# Computational Mechanics for Mathematical Approximation Processes 

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## Motivation

- Can mathematical approximation processes be viewed as dynamic systems?
- These systems seem to have interesting nonlinear structure (Gibbs \& Runge phenomena)
- If so, can computational mechanics be used to develop an increased understanding of the information processing properties of these methods?


## Specific Motivation

- Climate change modelling
- Visualization of oceanographic data
- Approximation of scalar fields using various scattered data interpolation methods
- Limitations of having extremely sparse datasets
- Flow-field-aware directional interpolation



## Longitude










## Directional Interpolation



## Directional Interpolation



## Directional Interpolation

Nondirectional interpolation (OI) $($ CORRLEN $=0.1)$


## Directional Interpolation

Modified Hausdorff distance method $($ CORRLEN $=0.1)$


## Directional Interpolation



## Scalar Field Approximation in a Flow

 Field- Can we do something analogous to flow-fieldaware directional interpolation, but without a priori knowledge of the flow field?
- Might want to sample scalar fields at nearby points in order to get flow field approximations
- In general, a spatial statistics problem
- Can we determine where additional data points are needed?


## Simple Test Problems

- Approximation methods in 1D and 2D
- Spline interpolation
- Regression
- Scattered data interpolation


## Using Computational Mechanics

- How to formulate a mathematical approximation problem as a dynamical system?
- First approach : sequential sampling of a given (unknown) function
- As with computational mechanics, a primary goal of our approximation problem is prediction












































## Applying Computational Mechanics

- Because of the quick decay of the RMS error, the system becomes uninteresting
- Also, not enough statistics to do (epsilon machine) inference
- Need a new dynamic system definition
- Perturbation of sample points













































## Discretization of RMS to Define Process Alphabets

- 11 symbol alphabet

```
def get_symbol(RMS):
    if 0.000 <= RMS < 0.025 : return 0
    elif 0.025 <= RMS < 0.050 : return 1
    elif 0.050 <= RMS < 0.075 : return 2
    elif 0.075 <= RMS < 0.100 : return 3
    elif 0.100 <= RMS < 0.125 : return 4
    elif 0.125 <= RMS < 0.150 : return 5
    elif 0.150 <= RMS < 0.175 : return 6
    elif 0.175 <= RMS < 0.200 : return 7
    elif 0.200 <= RMS < 0.225 : return 8
    elif 0.225 <= RMS < 0.250 : return 9
    elif 0.250 <= RMS : return 10
    else : raise Exception('Range Error')
```

- Binary alphabet: Threshold of RMS = 0.01


## Preliminary Results

- Could not get epsilon machine inference to work for the 11 symbol alphabet
- For the discretized RMS bit string output, epsilon machines can be obtained


## Epsilon Machine for degree=1



## Epsilon Machine for degree=2



## Epsilon Machine for degree=3



## Epsilon Machine for degree=4



## Epsilon Machine for degree=5



## Entropy Rate, Statistical Complexity, and Excess Entropy



## In progress / To do

- Try to get results with a non-binary alphabet
- Try different discretization thresholds
- Try different functions
- Make sense of the results?
- Investigate spatial correlations?
- Try other approximation methods
- Try higher dimensions

