EPSRC

UNIVERSITY OF OXFORD

Machine learning and algorithmic approaches in ICF Capsule Design

Peter Hatfield, University of Oxford

LLNL Inaugural Data Science Workshop

7th August 2018

Collaborators:

University of Oxford: **Steve Rose** (also IC)

Rutherford Appleton Laboratory: **Robbie Scott** (CLF)

Imperial College: Jeremy Chittenden, Kris McGlinchey

AWE plc: Warren Garbett

LLNL: Jim Gaffney, John Edwards

Also:

Oxford Centre for High Energy Density Science (Oxford)
Centre for Inertial Fusion Studies (Imperial)

Talk Summary

1. Motivation
2. Automated Production of New ICF Designs
3. Uncertainty Decomposition in Surrogate Building

1.Motivation

- Inertial Confinement Fusion (ICF) is one of the key pathways to nuclear fusion as a clean, renewable power source
- National Ignition Facility (NIF) world's largest laser and premier facility for achieving ICF
- Many milestones reached, but reaching ignition has proved challenging – leading to interest in exploring a wider parameter space of experiment designs

The “Designer’s Algorithm”

1. Think of a *physical principle* (e.g. concept of using a shock wave to increase adiabat)
2. Simulate a minimal working design that incorporates this principle
3. Using a physical understanding of the implosion, change design incrementally to improve performance
4. Repeat N times
5. End when desired performance reached, or no obvious improvement

The "Designer's Algorithm"

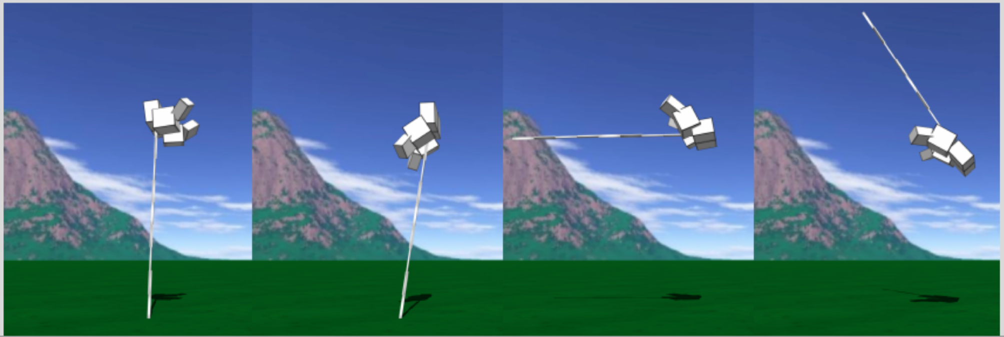
1. Think of a *physical principle* (e.g. concept of using a shock wave to increase adiabat)
2. Simulate a minimal working design that incorporates this principle
3. Using a physical understanding of the implosion, change design incrementally to improve performance
4. Repeat N times
5. End when desired performance reached, or no obvious improvement

Humans are really good at understanding problems

Computers are good at repeating things multiple times

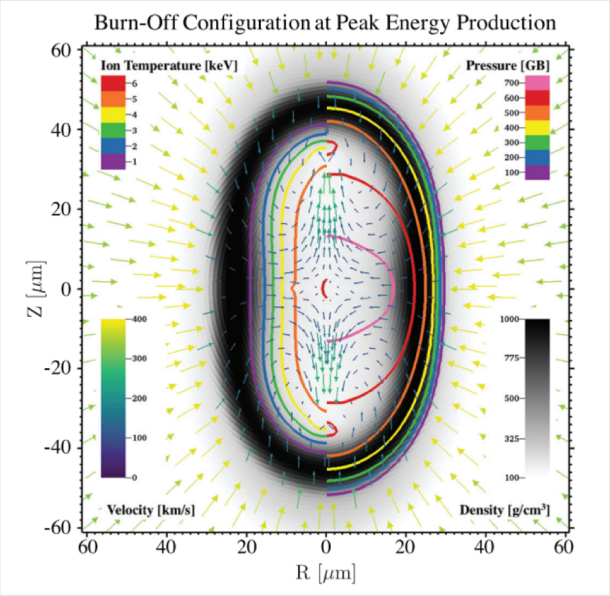
“The Surprising Creativity of Digital Evolution” (Lehman et al., 2018)

- Evolutionary algorithms can often produce new and unexpected solutions to problems
- Tic-tac-toe memory bomb, robot that found it could walk on elbows, robot that flips instead of jumping…
- For ICF we would like to find any interesting new designs, or convince ourselves that none are possible (c.f. 2020 goal)



Increasing Interest in Algorithmic Approaches to Finding New Designs

- Peterson+2017 (LLNL) found a new class of NIF designs by optimizing over a machine learning based surrogate
- Baltz+2017 used "Optometrist Algorithm" to find unexpected confinement regime at Tri Alpha Energy



2. Automated Design

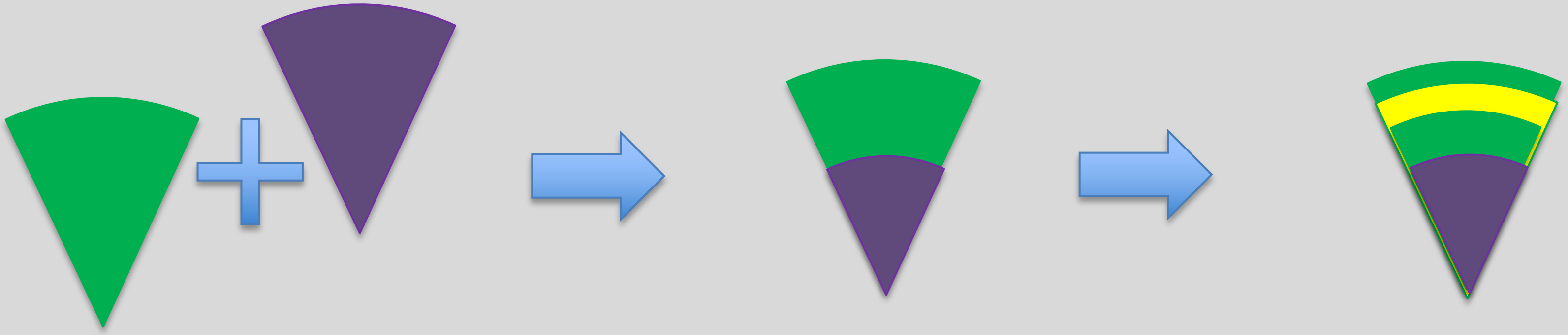
- Interested in finding an algorithm to take you from absolutely no idea what a design would look like, to a working design
- ICF as an optimisation problem – wish to maximise yield within constraints of what designs possible to field
- Design space considered in Peterson+2017 is 9D - design space of absolutely everything is even bigger
- Investigate use of meta-heuristics – specifically genetic algorithms

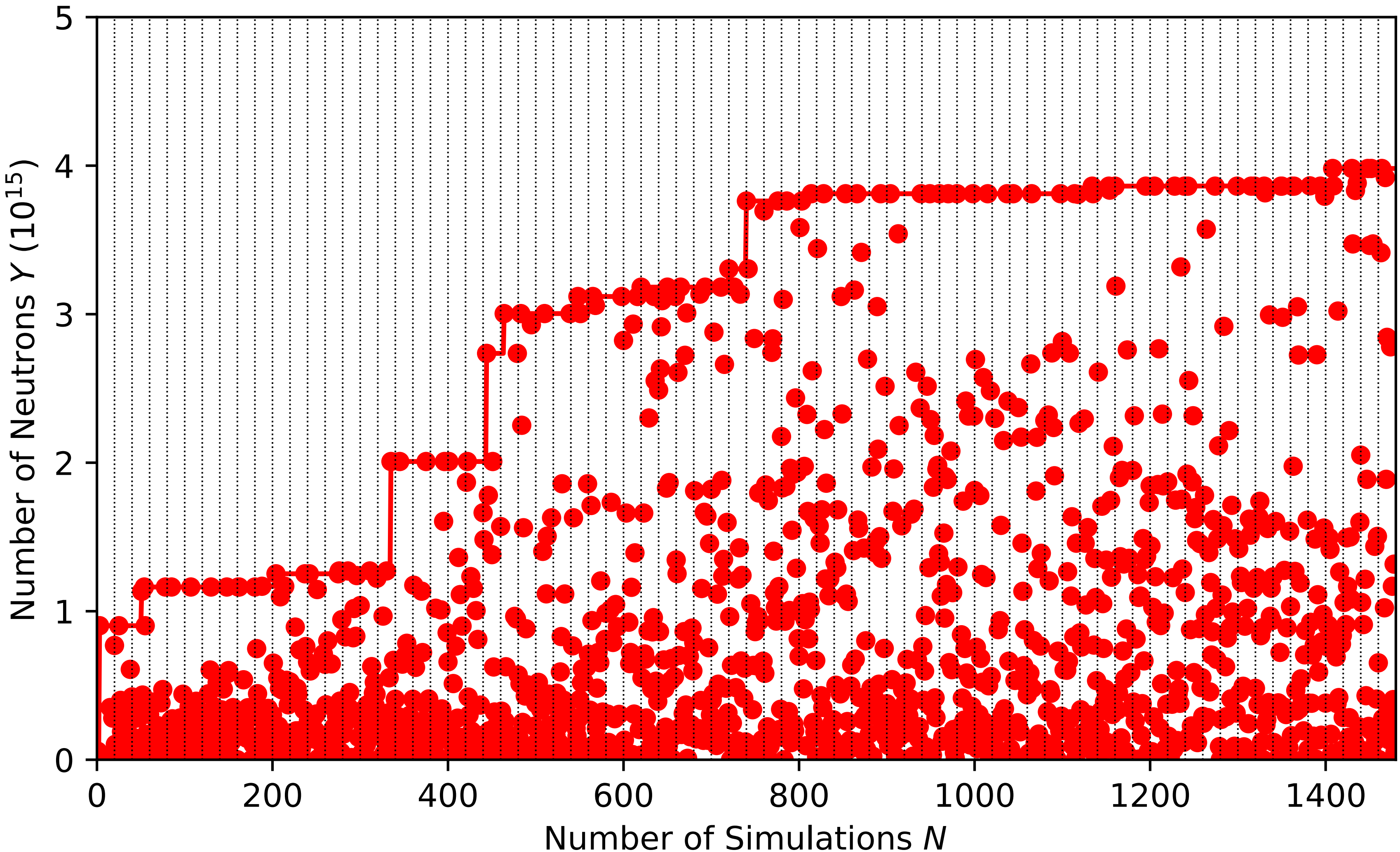
Design Space Considered

- Investigate space of robust low convergence designs for NIF-like configurations
- Design is permitted DT gas (ρ>10mg/cc), DT ice and CH in 5 different sections and otherwise almost no restrictions
- Fixed thermal drive with Gaussian pulse shape
- 1D implementation in Hyades - radiation hydrodynamics simulation code for HED experiments, Lagrangian, average atom LTE ionization, no magnetic field, SESAME EOS and opacities…
- Not modelling hohlraum (putatively gold) or plasma-laser interactions
- Run on SCARF at Central Laser Facility

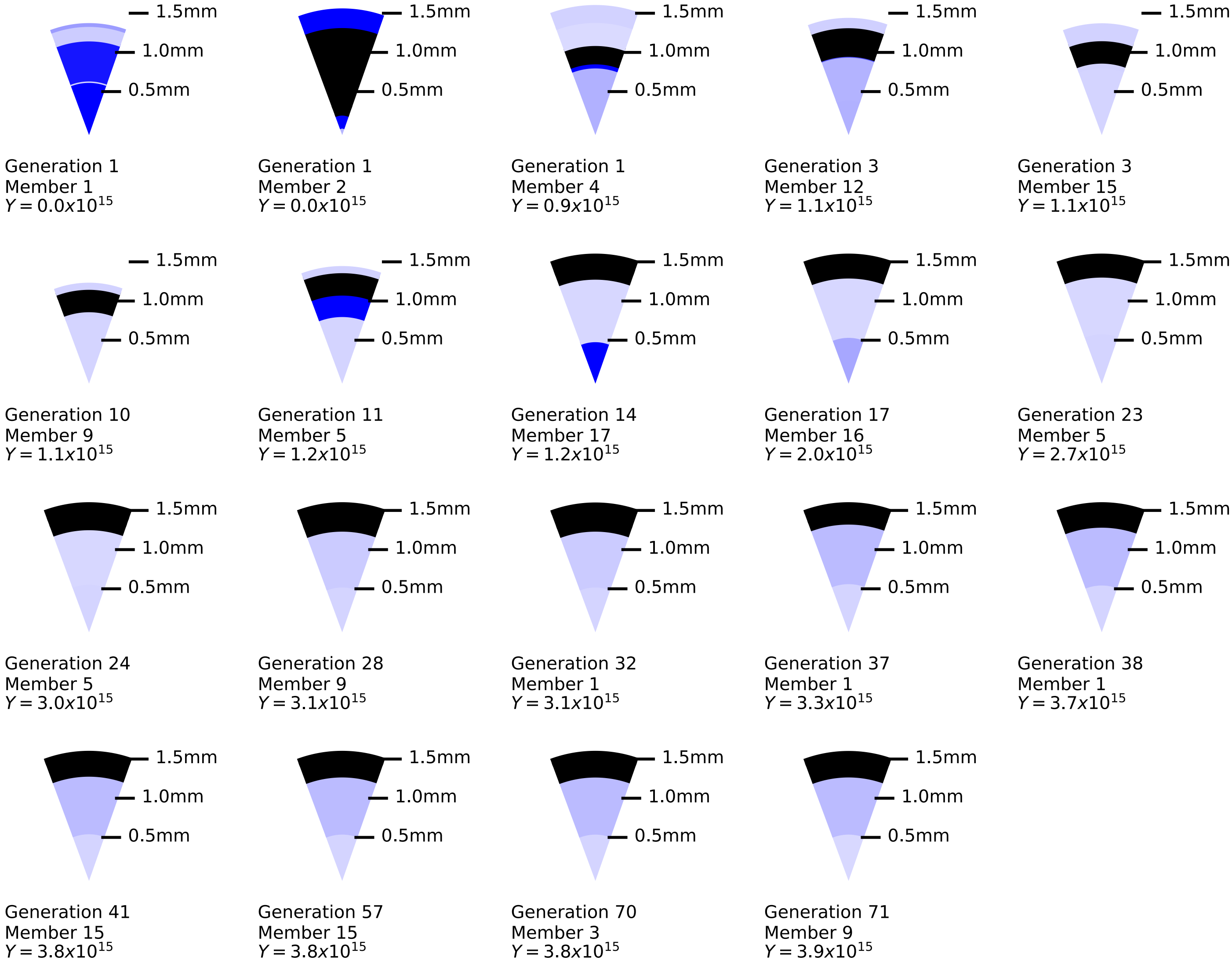
Genetic algorithms

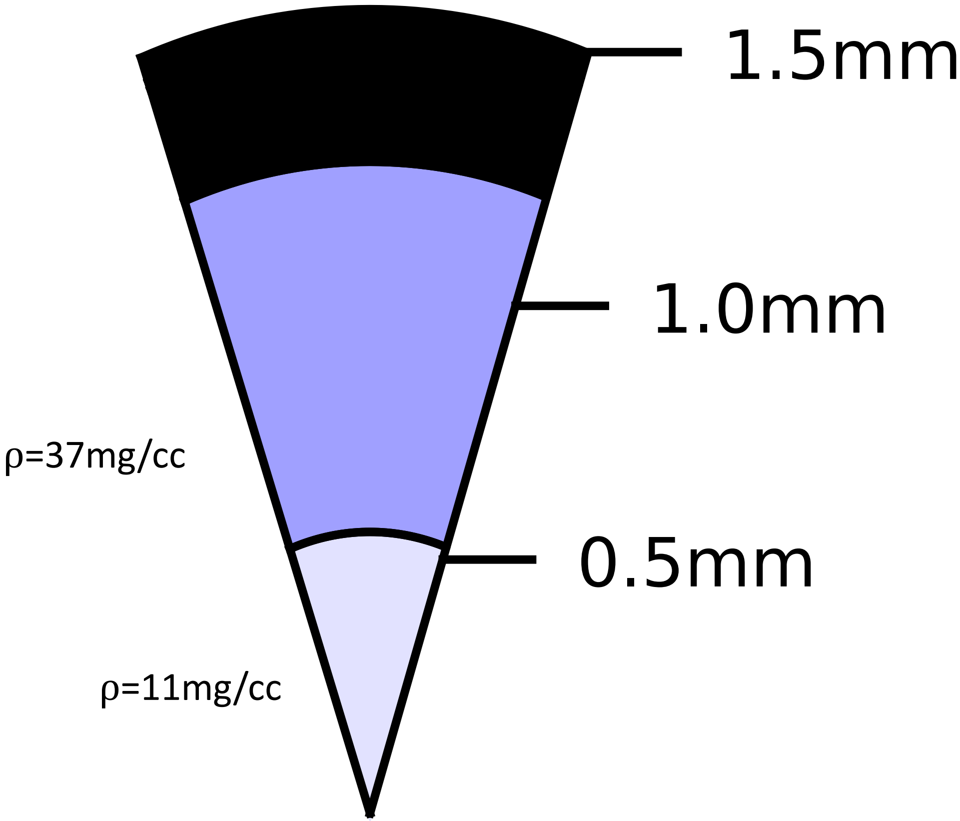
- **Population** of designs
- **Fitness** of each design is evaluated (based on simulated yield)
- Pairs of parents **crossover** to produce offspring
- Offspring receive **mutations**
- New generation formed

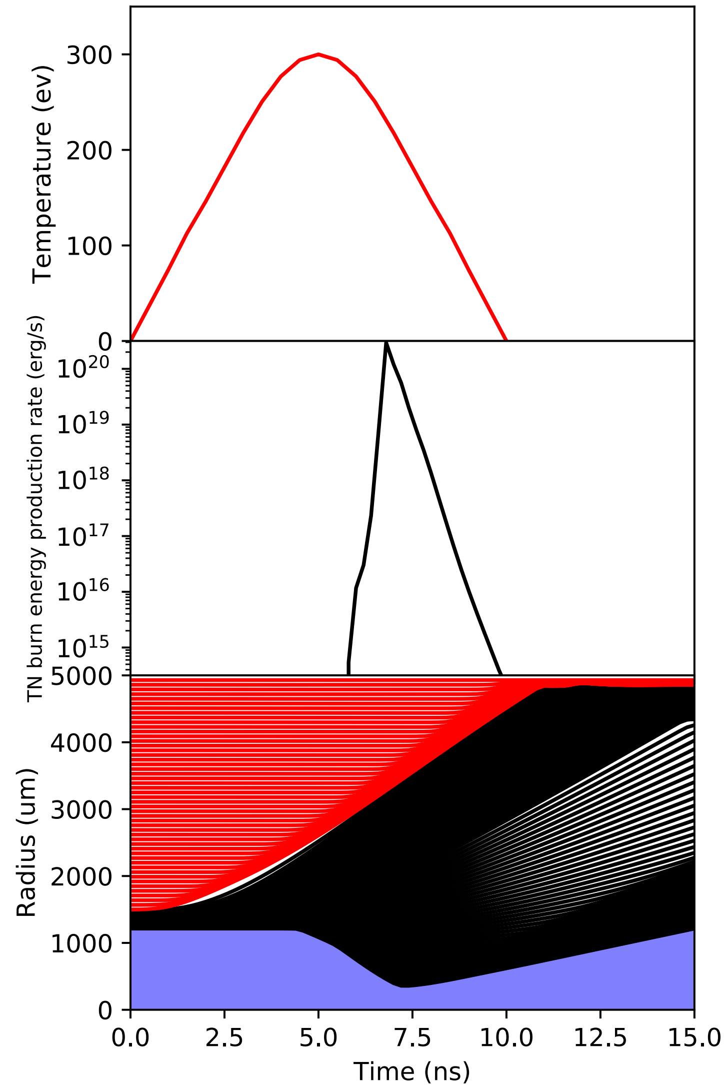




5
4
3
2
1
0
Number of Neutrons Y (10^{15})
0
200
400
600
800
1000
1200
1400
Number of Simulations N

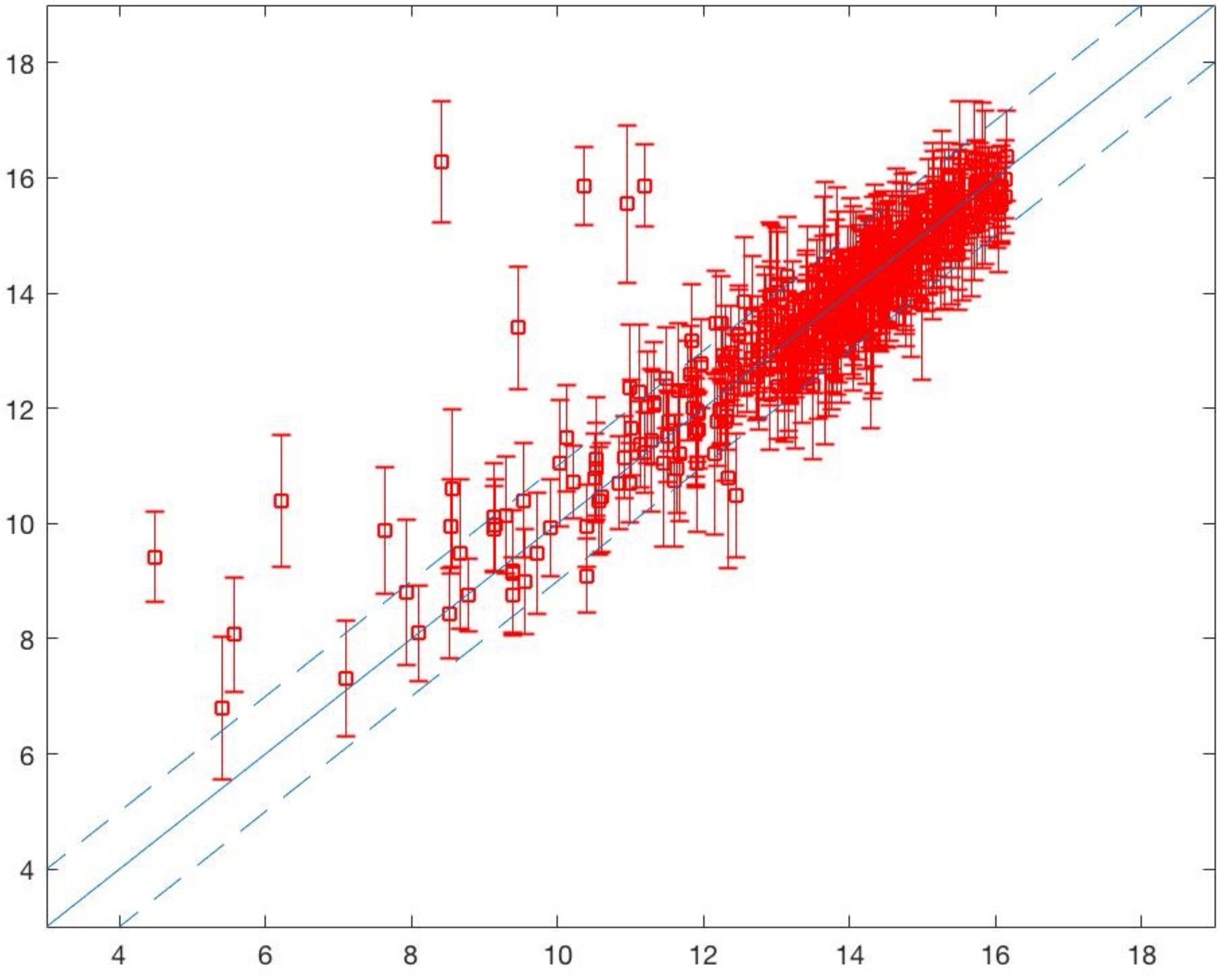

1.5mm
1.0mm
0.5mm
Generation 1 Member 1 $Y = 0.0x10^{15}$
Generation 1 Member 2 $Y = 0.0x10^{15}$
Generation 1 Member 4 $Y = 0.9x10^{15}$
Generation 3 Member 12 $Y = 1.1x10^{15}$
Generation 3 Member 15 $Y = 1.1x10^{15}$
Generation 10 Member 9 $Y = 1.1x10^{15}$
Generation 11 Member 5 $Y = 1.2x10^{15}$
Generation 14 Member 17 $Y = 1.2x10^{15}$
Generation 17 Member 16 $Y = 2.0x10^{15}$
Generation 23 Member 5 $Y = 2.7x10^{15}$
Generation 24 Member 5 $Y = 3.0x10^{15}$
Generation 28 Member 9 $Y = 3.1x10^{15}$
Generation 32 Member 1 $Y = 3.1x10^{15}$
Generation 37 Member 1 $Y = 3.3x10^{15}$
Generation 38 Member 1 $Y = 3.7x10^{15}$
Generation 41 Member 15 $Y = 3.8x10^{15}$
Generation 57 Member 15 $Y = 3.8x10^{15}$
Generation 70 Member 3 $Y = 3.8x10^{15}$
Generation 71 Member 9 $Y = 3.9x10^{15}$


1.5mm
1.0mm
0.5mm
ρ=37mg/cc
ρ=11mg/cc


Temperature (ev)
TN burn energy production rate (erg/s)
Radius (um)
Time (ns)
0
100
200
300
10^{15}
10^{16}
10^{17}
10^{18}
10^{19}
10^{20}
0
1000
2000
3000
4000
5000
0.0
2.5
5.0
7.5
10.0
12.5
15.0

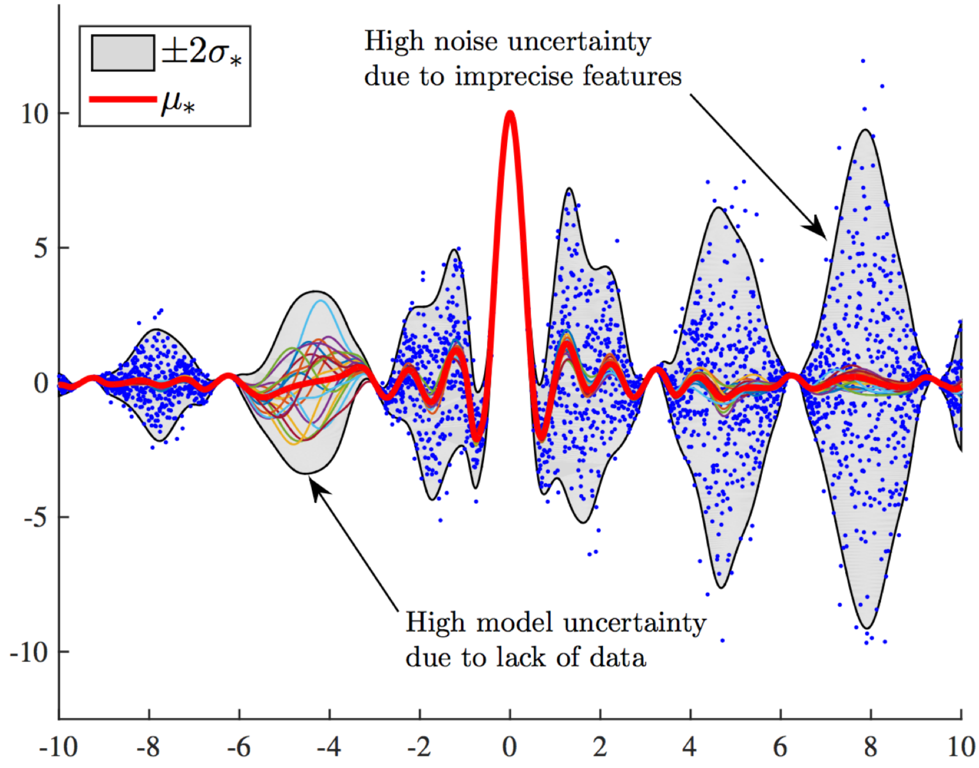
3. Surrogate Building

- Once basic design produced, can then investigate using surrogates (see Peterson talk)
- Use machine learning for cheap predictions in large parameter space
- Investigate modelling the “Simplest” ICF capsule design with ~10^3 simulations in 5D
- Model space with heteroscedastic sparse gaussian process framework described in Almosallam+2015,2016, Gomes+2018; GPz, developed for photometric redshifts for NSF-DOE project the Large Synoptic Survey Telescope



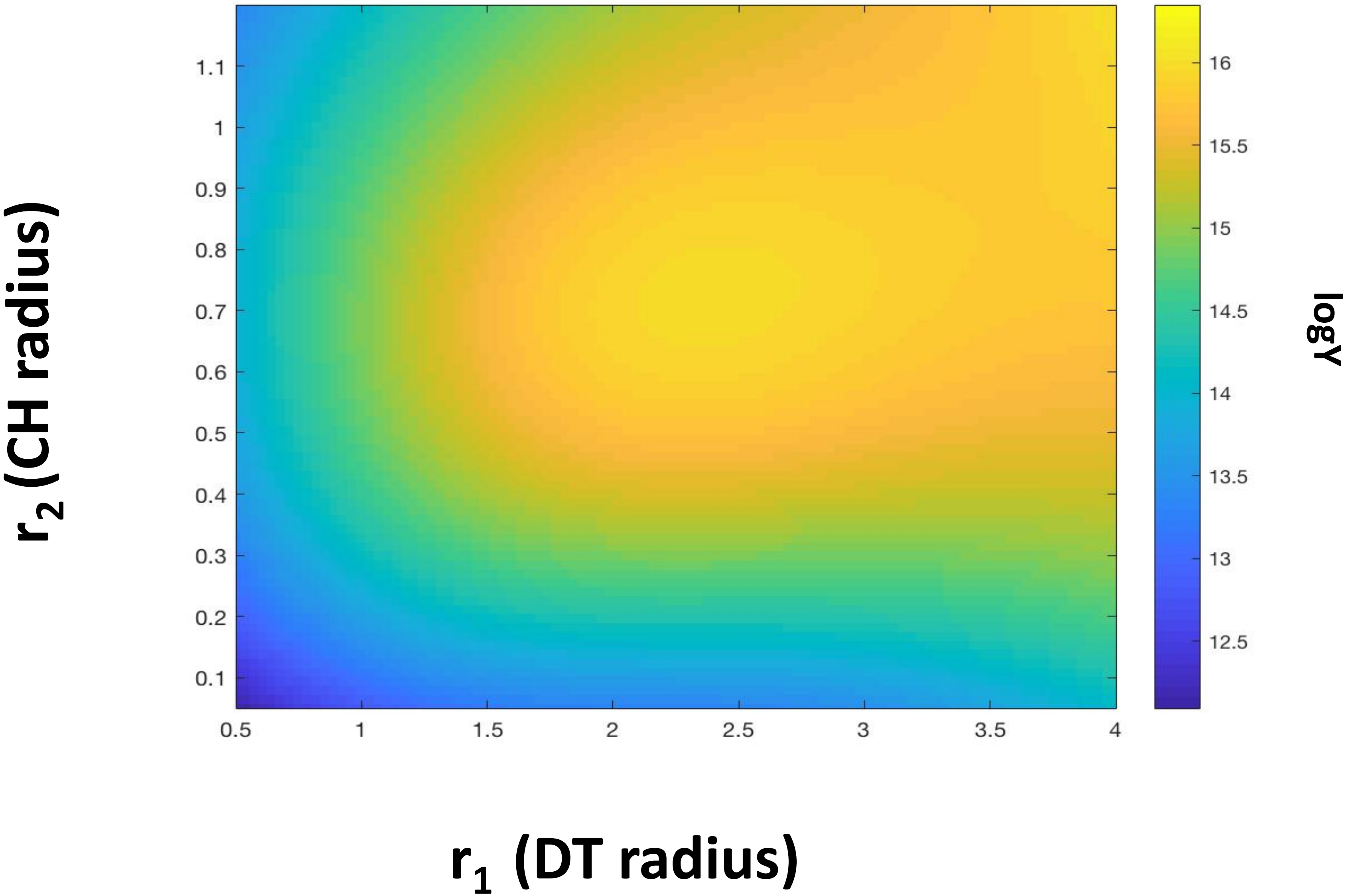
Surrogate logY

True logY



Uncertainty Decomposition

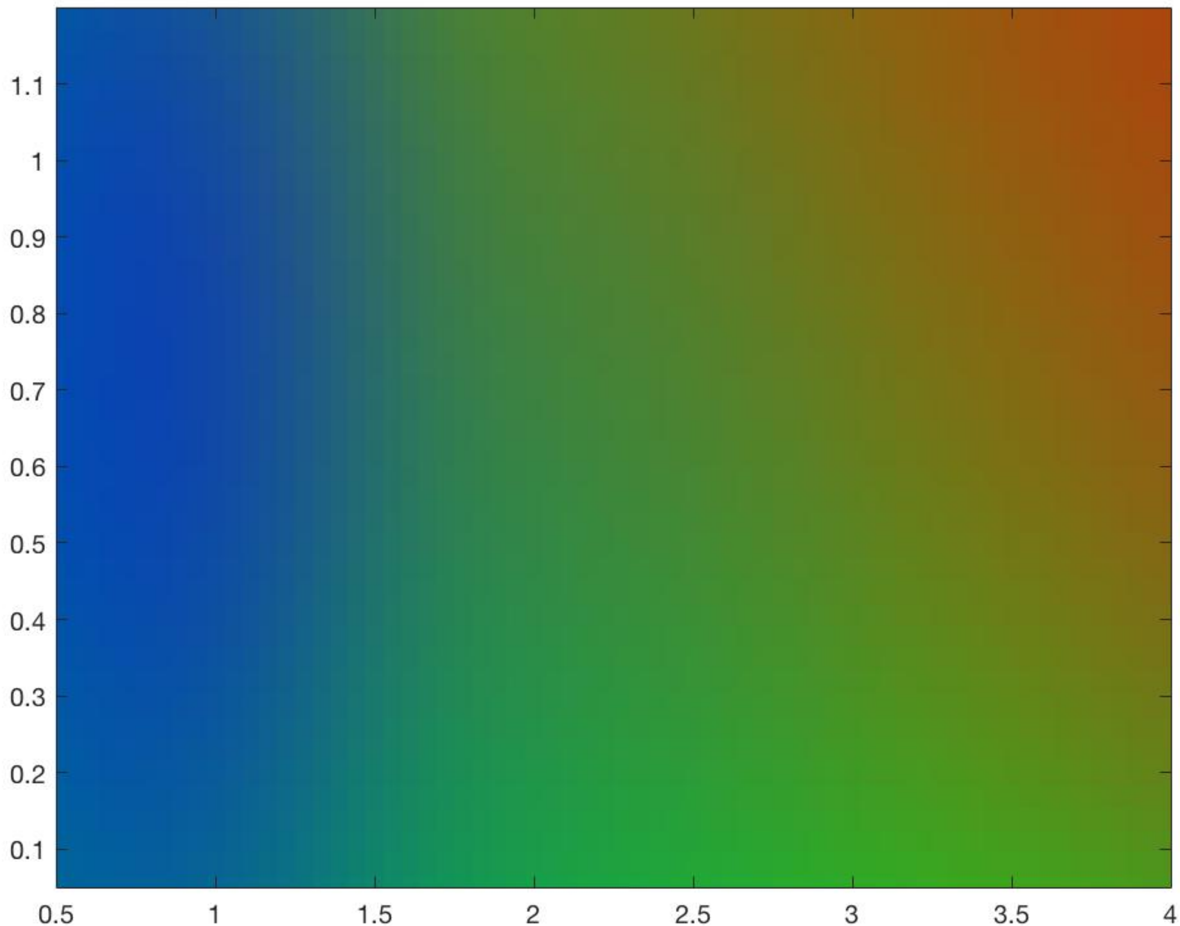
- Uncertainty from lack of training data in part of parameter space (“freedom in fitting GP”)
- Uncertainty from intrinsic degeneracy (“variance of GP”)
- Uncertainty from error bars on input parameters (“uncertainty followed through”)



r_2 (CH radius)
r_1 (DT radius)
logY
1.1
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.5
1
1.5
2
2.5
3
3.5
4
16
15.5
15
14.5
14
13.5
13
12.5

EPSRC

UNIVERSITY OF OXFORD



r_2 (CH radius)

r_1 (DT radius)

Red is dominated by uncertainty from lack of data

Green is uncertainty from errors on input

Blue is intrinsic degeneracy

Conclusions

- ICF capsule designs can be produced “from scratch” by genetic algorithms with little/no assumptions about what designs should look like
- Exploration of “Simplest” ICF design
- Decomposition of uncertainty on surrogate models of ICF yield
- Meta-heuristics and surrogates together can produce new classes of design that can then be explored in greater detail