

# Training Knowledge Bots for Physics Based Simulations Using Artificial Neural Networks

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# Overview

## Introduction

Purpose and Motivation

## Knowledge Bot

Training the Knowledge Bot for Physics Based Simulations

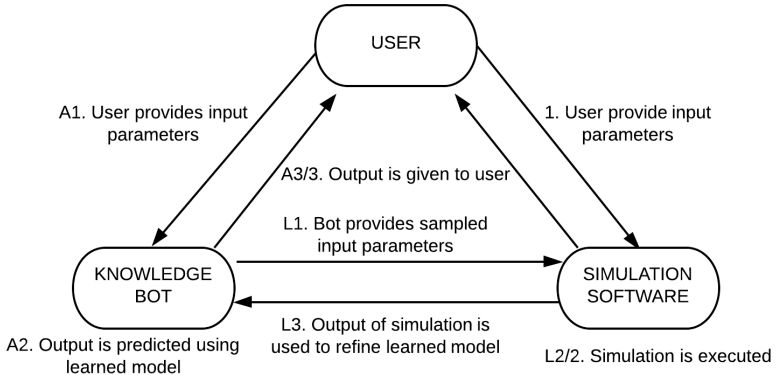
## Trajectory Analysis

Trajectory Analysis with POST2, Program to Optimize Simulated Trajectories

## Conclusion

Summary and Final Thoughts

# Purpose of the Knowledge Bot

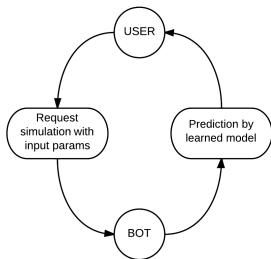


*Role of the knowledge bot in system analysis and design process*

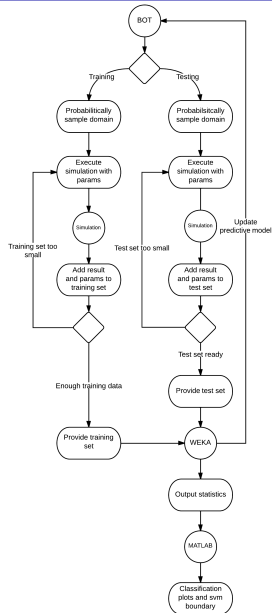
# Purpose of the Knowledge Bot

- ▶ In system analysis the following physics base simulations are essential in the design and analysis process,
  1. Computational Fluid Dynamics (CFD)
  2. Trajectory Analysis (POST2)
  3. Finite Element Analysis (NASTRAN)

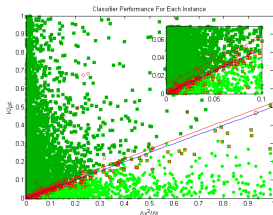
# Approach



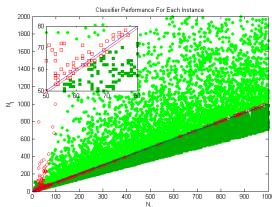
*User-Bot relationship*



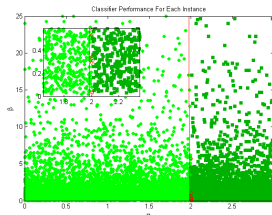
# Classification Results



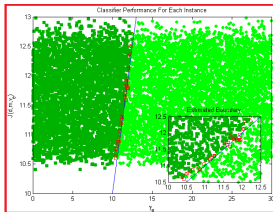
*Parabolic 1D Heat Conduction*



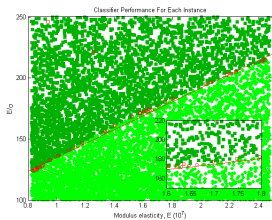
*Hyperbolic Wave Equation*



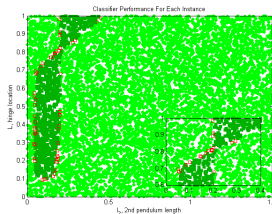
*Elliptic Laplaces' Equation*



*Venus Direct Entry Trajectory*

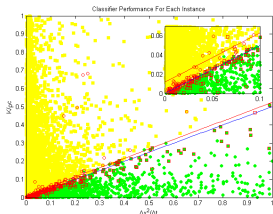


*Pressure Vessel Design*

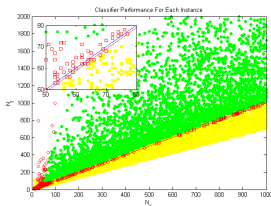


*Slosh Propellant Dynamics*

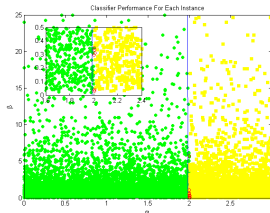
# Classification Results



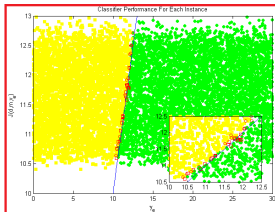
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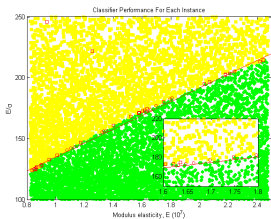
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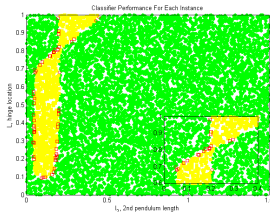
*Elliptic Laplace's Equation*



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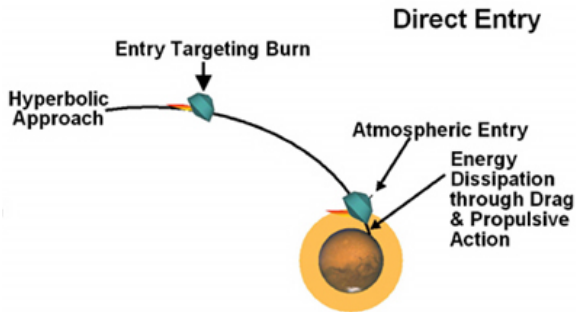


*Pressure Vessel Design*



*Slosh Propellant Dynamics*

# Direct Entry Problem



*Illustration of direct entry concept<sup>1</sup>*

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<sup>1</sup><http://cosmology.com/Mars128.html>

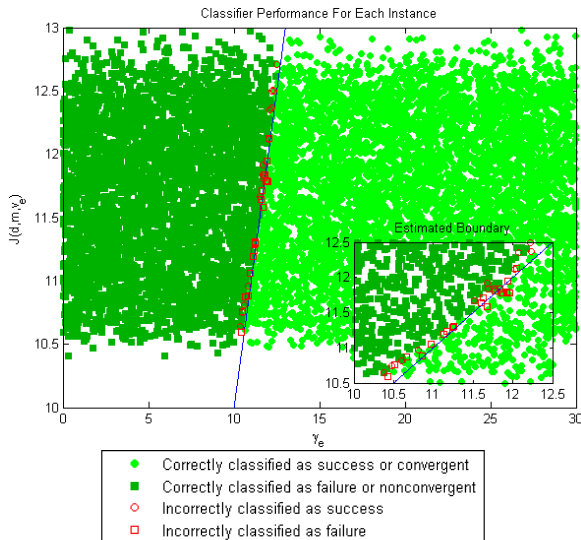


## Direct Entry Problem

- ▶ Purpose was to observe atmospheric-assisted direct entry of a 45-degree sphere-cone vehicle using  $d$  (diameter),  $m$  (mass),  $v_e$  (entry velocity),  $\gamma_e$  (entry flight path angle) on planet Venus
- ▶ Find region where successful entries and failed entries will occur at, some instances may be captured some may not
- ▶ Train neural network to classify when success or failure will occur based on input parameters
- ▶ Probabilistically sampled  $0.5m \leq d \leq 4.0m$ ;  
 $500kg \leq m \leq 5000kg$ ;  $10km/s \leq v_e \leq 13km/s$ ; and  
 $-30^\circ \leq \gamma_e \leq 0^\circ$
- ▶ Use SVM to discover clear boundary between success and failure
- ▶ Describe the boundary in a clear expression with least squares

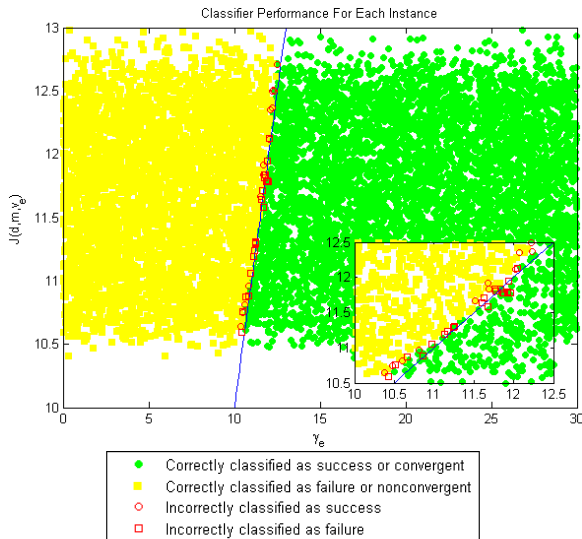
# Classification Results of Atmospheric-assisted Direct Entry

- ▶ Classification Plot demonstrates instances and their predictions
- ▶  $\gamma_e, J(d, m, v_e)$  boundary using SVM and least squares



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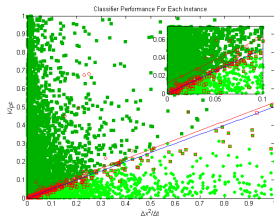
## What is $J(d, m, v_e)$ ?

- ▶  $J(\cdot)$  is an expression relating  $d, m, v_e$  to  $\gamma_e$  along the classified border between success and failure in direct entry
- ▶  $J(d, m, v_e) = \gamma_e$  lies along the border

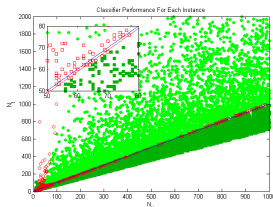
$$J(d, m, v_e) = 0.0219m^{0.0096}v_e^{0.6646}d^{-0.0017} \quad (1)$$

1. if  $\gamma_e < J(d, m, v_e)$ , direct entry failure
  2. if  $\gamma_e > J(d, m, v_e)$ , direct entry success
- ▶ Artificial neural network classification shown to be over 99.6% accurate

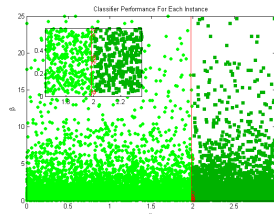
# Recall... Classification Results



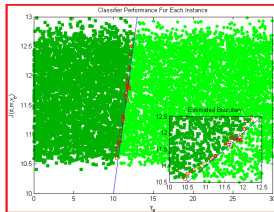
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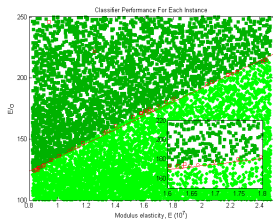
*Hyperbolic Wave Equation*



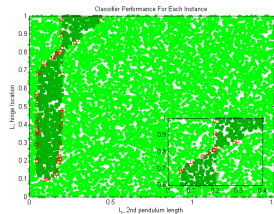
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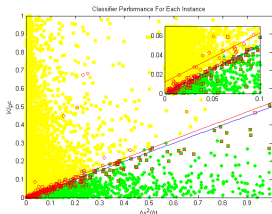


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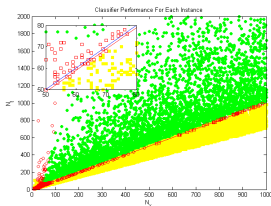


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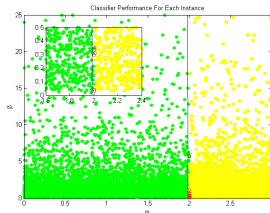
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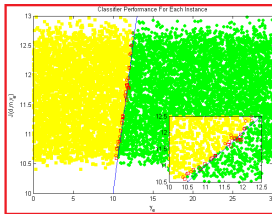
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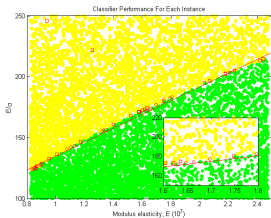
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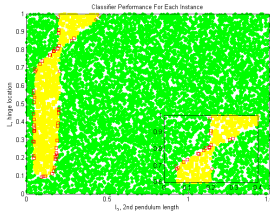
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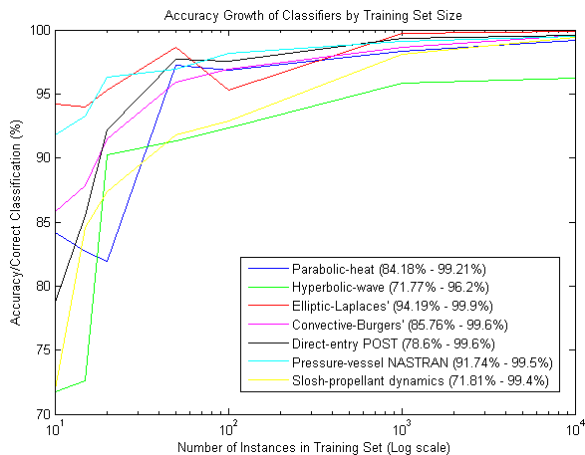


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# Classifiers Accuracy Growth



## Conclusions and Insights

1. Underlying properties of physics-based simulations (CFD, POST2, NASTRAN, slosh) can be accurately learned using ANN
2. All ANN classifications were over 99% accurate (Hyperbolic wave 96%)
3. SVM is an effective tool to identify classification boundaries