Advanced Modeling & Simulation (AMS) Seminar Series
NASA Ames Research Center, May 23rd, 2023

To Mars! Machine Learning with Supersonic Retropropulsion Wind Tunnel Test Data

Ames Seminar

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NASA RC: Karl Edquist, Ashley Korzun

Funding: NAA Early Stage Innovations (80NSSC22K0257)

Stanford University
Mechanical Engineering

Motivation

- Need: Human missions to Mars require technology that enables safe and reliable landing of significantly higher payloads at substantially better accuracy compared to existing capabilities



Venkatapathy et al. AIAA 2011-2608
Berry S., et al., IEEE Conference on Aerospace, 2011
Edquist K., et al., Journal of Spacecraft and Rockets, 2014.

Motivation

- Supersonic Retropropulsion (SRP): Rocket propulsion to decelerate supersonic vehicle

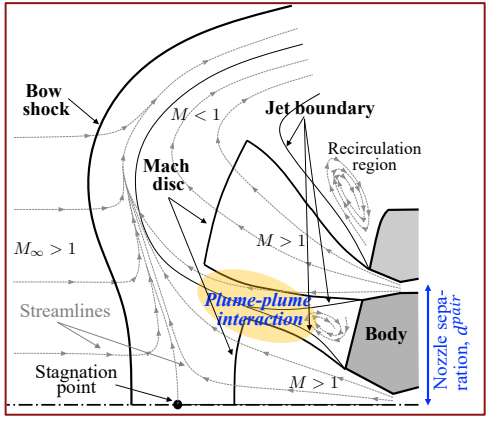
Experiments



Simulations

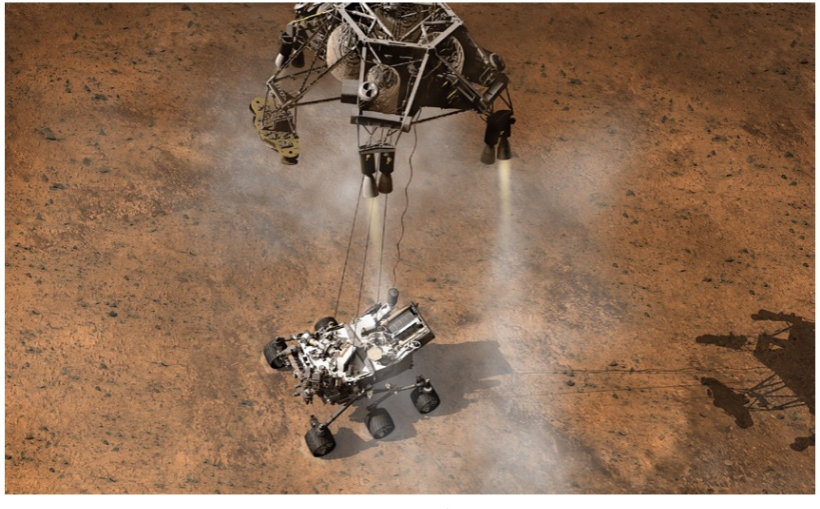


Physics



Motivation

- Past missions: Mars Science Laboratory and Mars 2020 both used retro-rockets (subsonic) in part to decelerate



Mars Science Laboratory

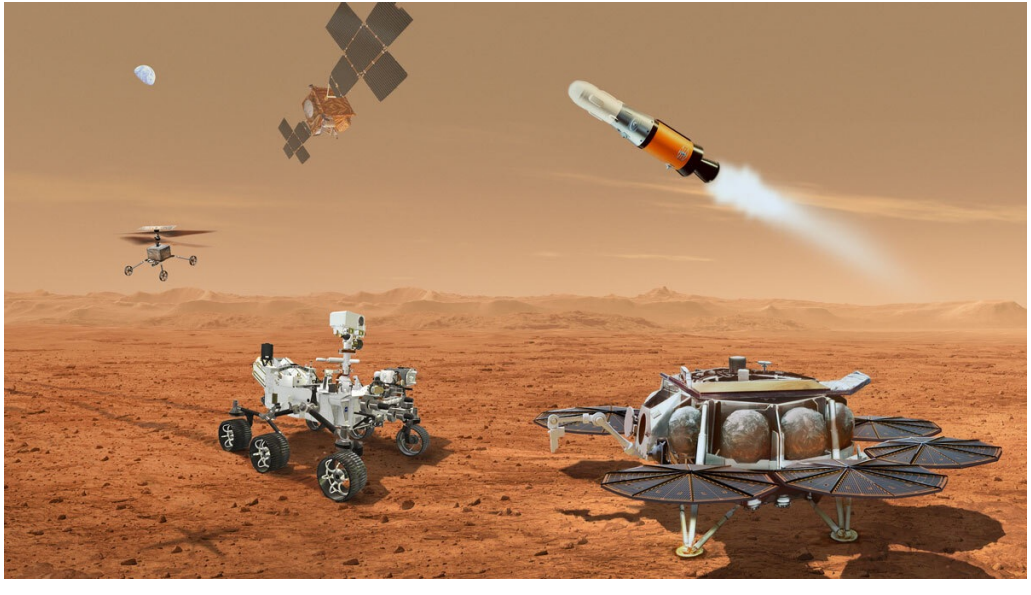


Mars 2020

https://mars.nasa.gov/internal_resources/824/;
https://mars.nasa.gov/mars2020/timeline/landing/

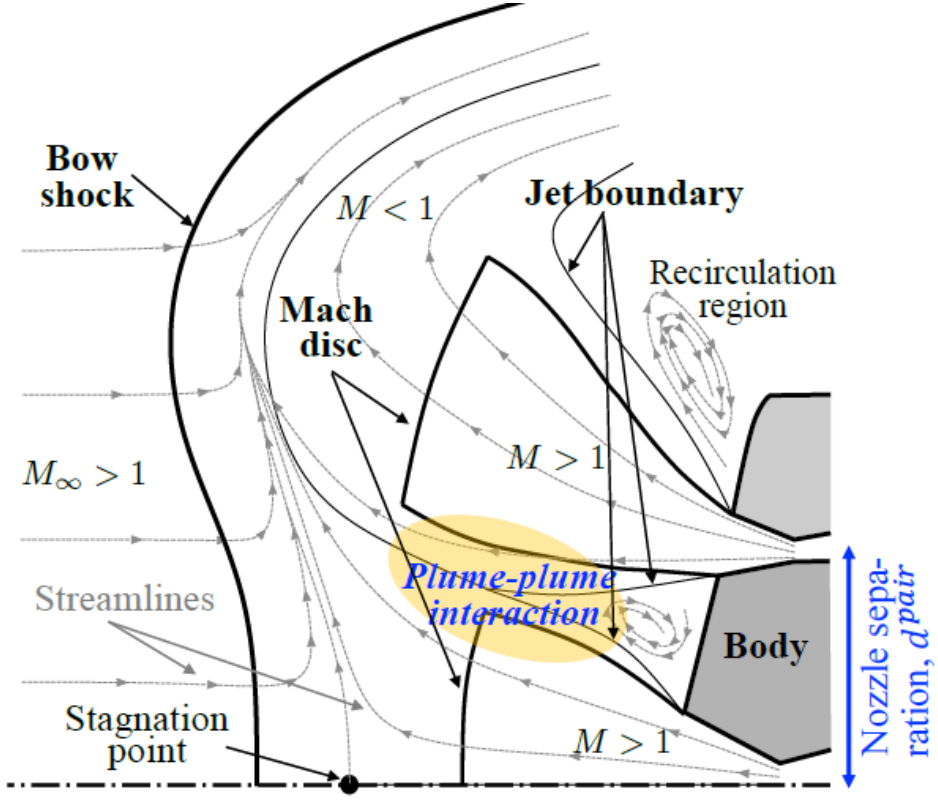
Motivation

- Future missions: Mars Sample Return Mission analyzing supersonic retropropulsion for potentially increasing mass of sample return



https//mars.nasa.gov/mars-exploration/missions/mars-sample-return/

Motivation: Multi-nozzle SRP



A. M. Korzun, R. D. Braun, and J. R. Cruz. J. Spacecr. Rockets, 46(5):929{937, 2009

Research Problem

Research question, objectives, and innovation

- Research Question: Can we employ emerging data-driven methods to existing wind tunnel data and develop improved low-order models for predicting SRP performance?

- Challenges
  - Ensure safety and optimize performance
  - Physical complexity of multi-nozzle flow physics
  - Limited flight data and sparse test data

Research question, objectives, and innovation

- Research Question: Can we employ emerging data-driven methods to existing wind tunnel data and develop improved low-order models for predicting SRP performance?

- Research objective
  - Develop hierarchical model framework to describe plume physics, plume-aerodynamics interaction, and sensitivity of aerodynamic forces and moments for relevant operating conditions and nozzle configurations

  - Integrate uncertainty quantification to consider experimental uncertainties, sparse and incomplete experimental data, and identify data gaps

Research question, objectives, and innovation

- Research Question: Can we employ emerging data-driven methods to existing wind tunnel data and develop improved low-order models for predicting SRP performance?

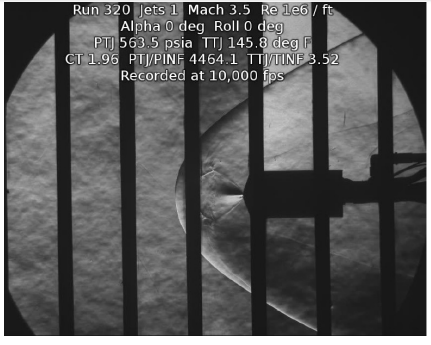
- Innovation
  - Combining novel data-analytic methods and physics-based analysis to develop hierarchical modeling framework for predicting multi-nozzle plume physics
  - Utilize interpretable data-analytic methods to represent complex physical processes and providing direct physical insight on SRP aerodynamics
  - Comprehensive verification, validation, and benchmark against experimental data and SOA-models

Background

Related Work

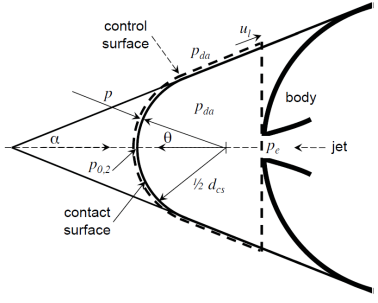
State-of-the-art in characterization of SRP

Wind tunnel tests



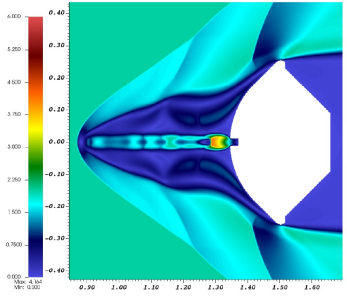
- Fundamental understanding
- Representative operating conditions
- Design concept evaluation
- Scale and application to realistic flight missions
- Limited diagnostics

Analytic methods



- Computationally efficient
- Physical insight
- Computational efficient
- Model assumptions
- Limitations to idealized flow problems
- Steady state

CFD simulations



- General approach, physics based; enables simulating very complex geometries and flows
- Representation of realistic flight conditions
- Limited predictive accuracy for complex flight scenario; inaccurate models
- Computationally expensive

Korzun, GA Tech, 2012; Cordell, GA Tech, 2013; Montgomery et al. AIAA, 2022; Daso AIAAJ 2009; Venkatachari, AIAA, 2013; Farr et al., AIAA 2015; Edquist et al., AIAA 2022; Berry, Rhode, NASA Technical Reports 2014.

State-of-the-art in characterization of SRP

Current Practice	Limits	Potential Contribution
Analytical reduced-order physical models	• Lower accuracy (especially $C_{TJ} < 0.8$) • Multi-nozzle model does not exist	• Derive a multi-nozzle physics model, leverage data to improve its accuracy
CFD	• Computationally expensive (NASA example: 48 hours with 900 processors https://www.nas.nasa.gov/SC11/demos/demo9.html)	• Build accurate & affordable machine learning model to identify designs worth simulating in CFD
Wind-tunnel experiments	• Expensive hardware • Scheduling constraints • Small-scale rocket (limited by wind tunnel size)	• Build accurate & affordable machine learning model to identify designs worth experimenting • Multi-nozzle physics model to address scaling
Uncertainty quantification	• Lack of advanced data-driven methods specifically applied to SRP	• Apply state-of-the-art data-driven methods to SRP

State-of-the-art in characterization of SRP

- NASA dedicated to more wind-tunnel tests, CFD, and planning for flight tests
- SpaceX flight testing in Mars-like conditions
- DLR dedicated to wind-tunnel tests, and CFD





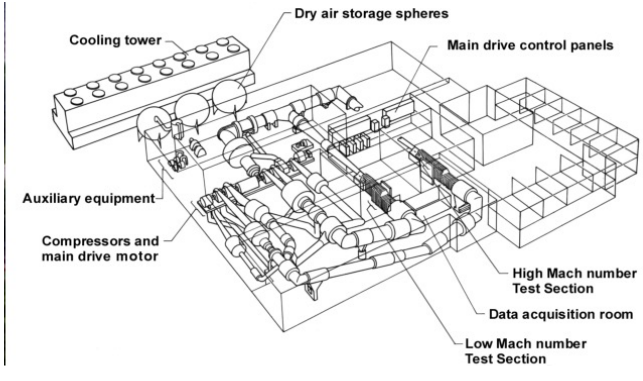
https://www.reddit.com/r/spacex/comments/kgnglz/supersonic_retropropulsion_burn_on_reentry_shot/

https://www.dlr.de/as/en/desktopdefault.aspx/tabid-15884/25745_read-66185/

Dataset

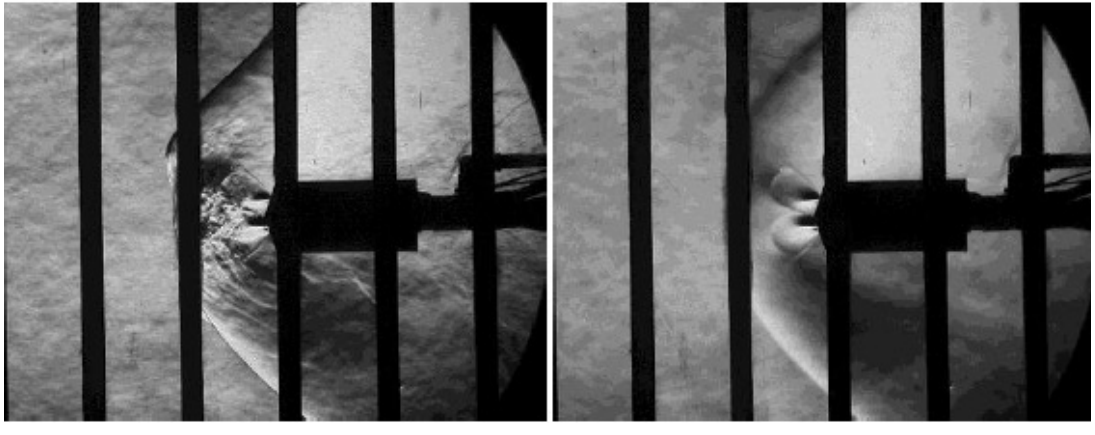
Experimental data: Langley Unitary Plan, Ames





Single Image

Average Intensity



Images and dataset: Berry, S. A. and Rhode, M. N. NASA/TP–2014-218256, Test 1853.

Data Interface Progress

- Approach: Generate common database for all test cases; Develop and implement analysis tools for browsing, analyzing, and pre-processing test-data
  - Use **Pandas** (https://pandas.pydata.org) to process wind tunnel data

➔ **Dataset with 1.7 million values**

  - Python module, to store and plot data
  - open-source data analysis and manipulation tool, built on top of the Python programming language

	TEST	RUN	POINT	ACQDATE	ACQTIME	DATAREV	CONFIGCO	FAC	\
0	1853.0	13.0	493.0	20100710.0	93154.57	1.6	0.0	8.0	
1	1853.0	13.0	494.0	20100710.0	93159.92	1.6	0.0	8.0	
2	1853.0	13.0	495.0	20100710.0	93228.13	1.6	0.0	8.0	
3	1853.0	13.0	496.0	20100710.0	93241.72	1.6	0.0	8.0	
4	1853.0	13.0	497.0	20100710.0	93551.73	1.6	0.0	8.0	
...	...	...	...	...	...	...	...	...	
2945	1853.0	321.0	3662.0	20100730.0	164023.50	1.6	1.0	8.0	
2946	1853.0	321.0	3663.0	20100730.0	164049.80	1.6	1.0	8.0	
2947	1853.0	321.0	3664.0	20100730.0	164121.00	1.6	1.0	8.0	
2948	1853.0	321.0	3665.0	20100730.0	164218.10	1.6	1.0	8.0	
2949	1853.0	321.0	3666.0	20100730.0	164306.90	1.6	1.0	8.0	

	SREF	LREF	...	CP169	CP170	CP171	CP172	CP173	\
0	0.13635	0.41667	...	-0.013136	-0.046248	-0.070952	-0.068860	-0.050740	
1	0.13635	0.41667	...	-0.013058	-0.046088	-0.070330	-0.068476	-0.050964	
2	0.13635	0.41667	...	-0.013062	-0.045951	-0.070622	-0.068587	-0.050765	
3	0.13635	0.41667	...	-0.013058	-0.045638	-0.070573	-0.068661	-0.050711	
4	0.13635	0.41667	...	-0.020370	-0.030514	-0.042182	-0.045102	-0.044248	
...	...	...	...	...	...	...	...	...	
2945	0.13635	0.41667	...	-0.000208	0.036658	0.035388	0.045508	0.051067	
2946	0.13635	0.41667	...	-0.010372	0.025374	0.035413	0.058526	0.070129	
2947	0.13635	0.41667	...	-0.010747	0.025989	0.035607	0.058808	0.070341	
2948	0.13635	0.41667	...	0.000520	0.037515	0.035176	0.045376	0.051831	
2949	0.13635	0.41667	...	0.016434	0.055658	0.037935	0.030228	0.028922	

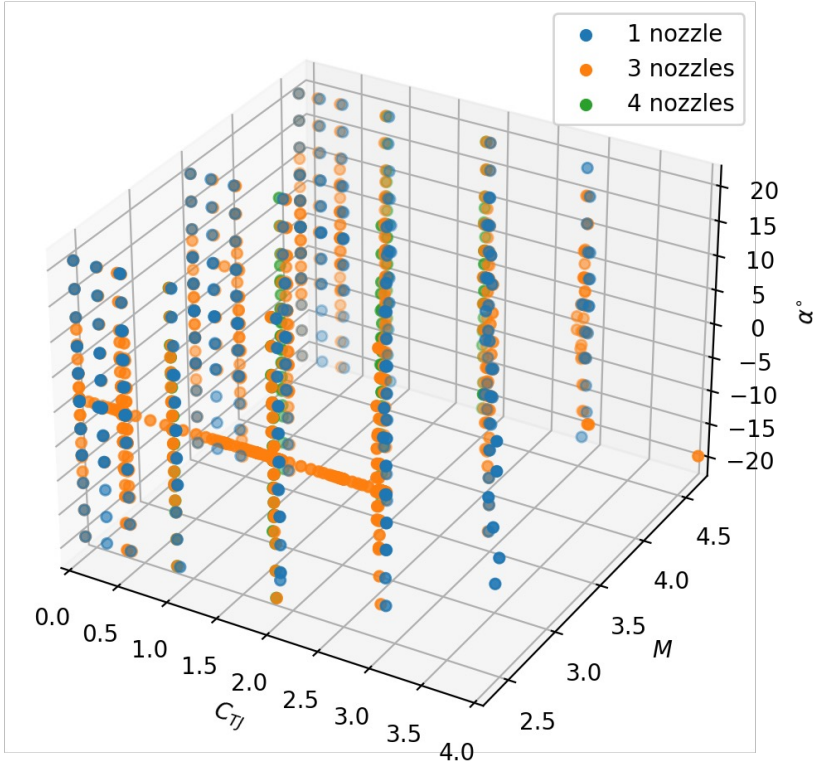
	CP174	CP175	CP176	MODELNO	JET
0	-0.019511	-0.074048	-0.030556	1.0	0.0
1	-0.019321	-0.073916	-0.030902	1.0	0.0
2	-0.018750	-0.073657	-0.030227	1.0	0.0
3	-0.018940	-0.073977	-0.030755	1.0	0.0
4	-0.021669	-0.041842	-0.035578	1.0	0.0
...	...	...	...	...	...
2945	0.024183	0.022352	0.039255	1.0	1.0
2946	0.013955	0.021434	0.056945	1.0	1.0
2947	0.014229	0.021624	0.057556	1.0	1.0
2948	0.025183	0.022215	0.039659	1.0	1.0
2949	0.041160	0.026094	0.019442	1.0	1.0

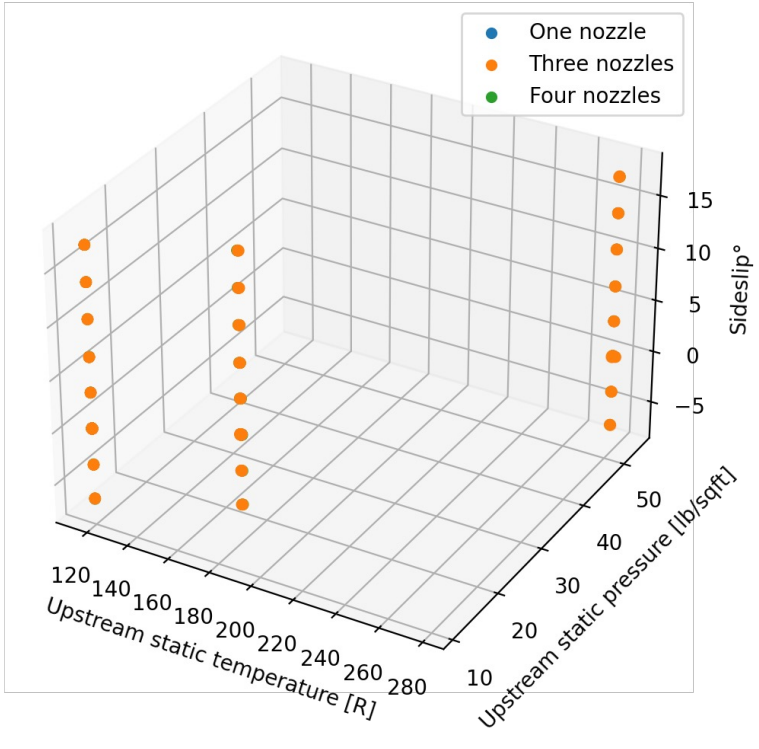
[2950 rows x 581 columns]

pandas

Dataset and Pipeline

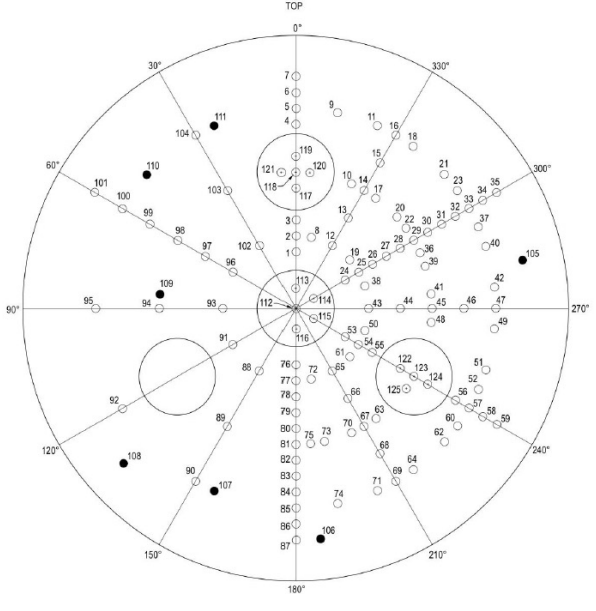
- Visualization of data set

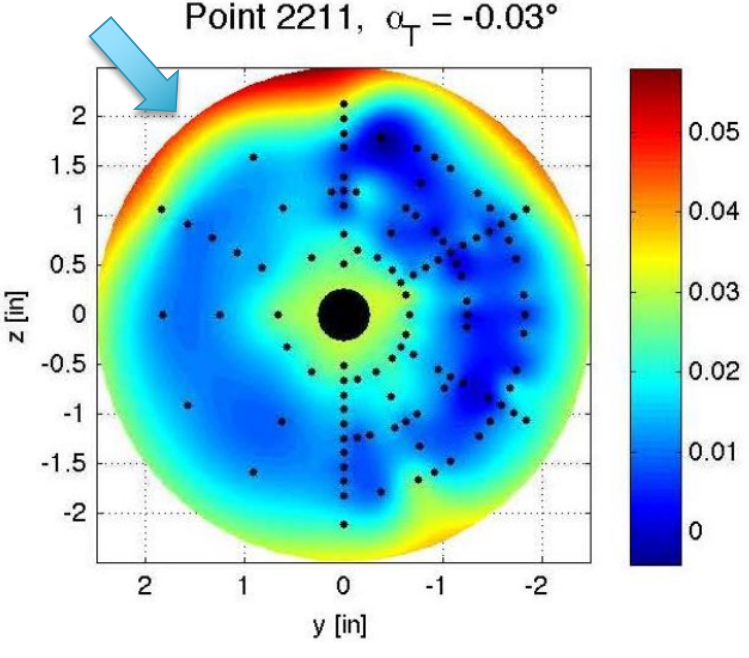




Data analysis

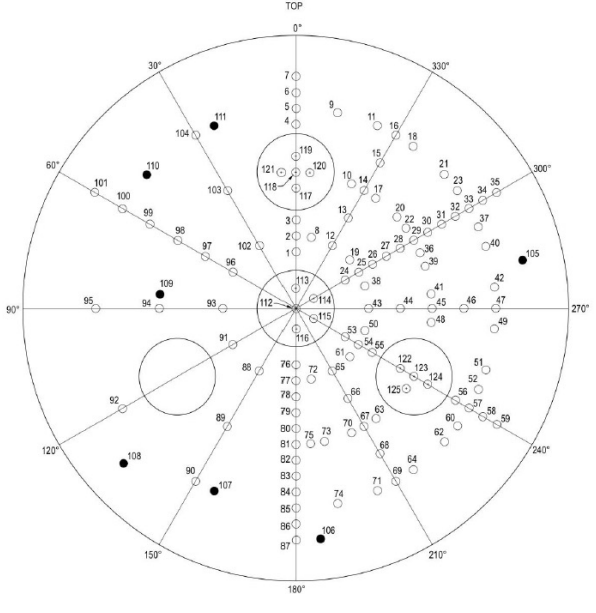
- Pressure probes on surface, compute surface pressure from biharmonic split fit

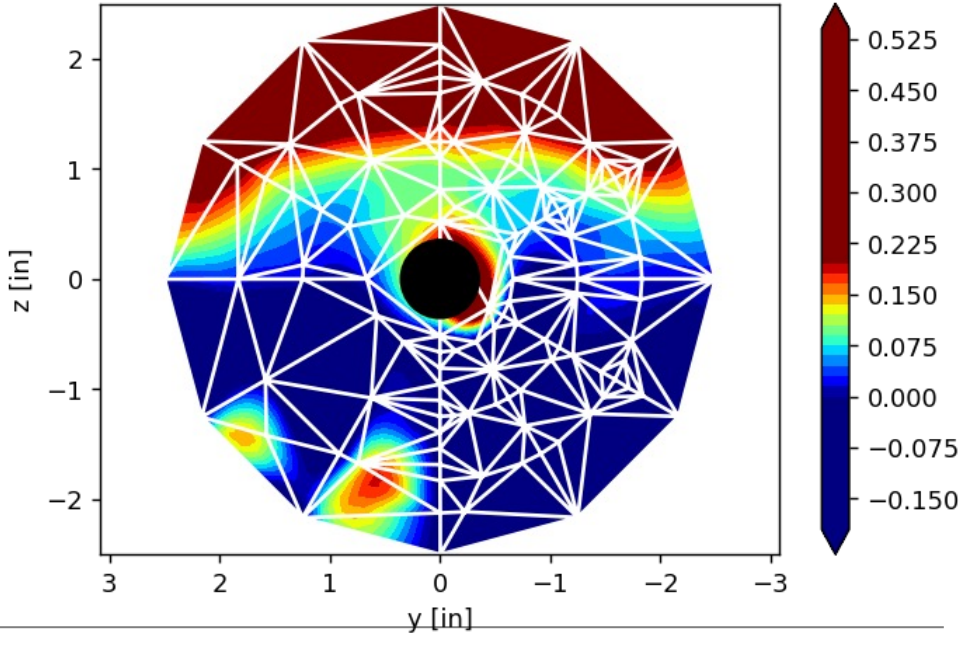




Data analysis

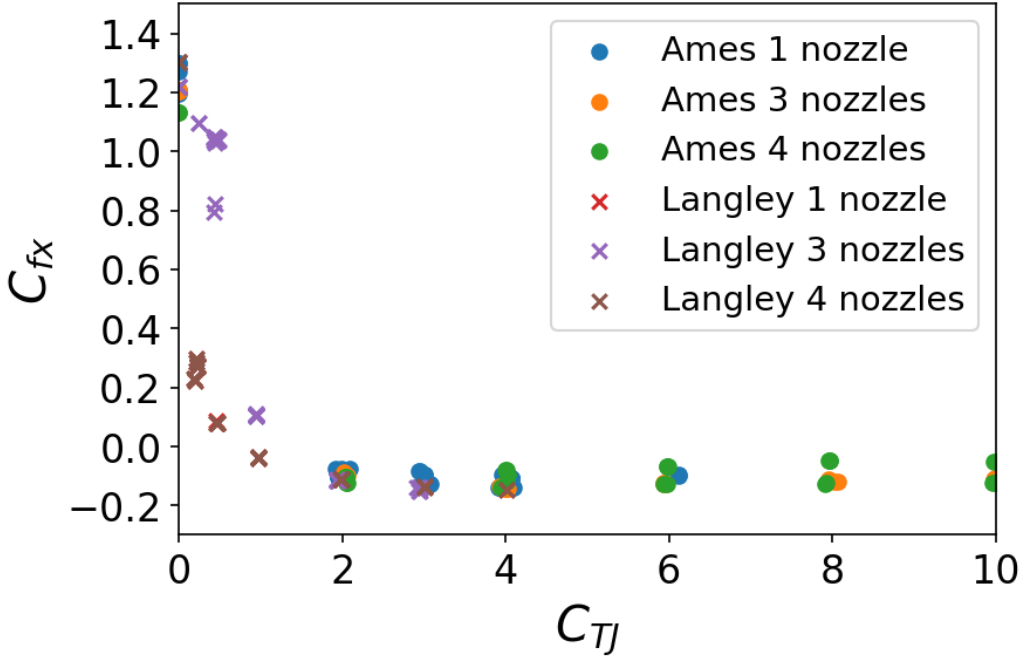
- Compute surface pressure from Delaunay Triangulation





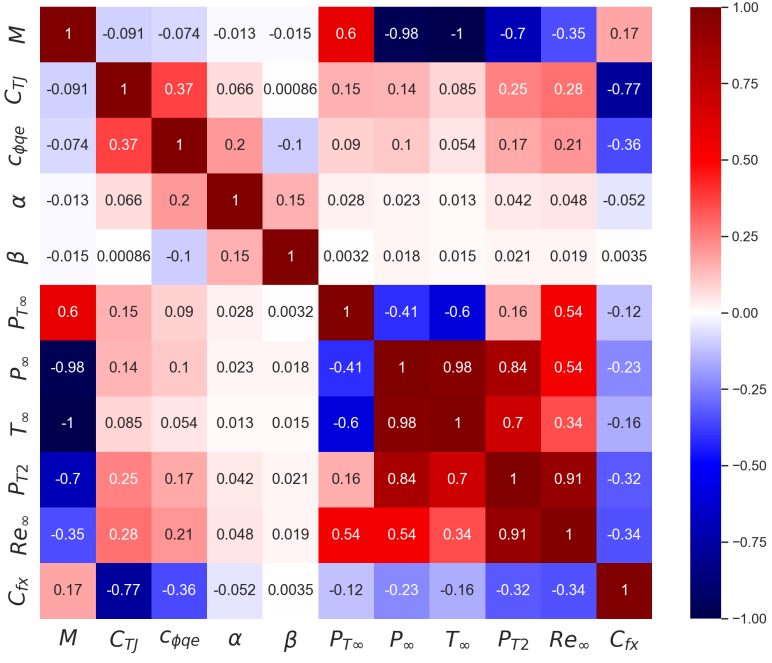
Integration of Ames and Langley data

- Overlapping conditions shows good agreement ($\mathrm{M} = 2.4;\ \alpha = \beta = 0°$)

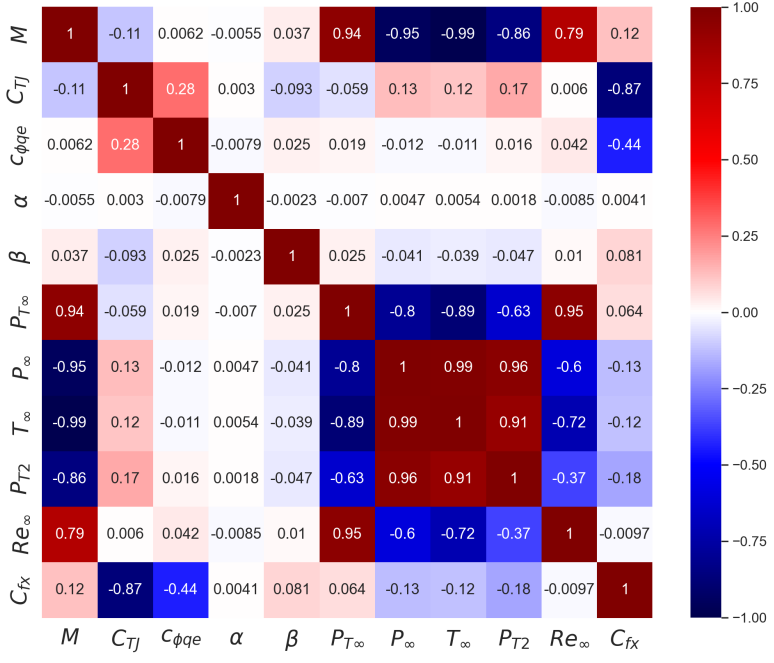


Analysis of Ames data

- Ames Data Heatmap



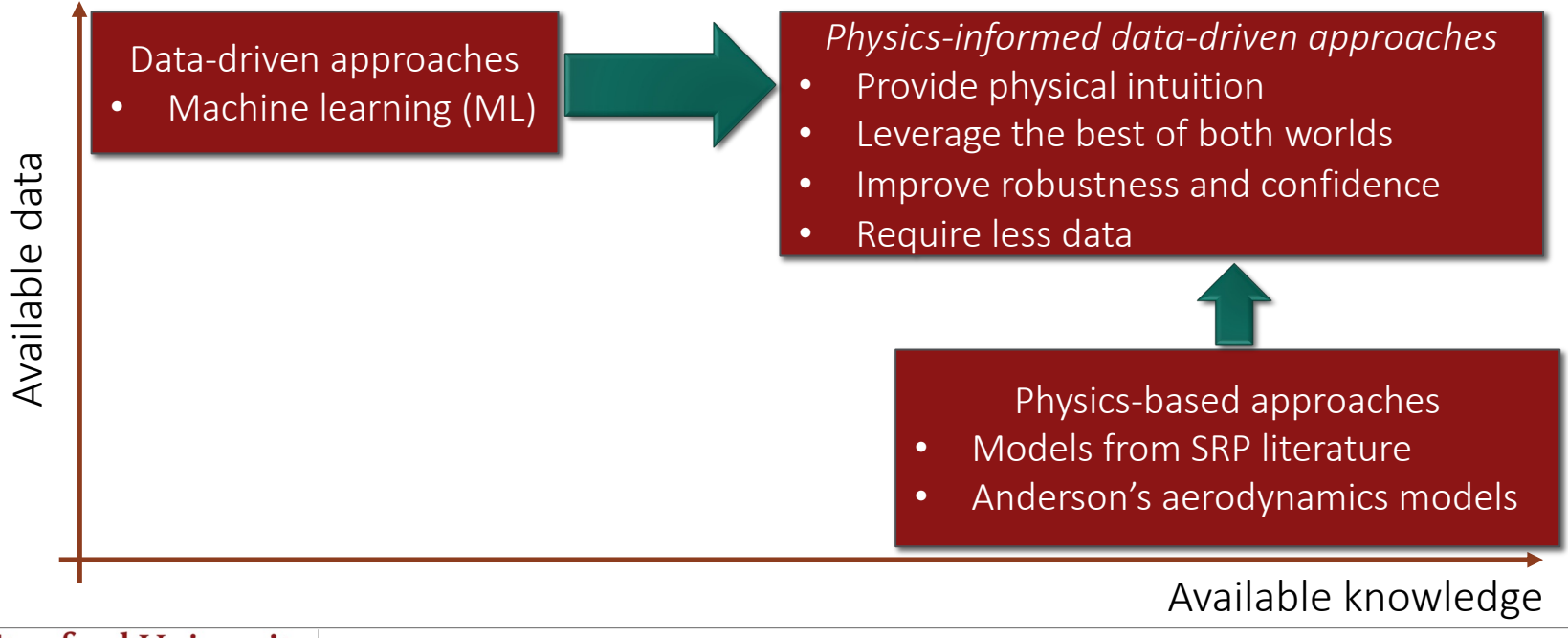
- Langley Data Heatmap



Model formulation

Data-driven methods

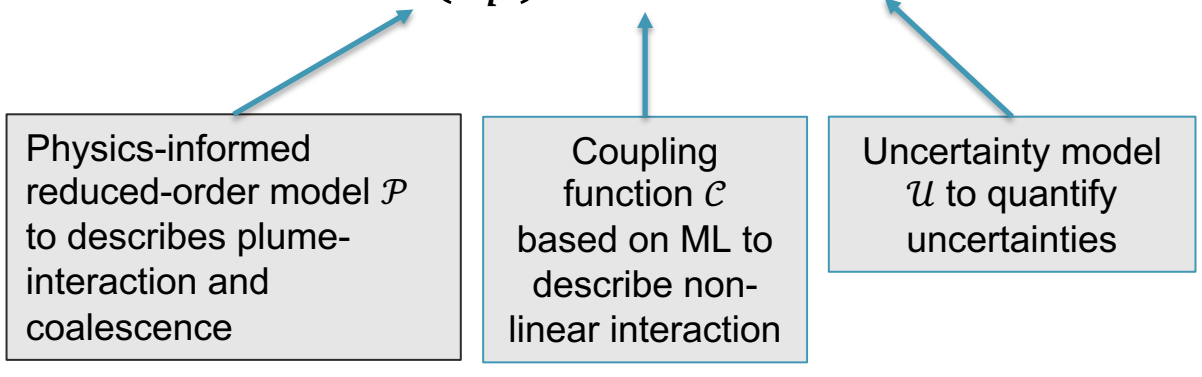
- Key idea: develop hierarchical physics-informed data-driven approach



Mathematical model

- Develop data-driven modeling framework to predict aerodynamic quantities C

$$C = \mathcal{P}(\theta_p) * \mathcal{C}(\theta_c) + \mathcal{U}(\theta_u)$$



- Employ data-analytics and physics knowledge to identify key input parameters θ_p, θ_c that capture flow field behavior

Mathematical Model

- QoI: Total decelerative force C_A: $C_A = C + C_{TJ}$
- Additive framework: target quantity of interest C at rocket heatshield

$$C = \underbrace{C_0 + C_{SRP}}_{\mathcal{P}(\theta_p)} + \underbrace{C_{NN}}_{\mathcal{C}(\theta_c)}$$

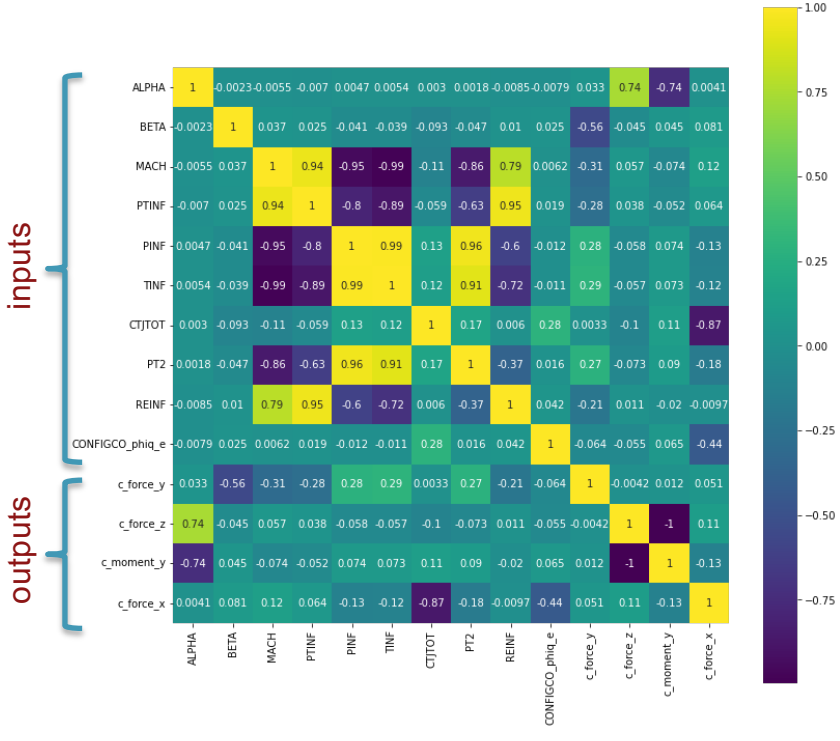
C: Aerodynamic x-force coefficient on heatshield
C_0: zero thrust vehicle model
C_{SRP}: model with SRP rocket on
C_{NN}: multilayer perceptron residual regression NN model
C_A: total decelerative force
C_{TJ}: thrust coefficient

➔Framework can assimilate new data to improve model accuracy and robustness

Korzun AM. Georgia Institute of Technology; 2012.
Anderson, J. D. McGraw-Hill Education; 2017.
AL-Ma'amari, M. Towards Data Science; 2018.

Identify reduced input for physical model, θ_p

- Feature correlation heatmap
  - Use heatmap to examine relationship between variables, and their relationship strength
  - C_{fx} ~ thrust and configuration
  - C_{fy} ~ sideslip and Mach
  - C_{fz} ~AoA and thrust; Mach
  - C_{fmy} ~ AoA and thrust; Mach

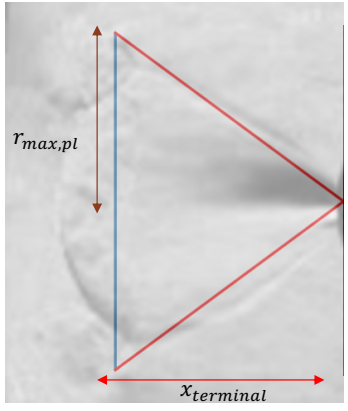


Development of physical model $\mathcal{P}$

- Introduce blockage ratio (BR) to relate the amount of blockage to C_{fx}
- Blockage Ratio (BR) model is based on Cordell (2013)

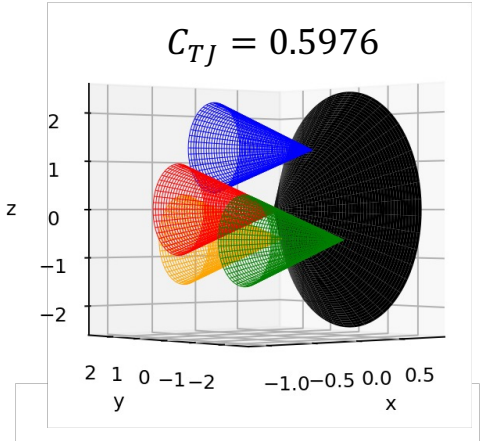
$$BR = f \quad (\boldsymbol{r}, N_{nozzles}, \boldsymbol{c_\theta}, \alpha_T, \boldsymbol{c_{VA}}, \boldsymbol{P_J}, P_{T2})$$

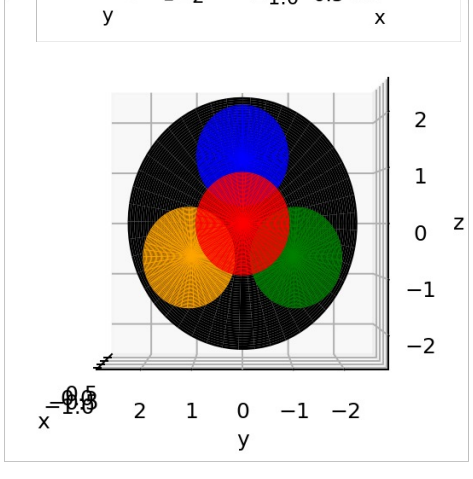
$$r_i = f \quad \left(M_\infty, \frac{P_{J,i}}{P_{T2}}, P_\infty\right)$$

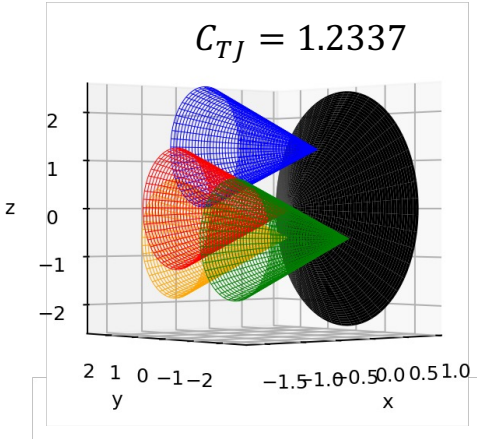


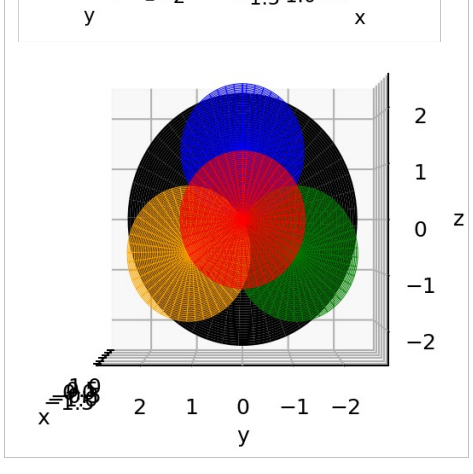
$Subscript\ i: for\ an\ individual\ nozzle$
$r: maximum\ radius$
$M_\infty: freestream\ Mach$
$P_J: Nozzle\ exit\ static\ pressure$
$P_{T2}: post\ normal\ shock\ stagnation\ pressure$
$P_\infty: freestream\ pressure$
$N_{nozzles}: number\ of\ nozzles$
$A_{plume}: plume\ area$
$A_{ref}: forebody\ area$
$c_\theta: Nozzles'\ inboard\ angles\ from\ central\ axis$
$\alpha_T: total\ angle\ of\ attack$
$c_{VA}: 2D\ Voronoi\ diagram\ area$

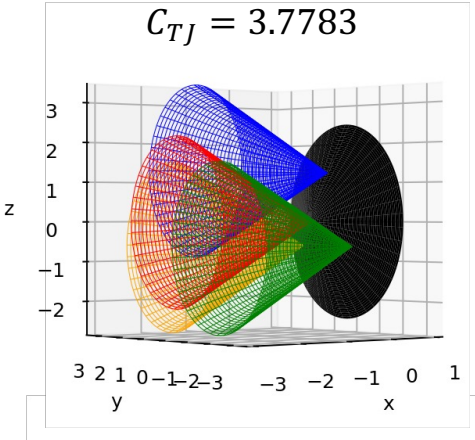
Blockage ratio: 4 nozzles, $M_\infty = 3.5, \alpha = \beta = 0°$

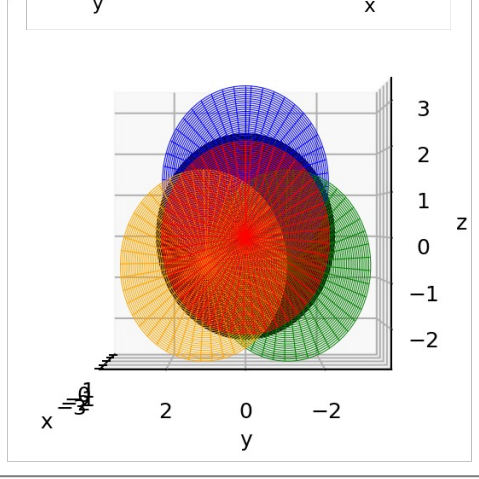






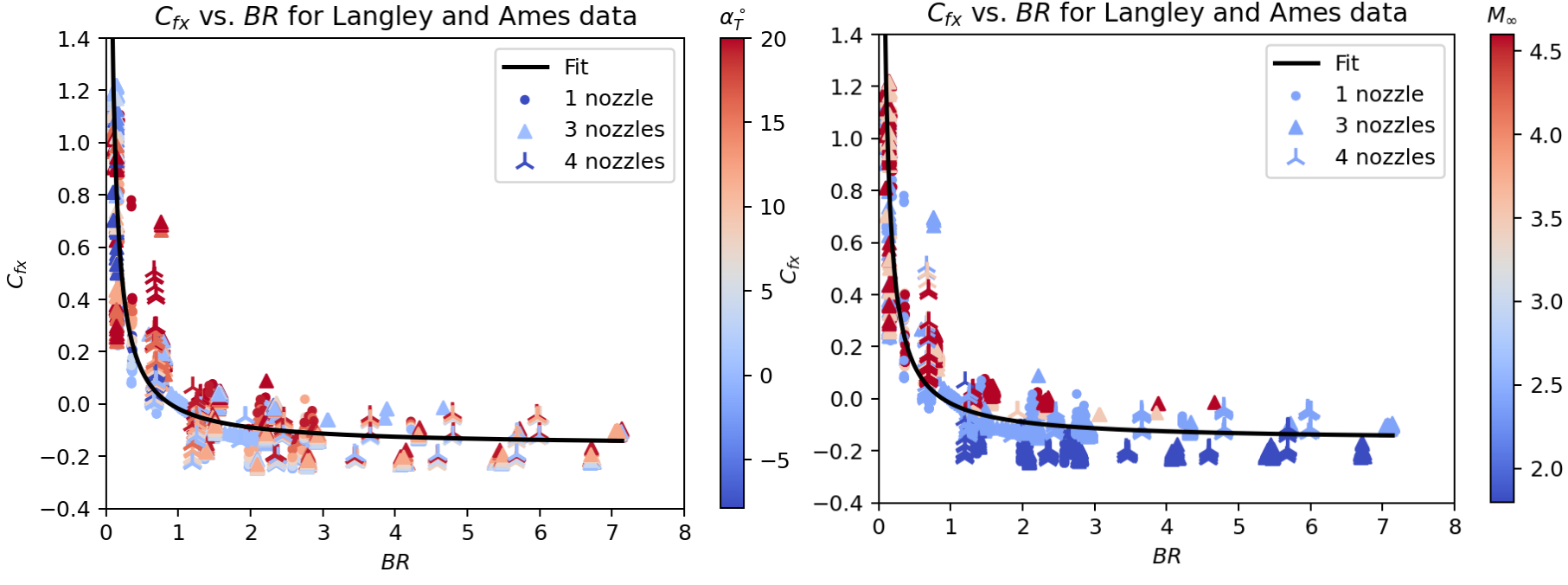






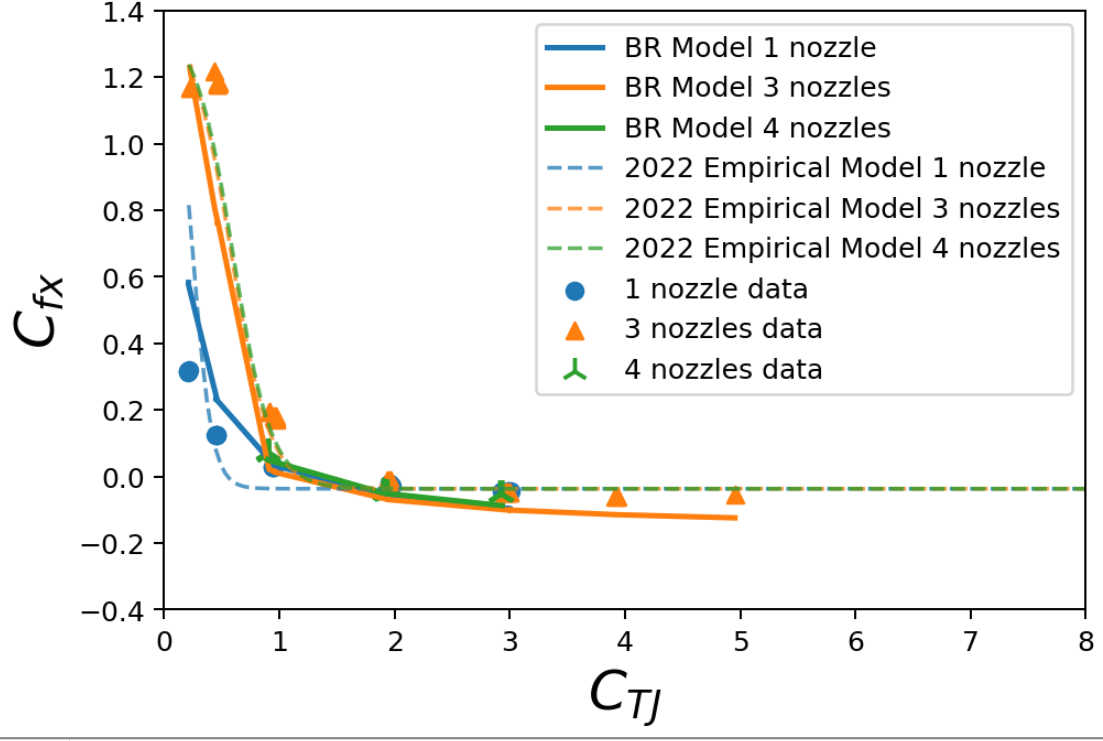
Blockage ratio model

- Regress data to obtain parametric blockage model $C_{fx} = \frac{a}{\mathrm{BR}} + b$



Result #2: BR Model

- BR model's $\mathcal{P}$ compared to 2022 model's $\mathcal{P}$. $M_\infty = 3.5, \alpha = \beta = 0°$



$$C = \mathcal{P}(\theta_p) * \mathcal{C}(\theta_c) + \mathcal{U}(\theta_u)$$

Development of coupling model $\mathcal{C}$

- Key idea
  - Augment physical model by coupling function to capture complex physical processes not captured by the foundational model ➔ residual model
  - Construct coupling function from neural network
  - Leveraging physical knowledge enhances
    - NN architecture design
    - Robustness of predictions
    - Generalization capability

Identify input for coupling model, θ_c

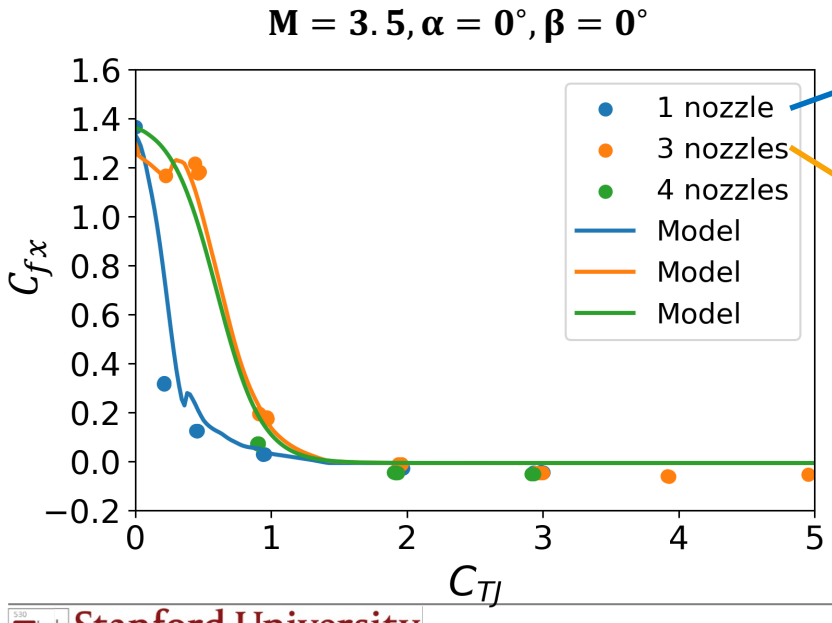
- Used data-driven methods to corroborate physics model inputs, and physics domain knowledge to determine ML model inputs

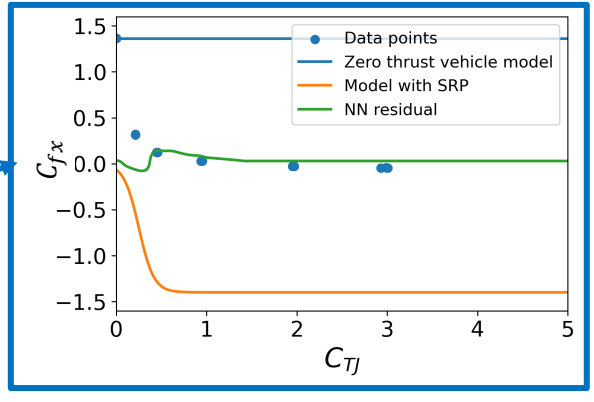
$$\theta_c = \{\alpha, \beta, M, P_{T\infty}, P_\infty, \mathrm{T}_\infty, C_{TJ}, P_{T2}, Re_\infty, c_{\varphi qe}\}$$

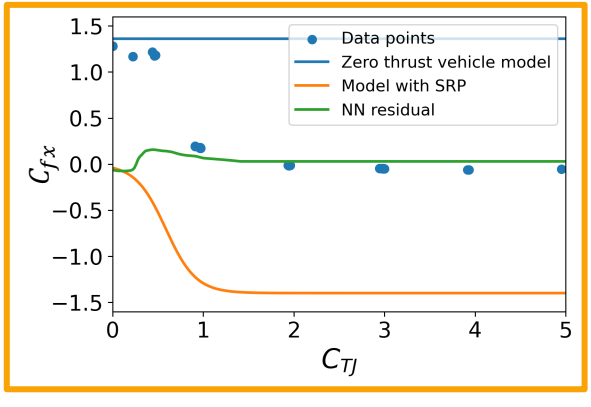
- Trained standard residual regression NN architecture with:
  - Input θ_c, Output C_{fx}
  - Adam optimizer w.r.t. mean squared error loss
  - Affordable: 105 seconds to train, 0.03 seconds for each prediction on i7 CPU

Model performance

$$C_{fx} = \underbrace{\mathcal{P}(\theta_p)}_{\text{Physical model}} + \underbrace{C_{NN}(\theta_c)}_{\text{NN residual}}$$







Summary and next steps

Conclusions

- Proposed physics-informed data-driven framework for modeling SRP
  - Low-order physical model
  - Coupling function to account for non-linear coupling
  - Uncertainty quantification
- Developed data pipeline for experimental data
- Model development
  - Identify low-dimensional manifold that capture key-physical processes
  - Employ data-driven approach as non-linear coupling function
- Demonstrated hierarchical physics-informed data-driven approach in application to experimental data

Next steps

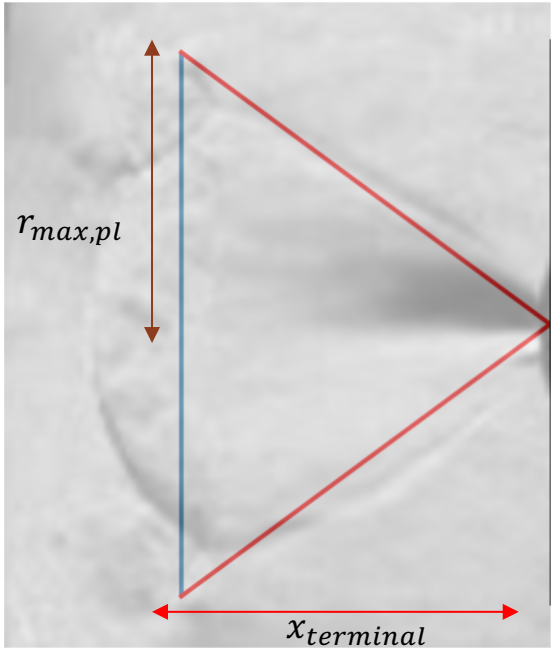
- Incorporate UQ analysis (DropoutNN, Gaussian Process Regressor)
- Extend experimental database by incorporating most recent measurements
- Improve physics-based model consider NS-based approach
- Employ model for UQ-analysis and flight trajectory planning

Related publications

- Wu, D., Chung, W. T., Ihme, M., Edquist, K., Korzun, A. “Physics-informed Data-driven Modeling of Supersonic Retropropulsion” 19th International Planetary Probe Workshop, Santa Clara, CA, 8/29-9/2/2022
- Wu, D., Chung, W. T., Ihme, M., Edquist, K. “Physics-informed Data-driven Modeling of Supersonic Retropropulsion” American Physical Society’s Division of Fluid Dynamics, Indianapolis, IN, 11/20-22/2022
- Wu, D., Chung, W. T., Ihme, M. “ML4LM: Machine Learning for Safely Landing on Mars” NeurIPS Workshop: Machine Learning and the Physical Sciences, New Orleans, LA, 12/3/22

Prior Work: Single-Nozzle (Cordell 2013) vs. Schlieren

$M_\infty = 3.5$, thrust coefficient $C_{TJ} \equiv \frac{Thrust}{q_\infty A_{ref}} = 0.94$



[3] Cordell, Christopher E. et al. "Analytical Modeling of Supersonic Retropropulsion Plume Structures". *Journal of Spacecraft and Rockets* 50.4 (2013): pg. 763-770.

Prior and Parallel Work

- To upscale small-scale wind-tunnel to full-scale vehicle

Rationalizing Equations	Applications	Requirements	Scaling Parameter(s)
Navier-Stokes	All SRP geometries and flows	Continuum gases Both plume and freestream gases Smooth, solid surfaces	M_∞, Re_∞ Geometric similitude in freestream and plume flows
Momentum conservation	Approximation of the scale of AI region relative to vehicle	Meet above requirements Similar freestream and plume gas physical properties	$C_{TJ} = \frac{\tau}{q_\infty A_{ref}}$
Mass conservation	Approximation of the scale of AI region relative to vehicle	Meet above requirements Similar freestream and plume gas physical properties	$\frac{\rho_e V_e A_e}{\rho_\infty V_\infty A_\infty}$
Momentum and mass conservation	Scaling of AI flow from one set of gases to another	Meet above requirements except that for similar gas properties	γ_∞, γ_e $\frac{MW_j T_{0,\infty}}{MW_\infty T_{0,j}}$
Energy conservation	Scaling of aeroheating effects	Meet above requirements	$\frac{c_{p,j} T_{0,j}}{c_{p,\infty} T_{0,\infty}}$

Korzun AM, Cassel LA. "Scaling and Similitude in Single Nozzle Supersonic Retropropulsion Aerodynamics Interference". *AIAA SciTech 2020.* DOI: 10.2514/6.2020-0039

Quantification of nozzle configuration

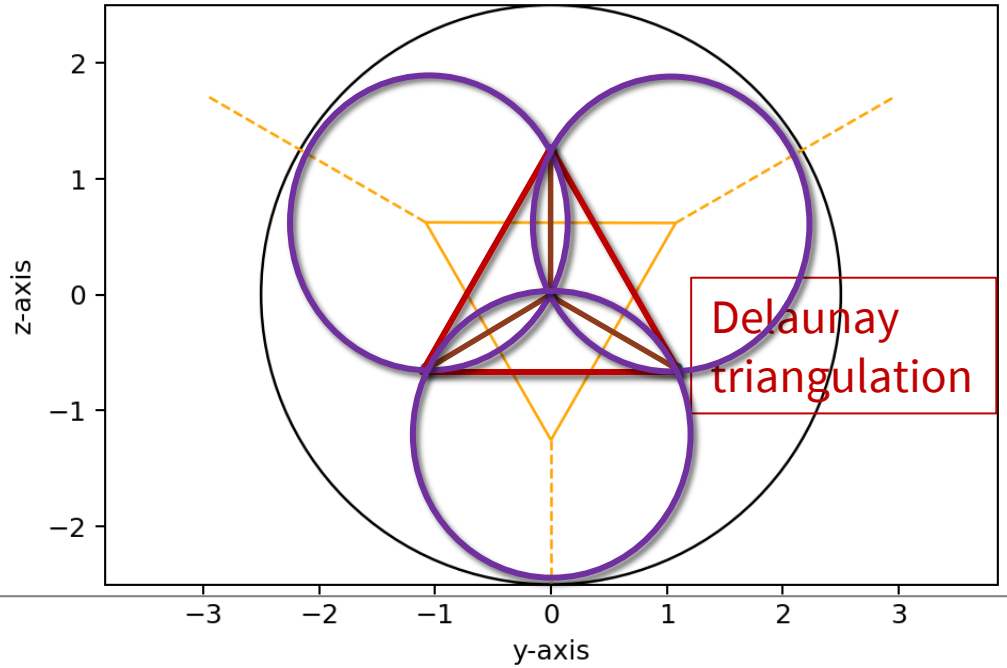
Number of nozzles	Polar Coordinates $[inch, °]$ R from center, Angle from z-axis +counterclockwise	Morris-Mitchell sum of distances between nozzles. e^{inch} $c_{\varphi qe}$	2D Voronoi diagram, area of each region. $inch^2$ c_{VA}	Nozzles' inboard canted angles [°] from central axis c_θ
1	$[0.003 \quad 193.0]$	1	$[19.635]$	$[0]$
3	$\begin{bmatrix} 1.247 & 0.095 \\ 1.248 & 240.0 \\ 1.248 & 120.0 \end{bmatrix}$	4.007	$\begin{bmatrix} 6.545 \\ 6.545 \\ 6.545 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
4	$\begin{bmatrix} 0.003 & 193.0 \\ 1.247 & 0.095 \\ 1.248 & 240.0 \\ 1.248 & 120.0 \end{bmatrix}$	39.7973	$\begin{bmatrix} 2.0226 \\ 5.8708 \\ 5.8708 \\ 5.8708 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$

2D Voronoi diagram: 4 nozzle configuration

The dual graph of a Voronoi diagram is a Delaunay triangulation. Compute C_{VA} using 2D area(s) of Voronoi diagram then account for rocket heatshield boundary.

Blue dots are nozzle' centers

Orange lines are Voronoi cell boundaries

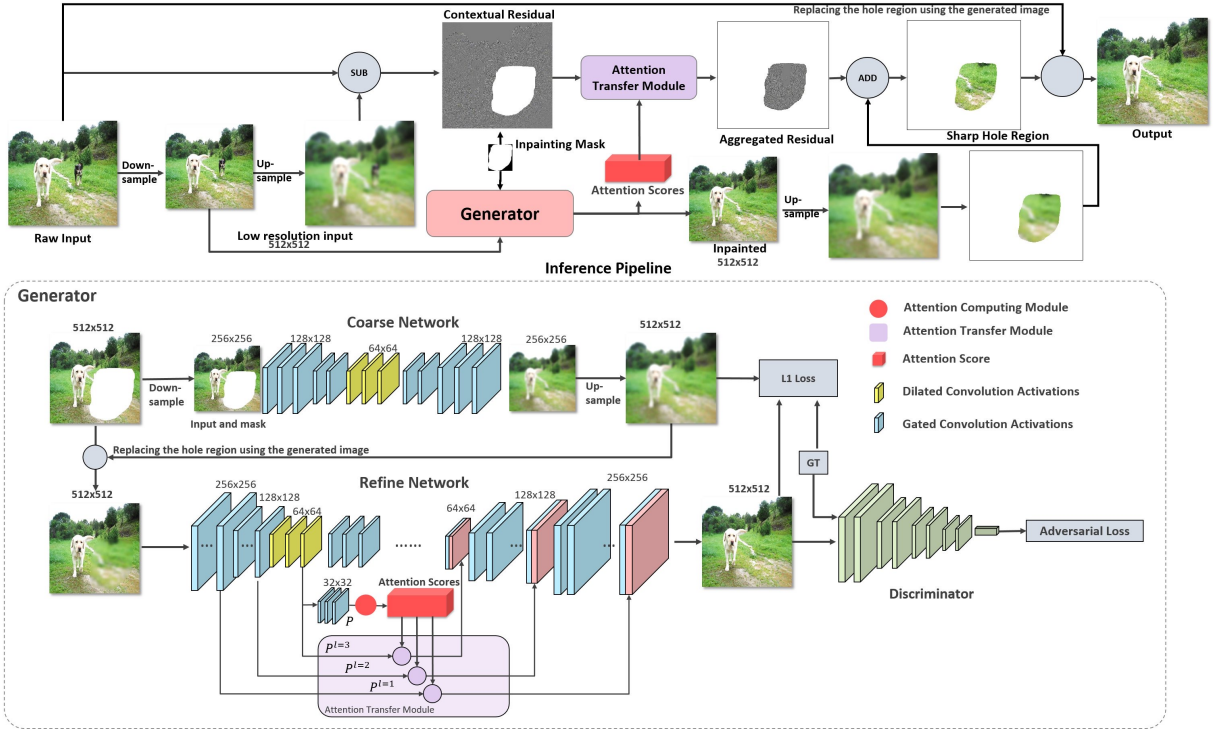


The circumscribing circles' centers are vertices of Voronoi diagram

mage Inpainting

Built a preprocessing tool that can remove obstructions from Schlieren images.

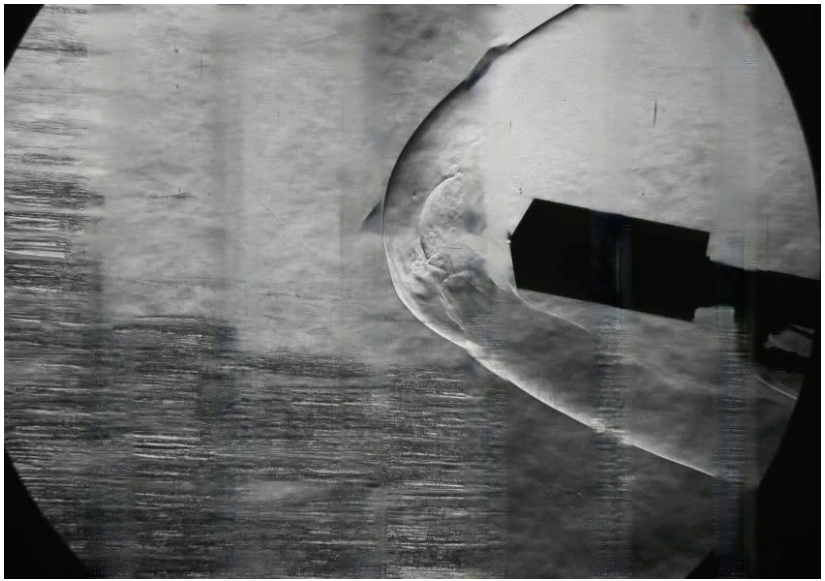
- CRA GAN Architecture (Yi et al. 2020)
- Customize GAN for schlieren images



mage Inpainting Results

- Center M4 A12 R165





mage Inpainting Results

- Center M4 A0 R165



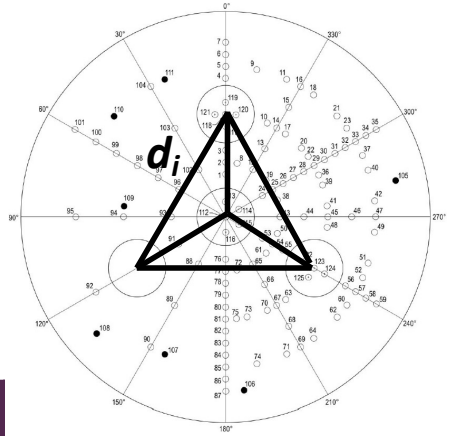


Result #1: HPDD Model

Quantify nozzle locations: use pairwise distance with Morris-Mitchell, then compute exponential

$$\Phi_q(X) = \left(\sum_i d_i^{-q} \right)^{1/q}$$

- X is input set of coordinates
- Used $q = 1$
- Used 2-norm for d_i



Number of Nozzles	Φ_q	$c_{\varphi qe} = e^{\Phi_q}$
0	None	0.0
1	0.0	1.0
3	1.3881	4.007