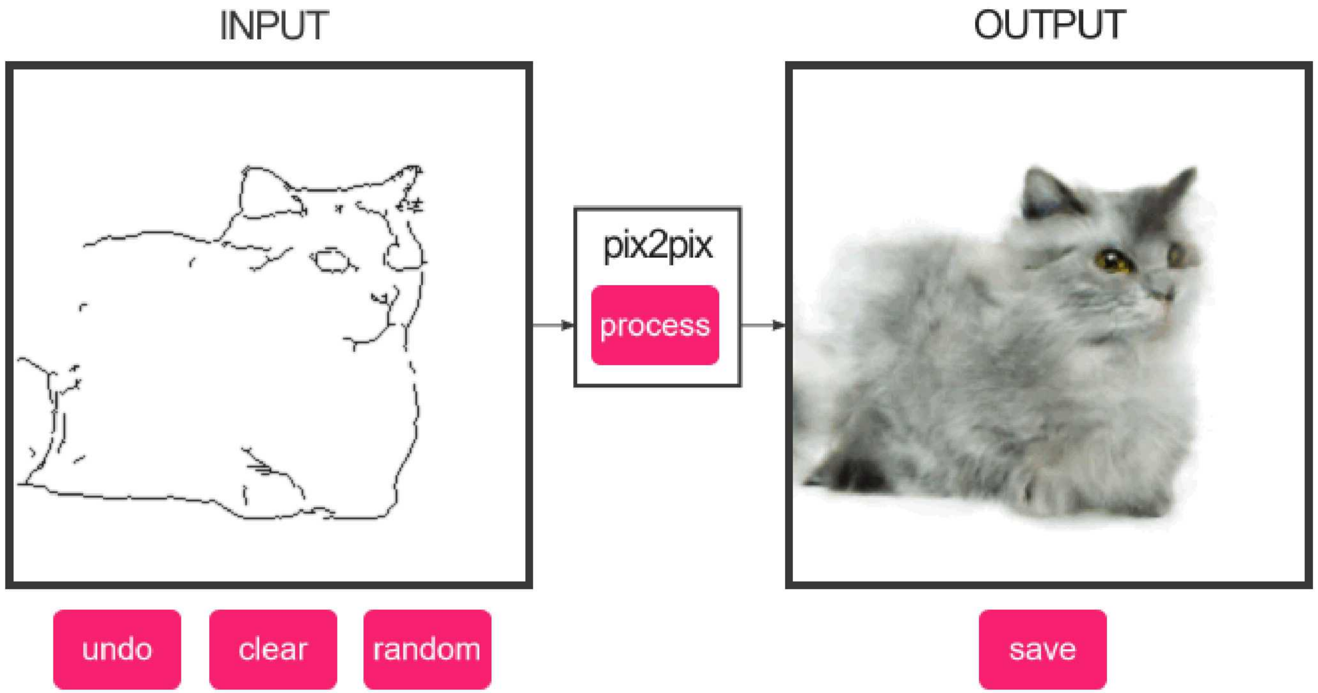
Input labels



Synthesized image

High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs (2018)

Generative Adversarial Networks (GANs) learn to mimic complex systems with wide applicability

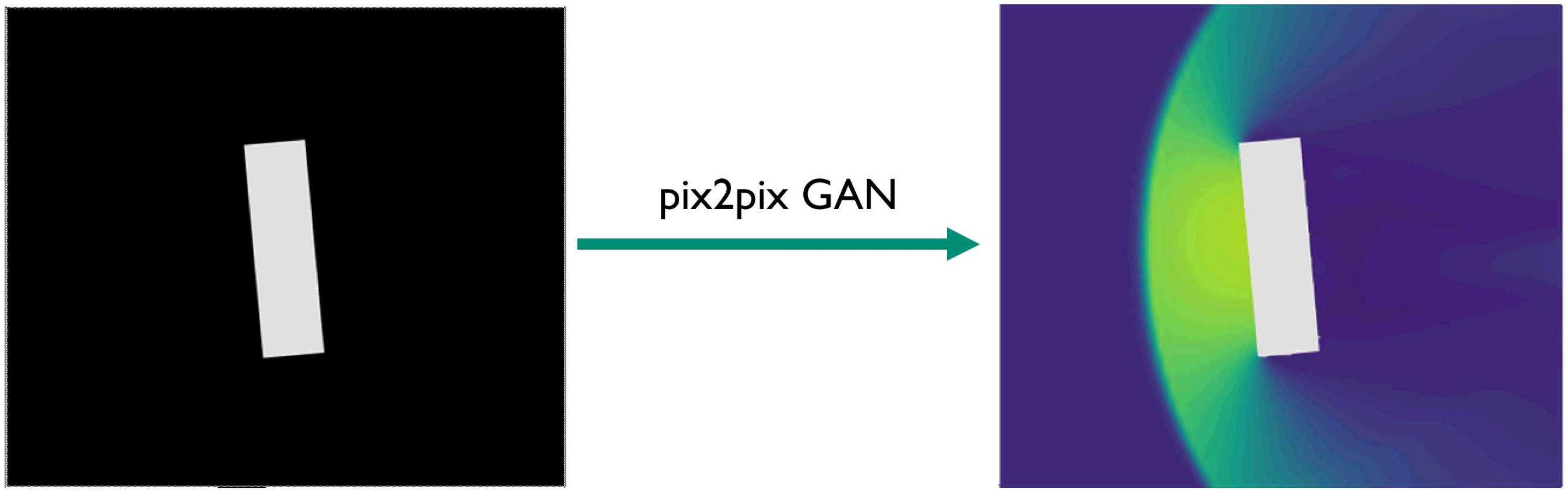


https://affinelayer.com/pixsrv/

Generative Adversarial Networks (GANs) for pressure field approximations

Train pix2pix GAN using computed flow solutions as ground truth

- Simulated 1000 rectangles with random orientations & aspect ratios,
- Fixed at Mach 5 external flow w/ ideal gas assumption for simplicity
- 900 training examples, 100 held out test examples
- Pressure fields calculated with compressible Euler equation solver (CE Solver)

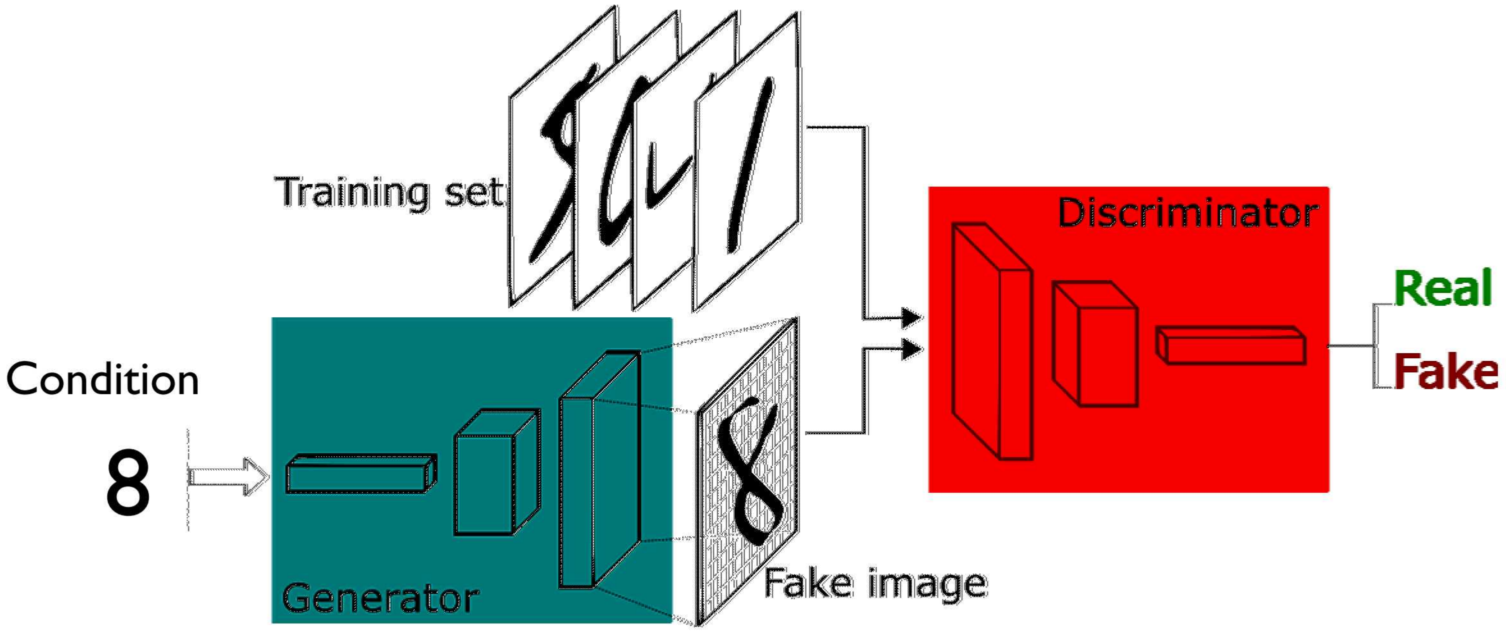


Input shape　　Target flow field

Training with a pix2pix GAN

Generative Adversarial Networks (GANs) pit two competing neural networks against each other

- **The generator**, tries to mimic real results
- **The discriminator**, tries to identify mimicked results from real results



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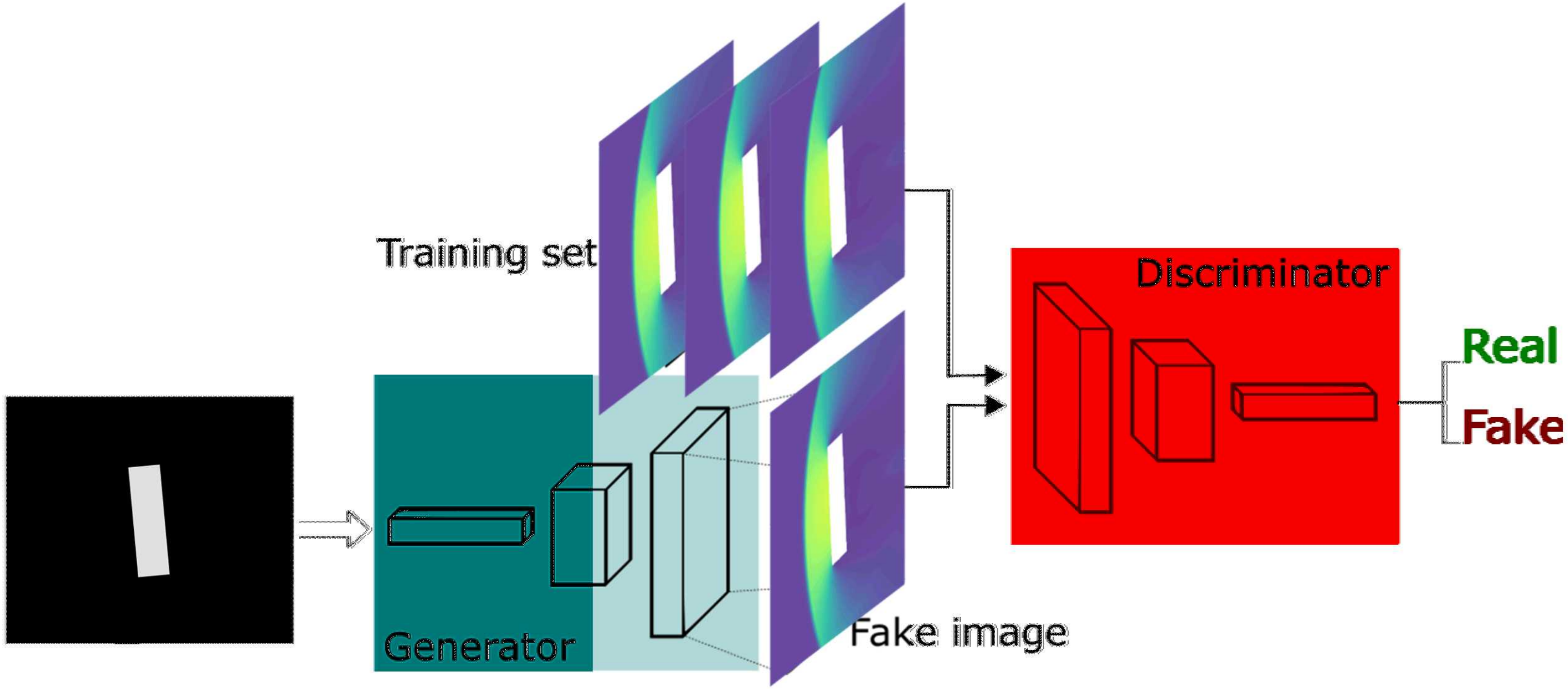


Pix2pix results out-of-the-box appear qualitatively accurate, but are quantitatively inaccurate

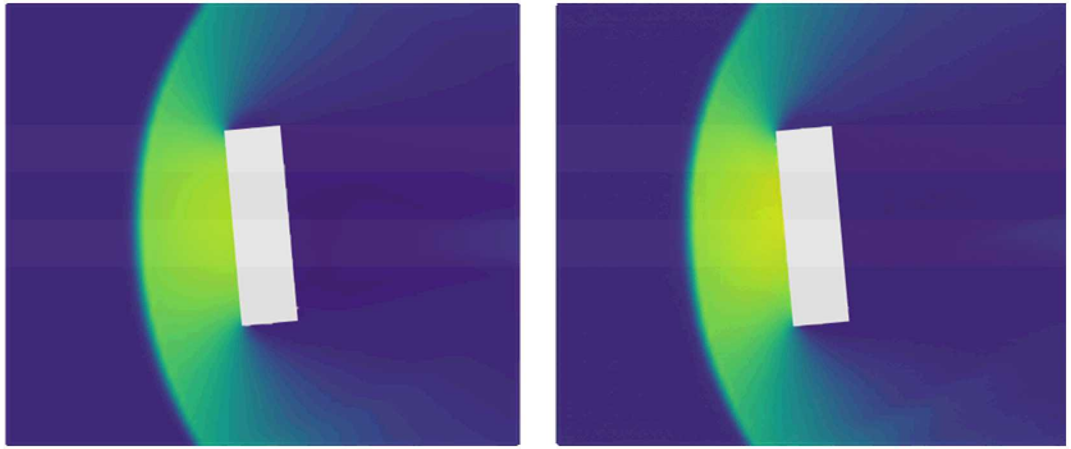
Pressure prediction along the leading edge of the shock front was relatively accurate

- These pixels had higher values and were more "salient"

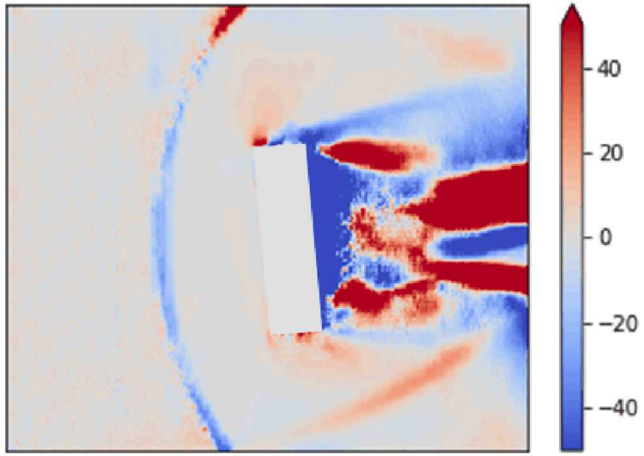
Predictions in finer variations behind the fragment were much less accurate

- These areas are still important as they contribute to the overall drag

CE Solver ML



Pressure Percent Difference



Idea: check that physics conservation laws are obeyed while the neural network is training

Euler equations for fluid dynamics govern the steady-state pressure field

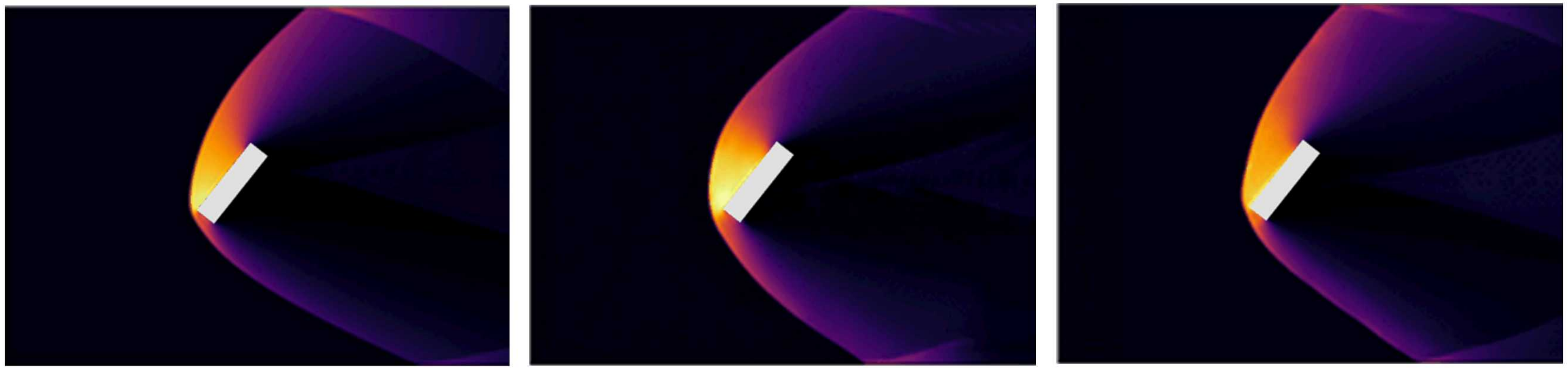
These equations are expensive to solve for (need HPC codes), but they are quick to check

We check these equations while training the generator, and add them to the loss function of the generator

$$\begin{cases} \dfrac{\partial \rho}{\partial t} + \boldsymbol{u} \cdot \nabla \rho + \rho \nabla \cdot \boldsymbol{u} = \boldsymbol{0} & \text{Conservation of mass} \\ \dfrac{\partial \boldsymbol{u}}{\partial t} + \boldsymbol{u} \cdot \nabla \boldsymbol{u} + \dfrac{\nabla p}{\rho} = \boldsymbol{g} & \text{Conservation of momentum} \\ \dfrac{\partial e}{\partial t} + \boldsymbol{u} \cdot \nabla e + \dfrac{p}{\rho} \nabla \cdot \boldsymbol{u} = 0 & \text{Conservation of energy} \end{cases}$$

Result: GAN learns to obey laws of physics and in turn, produces more accurate results

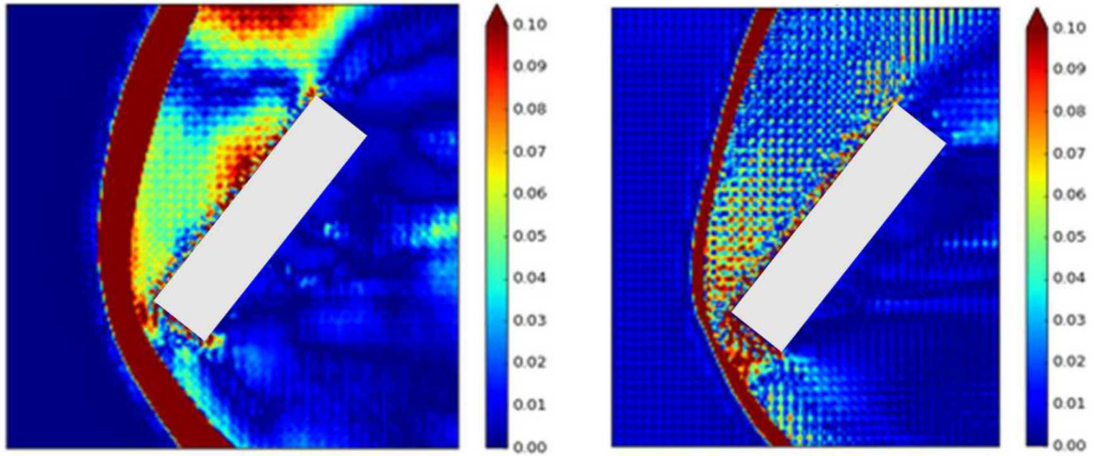
CE Solver | GAN Loss | GAN Loss + Physics Loss



ML predictions approximate CE solver results within 6%

	Mean Relative Error vs CE Solver
Drag	1.87%
Lift	5.63%
Torque	2.29%

Relative Error Maps

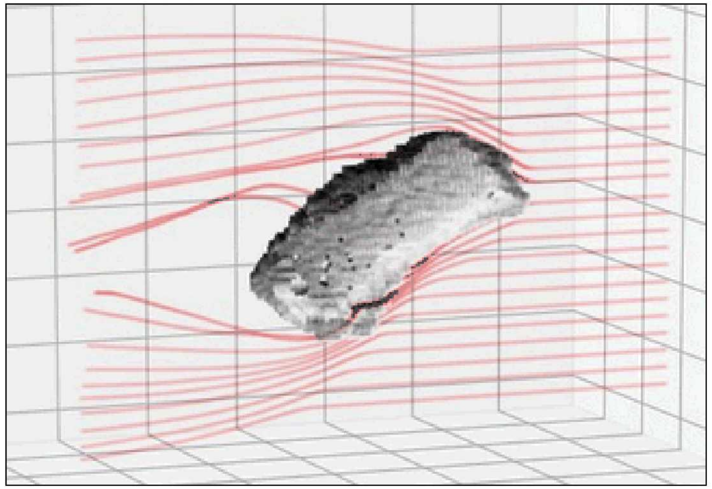


We are now extending this work to 3D complex geometry and expect a large speedup for HPC code approximation

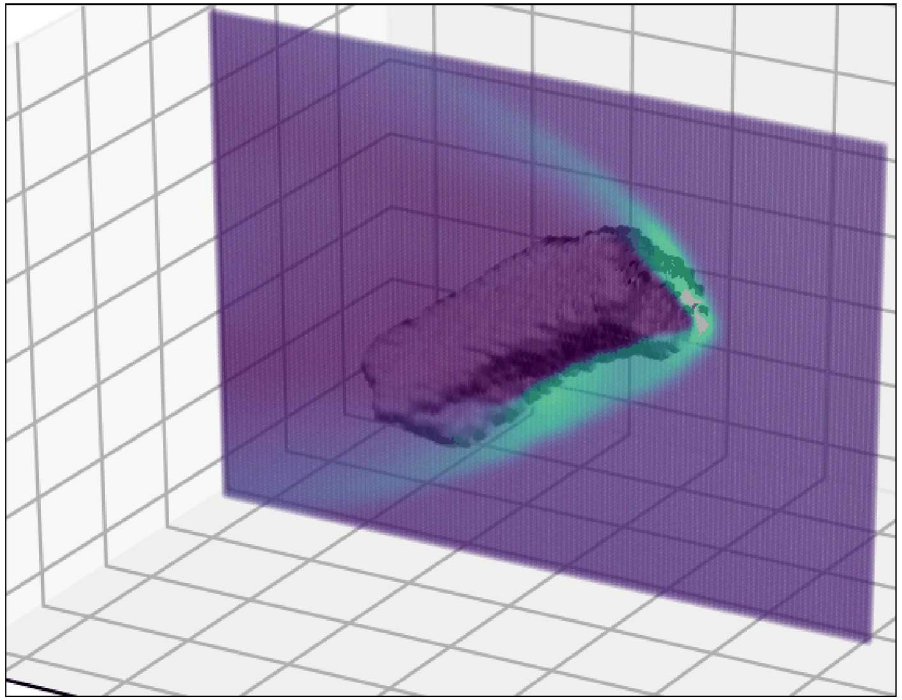
Qualitative results are visually similar to simulation output

Captures complex fragment geometries

~10,000x faster



Deep learning output on a fragment showing predicted streamlines



ML pressure prediction and fragment surface showing pressure field in a single plane

Computer vision techniques for segmentation and tracking

Sandia collects diagnostics from munitions experiments with high-speed cameras

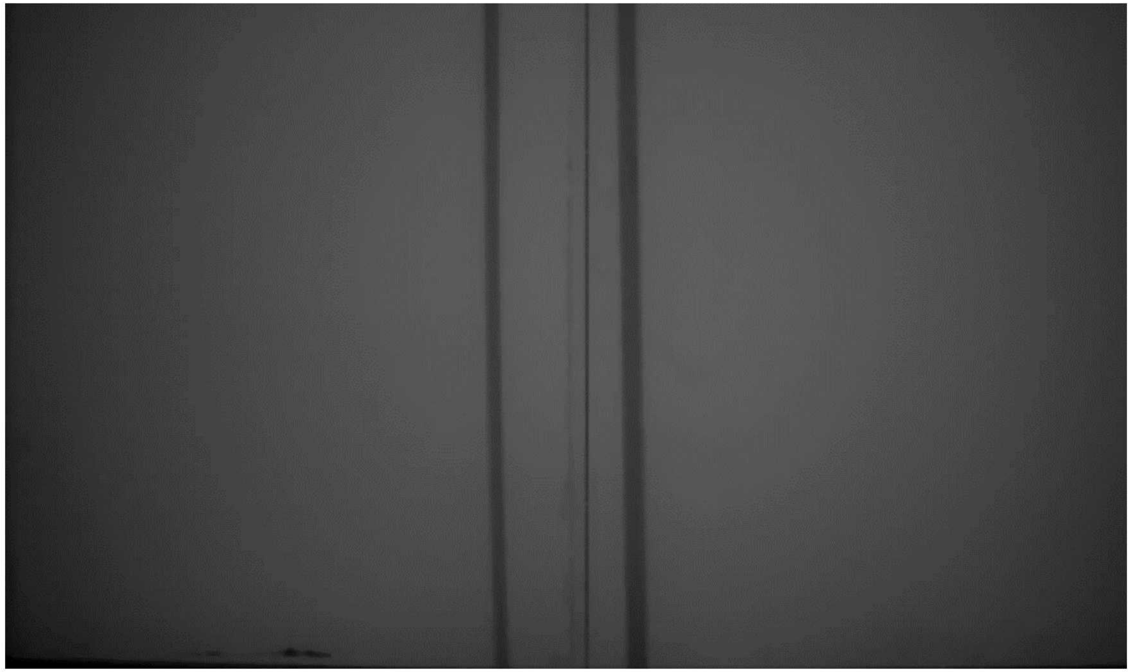
Multi-camera stereo system with synchronized videos

Fragments from experiment fly across field-of-view

Using machine learning & computer vision techniques, can we answer:

- How do fragments form?
- Where are the fragments located in 3d space?
- What are their velocities?
- What are their masses?

Stereo camera system



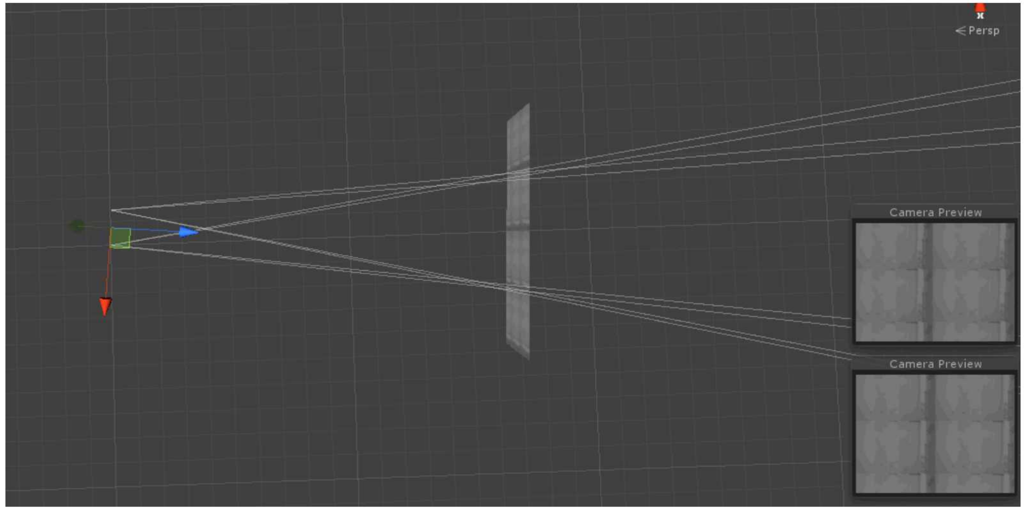
Fragment experiment

Deep learning algorithms are data-hungry, experimental data is scarce

The best-performing segmentation methods in deep learning rely on labelled data, which we don't have

Moreover, real tests are expensive to run

Instead, we simulated experiments with the Unity game engine, giving us labels for free



Bird's-eye view of Unity game engine setup showing stereo camera positions

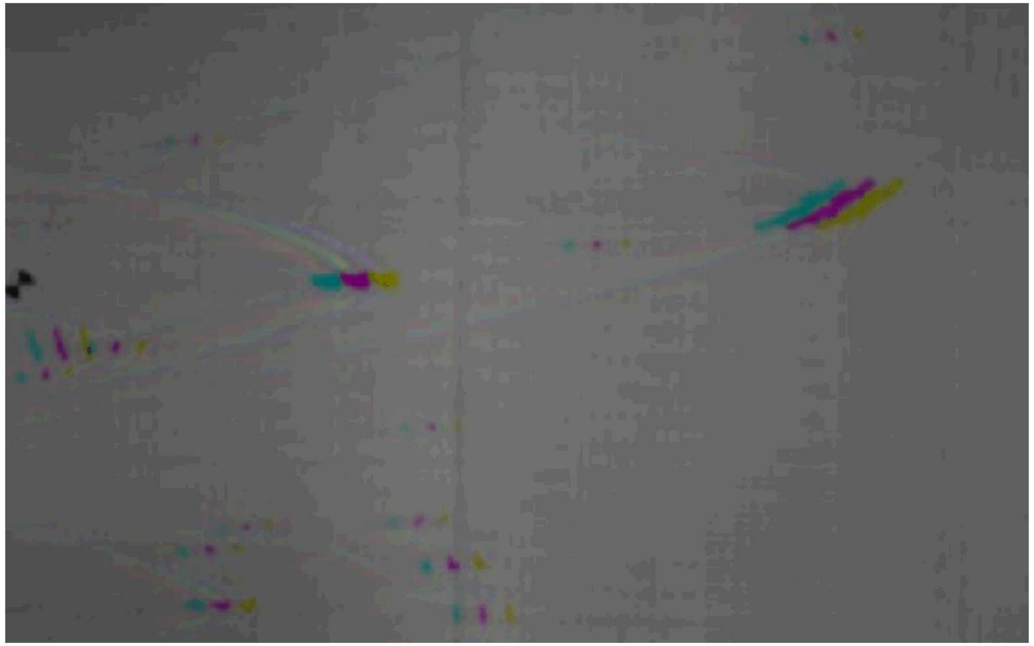
Unity simulation of fragment field from an explosive

We use state-of-the-art deep learning segmentation for highly accurate fragment detections

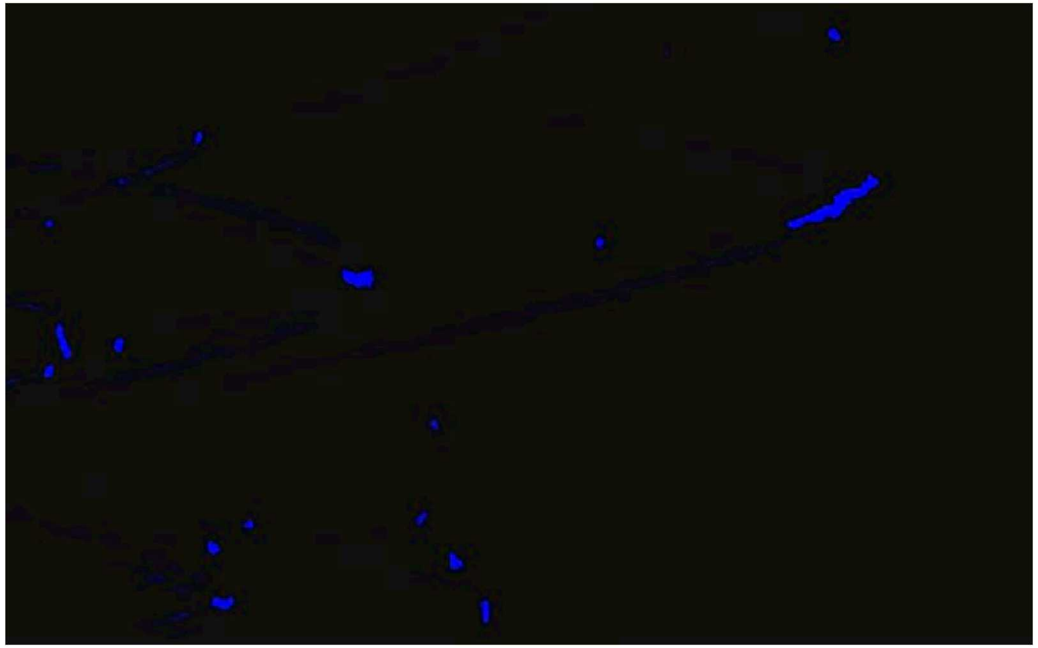
We trained pix2pixHD on simulated video frames, and their corresponding location labels

Hack to isolate moving objects: put 3 successive frames in each of the RGB images channels while training

Segmentation on real data is fairly good, future work will involve accounting for shock fronts



3 frames from a real test video stacked into color channels



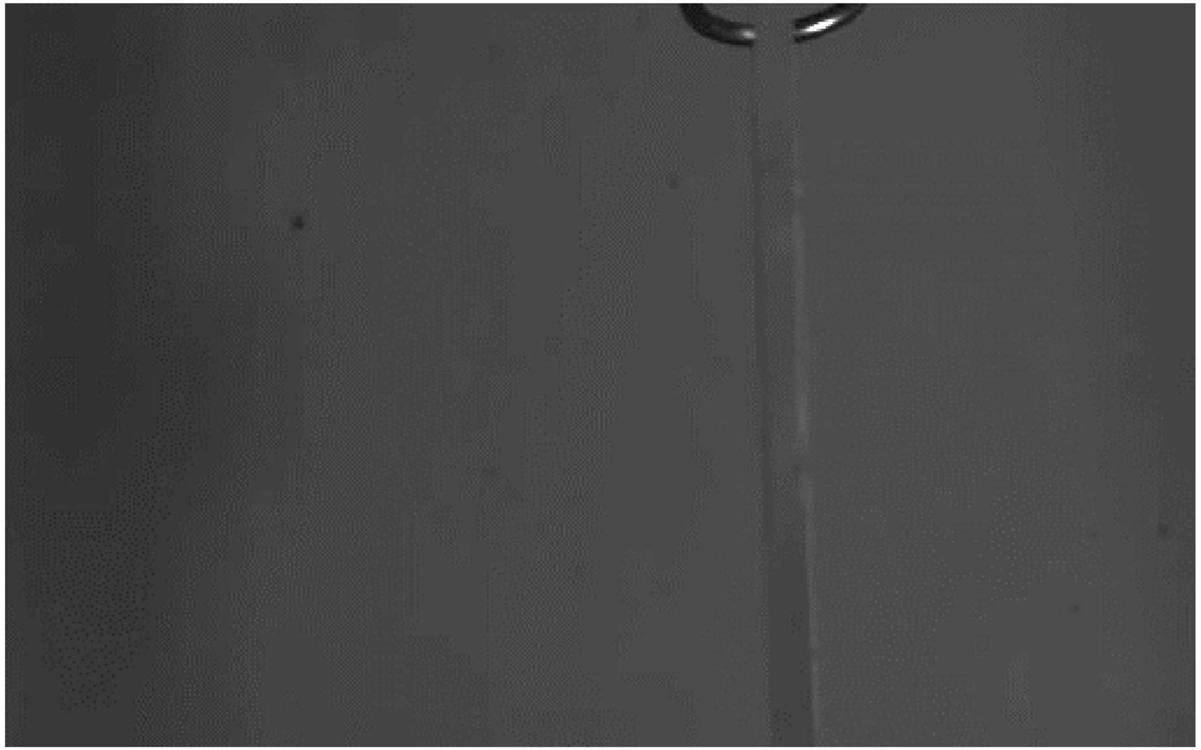
pix2pixHD segmentation

Ongoing work: Tracking and triangulation

Algorithms such as optical flow or the Hungarian algorithm can be applied for tracking the same fragment frame-to-frame

Once tracked, fragments can be correlated between stereo cameras for 3D positioning

After gathering and analyzing enough data, statistical arguments can then be made about fragment flight paths



Outcomes: higher confidence in flight path predictions and increased range safety

Sandia Overview

Sandia's Impact

Sandia is often called upon to respond to high-profile events, including 9/11 and the Ebola outbreak.

Ebola Outbreak

Sandia contributes to global response of Ebola outbreak by developing a sample delivery system cutting the wait time and potentially fatal exposure.

Cleanroom invented 1963

$50 billion worth of cleanrooms built worldwide. They're used in hospitals, laboratories and manufacturing plants today.

9/11

Sandia sets contingency plans for release of materials and aircraft attacks on critical facilities immediately after 9/11. Search dogs are equipped with cameras for search and rescue K-9 handlers. The capability allowed search efforts to be carried out in spaces inaccessible to humans.

Detecting IEDs

Combat personnel now have a new tool for uncovering improvised explosive devices: Sandia's highly modified miniature synthetic aperture radar system, which is being transferred to the U.S. Army.

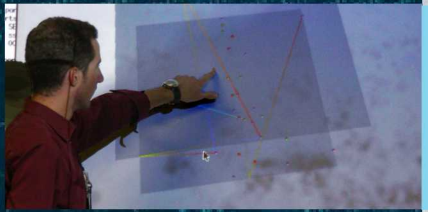
Fulfilling Our National Security Mission

Nuclear Deterrence

Defense Nuclear Nonproliferation

National Security Programs

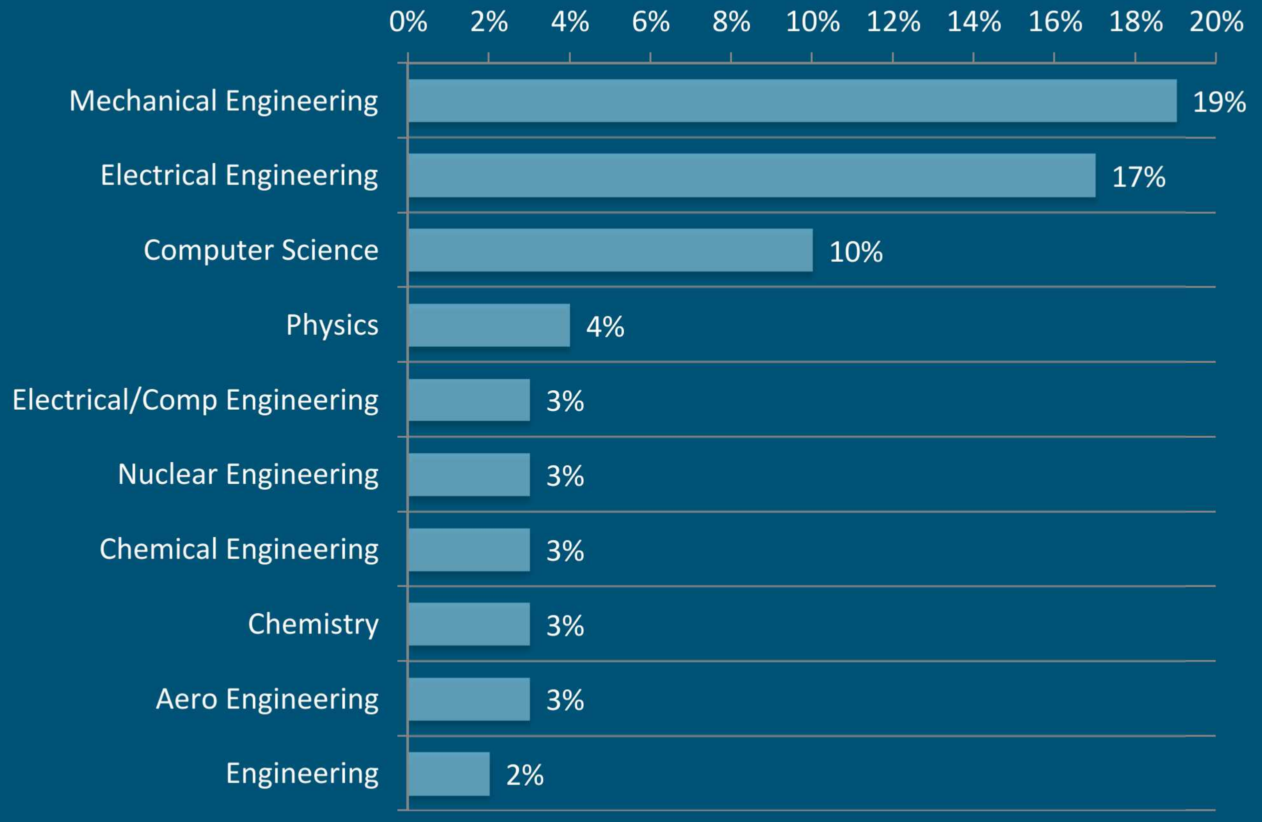
Energy & Homeland Security



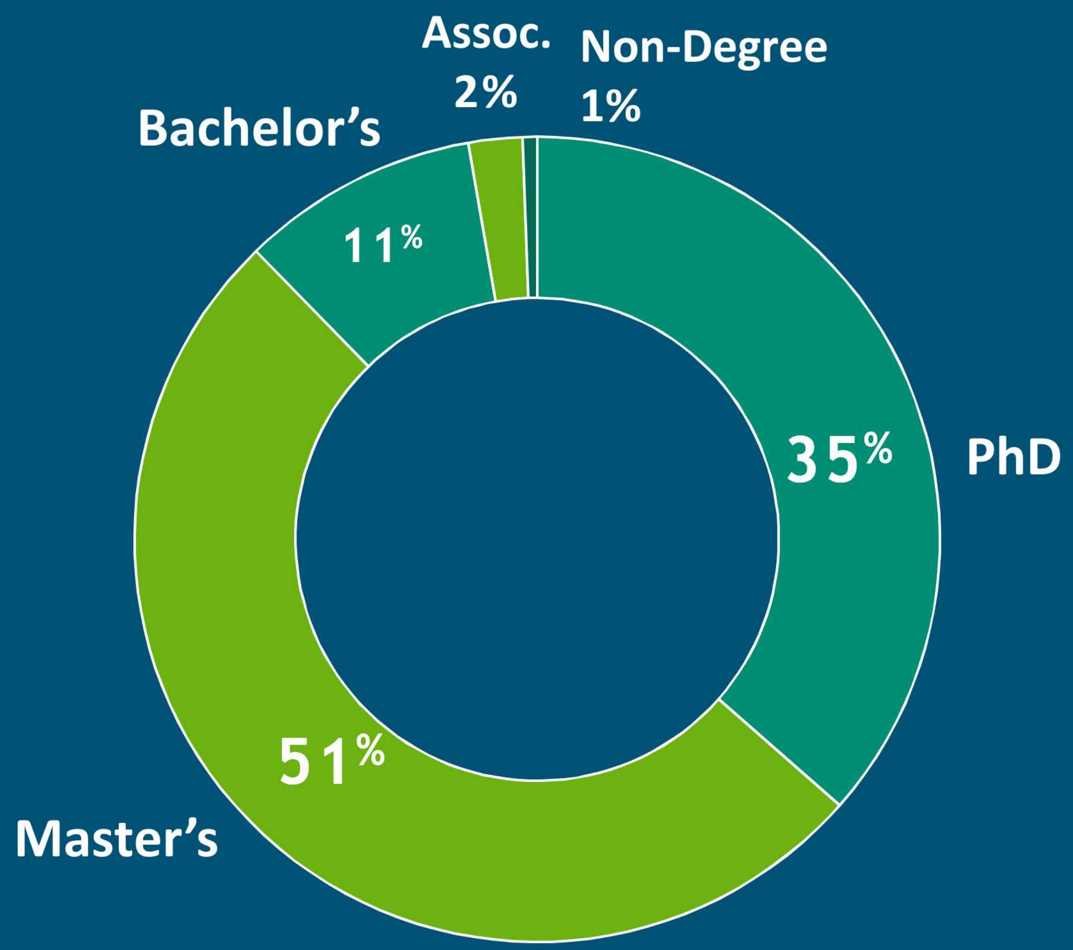
Advanced Science & Technology

Sandia provides the science needed to enable the U.S. nuclear stockpile, and does fundamental scientific, biomedical, and environmental research to enhance national security, economic competitiveness, and improved quality of life.

R&D by Discipline & Degree

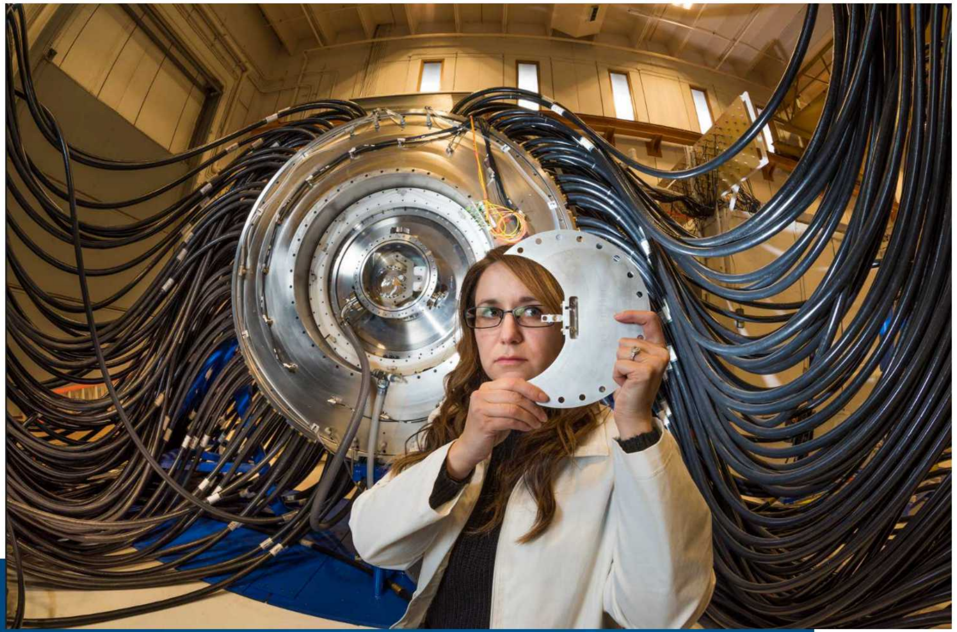


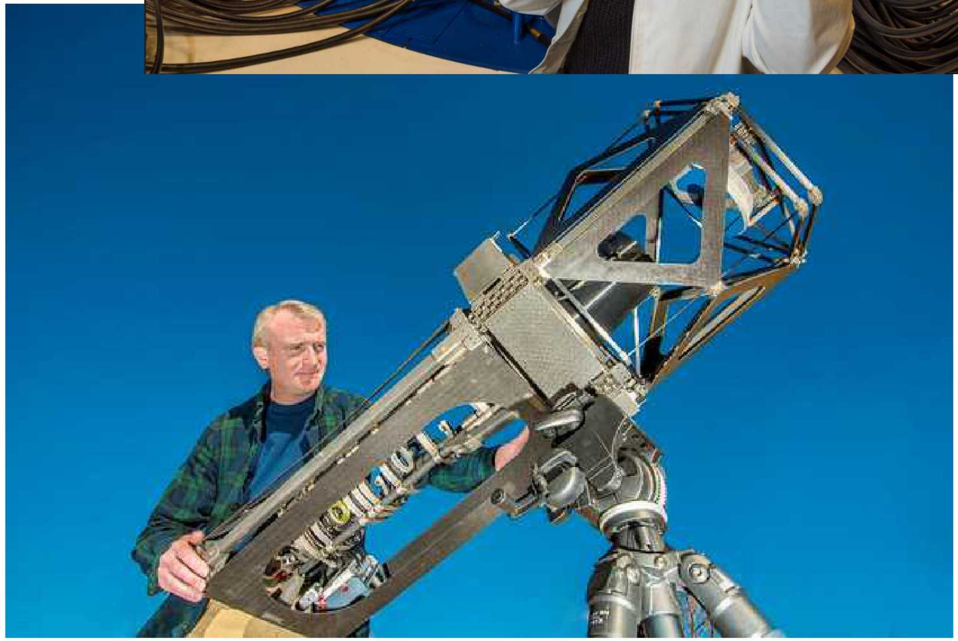
Top 10 job descriptions shown, Regular exempt non-management employees only



Data as of July 2019

The Work Experience





- Have meaningful & challenging work assignments
- Work in state-of-the-art research facilities
  Take a Virtual Tour @ tours.sandia.gov
- Work with top minds
- Join outreach and networking groups
- Receive award recognitions,
  like R&D 100 Awards *and more*
- Take a leave to pursue qualifying research and professional opportunities
- Receive patent royalties, if eligible
- Experience a career path in various areas at Sandia

Living in Albuquerque

Life in Albuquerque

- Albuquerque is the largest city in New Mexico with a population of over 500,000
- Affordable housing, reasonable cost of living
- Minimal traffic congestion compared to larger cities

Albuquerque Environment

- High desert climate with 278 annual days of sunshine
- Average temperatures between 78° and 40°
- Wide-open spaces

Things to Do

- Outdoor recreation - Ski, snowboard, hike, etc.
- Santa Fe – rich culture
- International Balloon Fiesta
- Explore Indian pueblos and our Hispanic heritage
- Green chile – NM Cuisine
- Museums, Parks, Sports

Photo Credit:
MarbleStreetStudio.com

Visit us tomorrow!
Text (505)-605-6276 to pre-register

Emily Donahue – eadonah@sandia.gov, ed353@cornell.edu

Peter Yeh – pdyeh@sandia.gov