Improving Genetic Algorithm Calibration of Probabilistic Cellular Automata for Modeling Mining Permit Activity

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This project is partially supported by the USGS and builds on previous work done by
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Genetic Algorithms

- Developed by John Holland
  - Natural selection – survival of the fittest
  - Natural genetics
- Used when problems are poorly defined, hard.
  - Multimodal
  - Discontinuous
  - Non-linear

Robotics	**How do we catch a ball, navigate, play basketball**
User Interfaces	**Predict next command, adapt to individual user**
Medicine	**Protein structure prediction, Is this tumor benign, design drugs**
Design	**Design bridge, jet engines, Circuits, wings**
Control	**Nonlinear controllers**

Genetic Algorithms

- Solutions are encoded as binary chromosomes
- A set of operators acts on a population of chromosomes to evolve better solutions
  - Selection
  - Crossover
  - Mutation
- **Quickly produces good (usable) solutions**
- **Not guaranteed to find optimum**

Searching for Optima

- Searching for optima
  - Traditional Methods
    - Calculus
      - Depend on existence of derivatives
      - Most real-world functions are not unconstrained, smooth, calculus friendly functions.
    - Hill Climbing
      - Fails when reaches local optima

Search as a solution to hard problems

- Strategy: generate a potential solution and see if it solves the problem
- Make use of information available to guide the generation of potential solutions
- How much information is available?
  - Very little: We know the solution when we find it
  - Lots: linear, continuous, …
  - Modicum: Compare two solutions and tell which is "better"

Algorithm

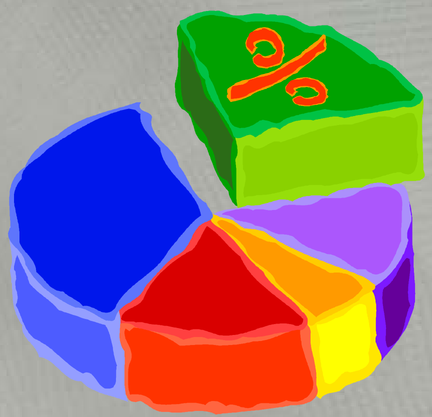
- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (not converged) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

GA – Evaluation

Application dependent fitness function

GA - Selection

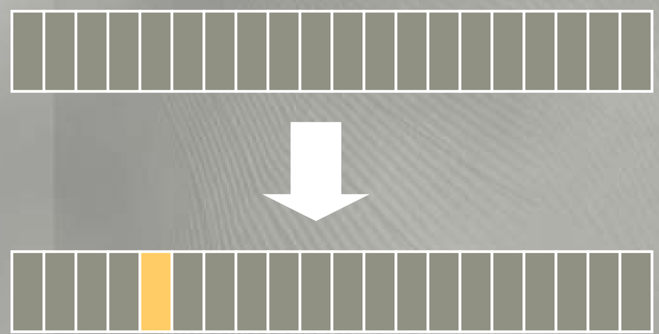
- Each member of the population gets a share of the pie proportional to fitness relative to other members of the population



- Spin the roulette wheel pie and pick the individual that the ball lands on

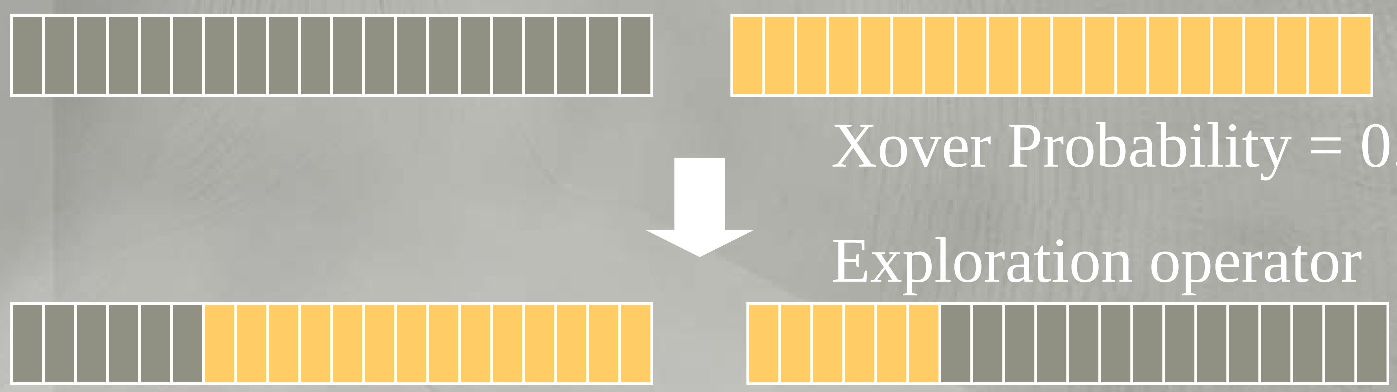
- Focuses search in promising areas

Crossover and Mutation



Mutation Probability = 0.001

Insurance



Xover Probability = 0.7

Exploration operator

GA – Exploration vs. Exploitation

- More exploration means
  - Better chance of finding solution (more robust)
  - Takes longer

- More exploitation means
  - Less chance of finding solution, better chance of getting stuck in a local optimum
  - Takes less time

GA - Example

String	decoded	f(x^2)	fi/Sum(fi)	Expected	Actual	
01101	13	169	0.14	0.58	1	
11000	24	576	0.49	1.97	2	
01000	8	64	0.06	0.22	0	
10011	19	361	0.31	1.23	1	
Sum		1170	1.0	4.00	4.00	
Avg		293	.25	1.00	1.00	
Max		576	.49	1.97	2.00	

GA - Example

String	mate	offspring	decoded	f(x^2)		
0110|1	2	01100	12	144		
1100|0	1	11001	25	625		
11|000	4	11011	27	729		
10|011	3	10000	16	256		
Sum				1754		
Avg				439		
Max				729		

Research

A harmonious marriage between

Cellular Automata

&

Genetic Algorithms

What is the project about?

- **What is the problem?**
  - Calibrating a CA
- **What is the technique?**
  - Genetic Algorithm
- **What are the issues?**
  - Encoding
  - Evaluation
- **What are our results ?**

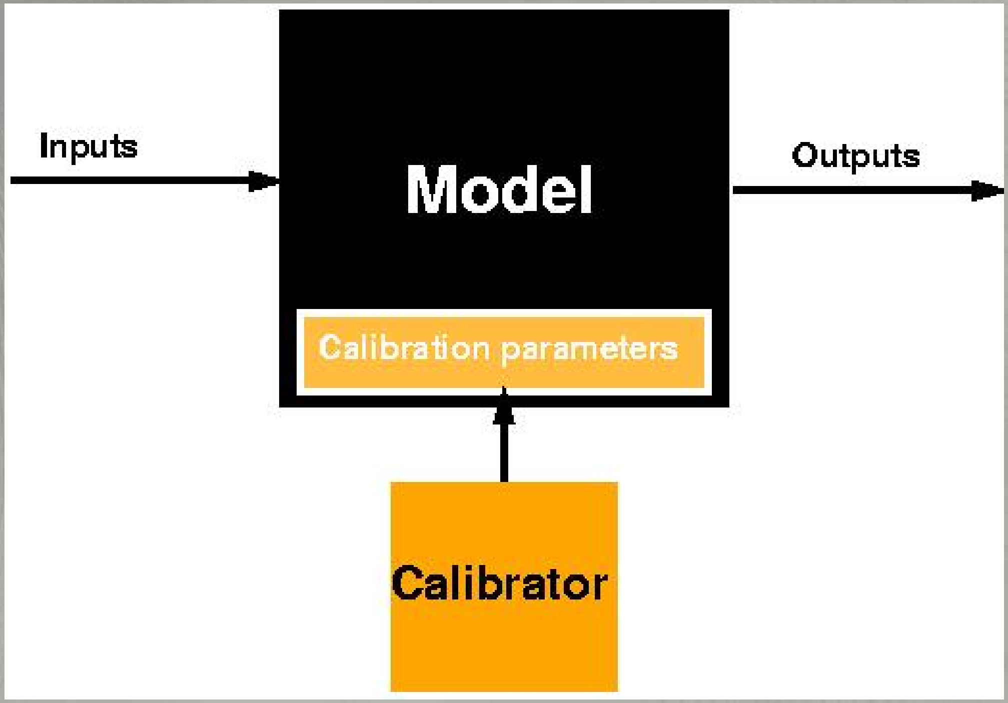
Problem

- Project mineral-related activity on public land to 2010
  - Predicting permit activity in an area
    - Spatially explicit
    - USGS
      - permit activity from 1989 – 1998
      - natural resources
    - Use cellular automata to model (predict) mining activity over next ten years
  - Problem: Takes weeks to tune CA rules to match available data

Problem

- **Can we automate calibrating a cellular automaton**
    - As good as CA calibrated by human
    - In the same or less time

Problem



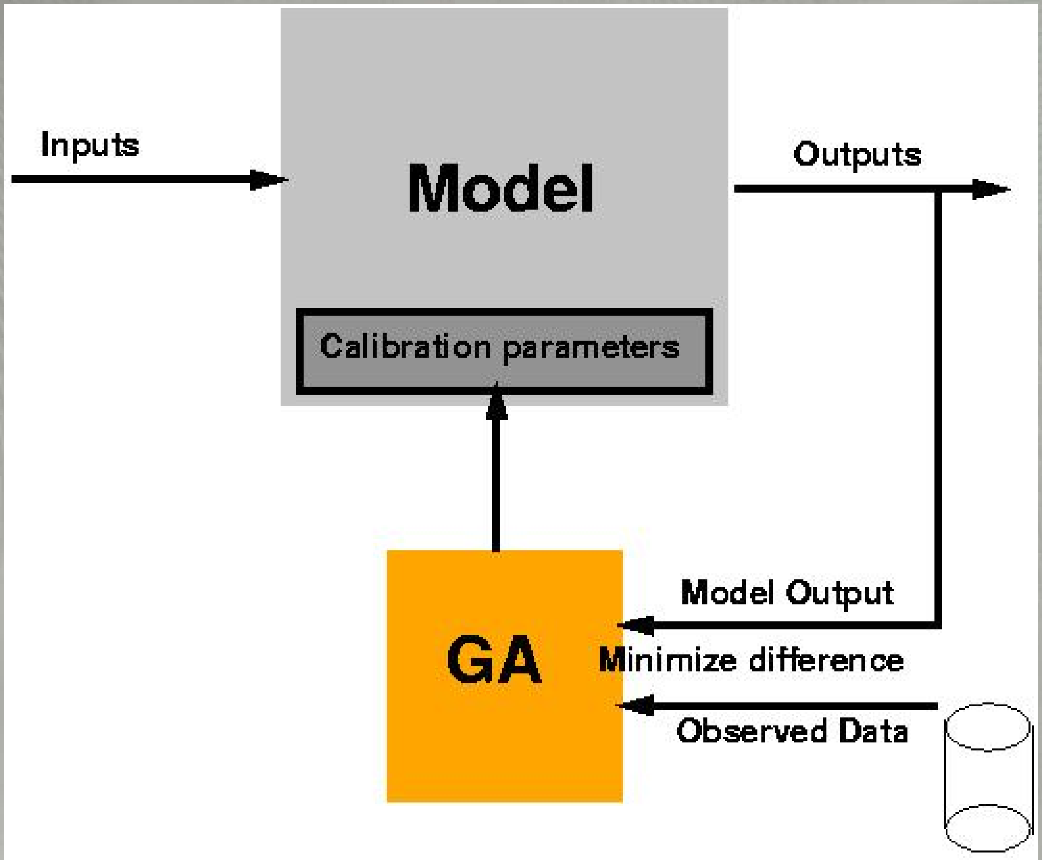
Model Parameters

- 496 X 503 = 249,488 cell CA
- 5 years (iterations)
- Average over 3 runs
- Roughly 4 Million computations.

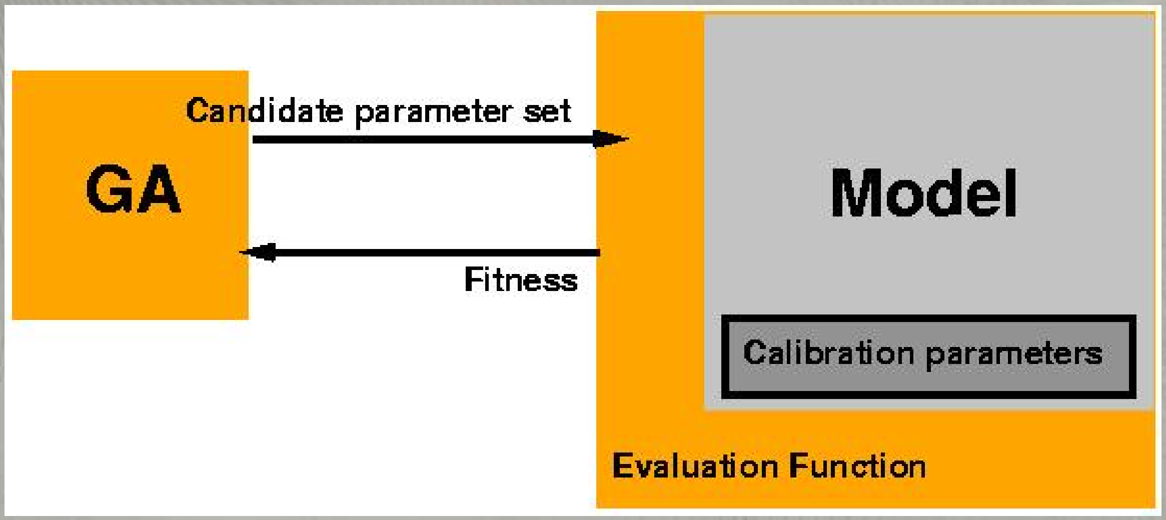
GA Calibration

- Empirical evidence to support their use in this kind of problem
  - **Physics models**
    - *Physical Review Letters, Volume 88, Issue 4*
    - *Journal of Quantitative Spectroscopy and Radiative Transfer. Volume 75, 2002, Pgs. 625 - 636*
  - **Seismic models**
    - *Congress on Evolutionary Computing 1999, pages 855 - 861*
  - **Hydrology models**
    - *In progress*
  - Proceedings of GECCO, CEC, …

GA Calibration



GA Evaluation



Modified Annealed Voting Rule

Probability of Life in Next Generation

Number of Live Neighbors	Status of Center Cell	
	Alive	Dead
> Annealing Window	**Very Likely**	**Likely**
Annealing Window	**Likely**	**Somewhat Likely**
< Annealing Window	**Very Somewhat Likely**	**Unlikely**

CA Parameters

Parameters	Definition
Very Likely	Square root of Likely (Larger)
Likely	A high probability of life.
Somewhat Likely	An intermediate probability of life
Very Somewhat Likely	Square root of Somewhat Likely (Larger)
Unlikely	A low probability of life
Resource Threshold	Minimum fuzzy membership defining where a reasonable explorationist would explore
Anneal Window	Position and width control response of CA

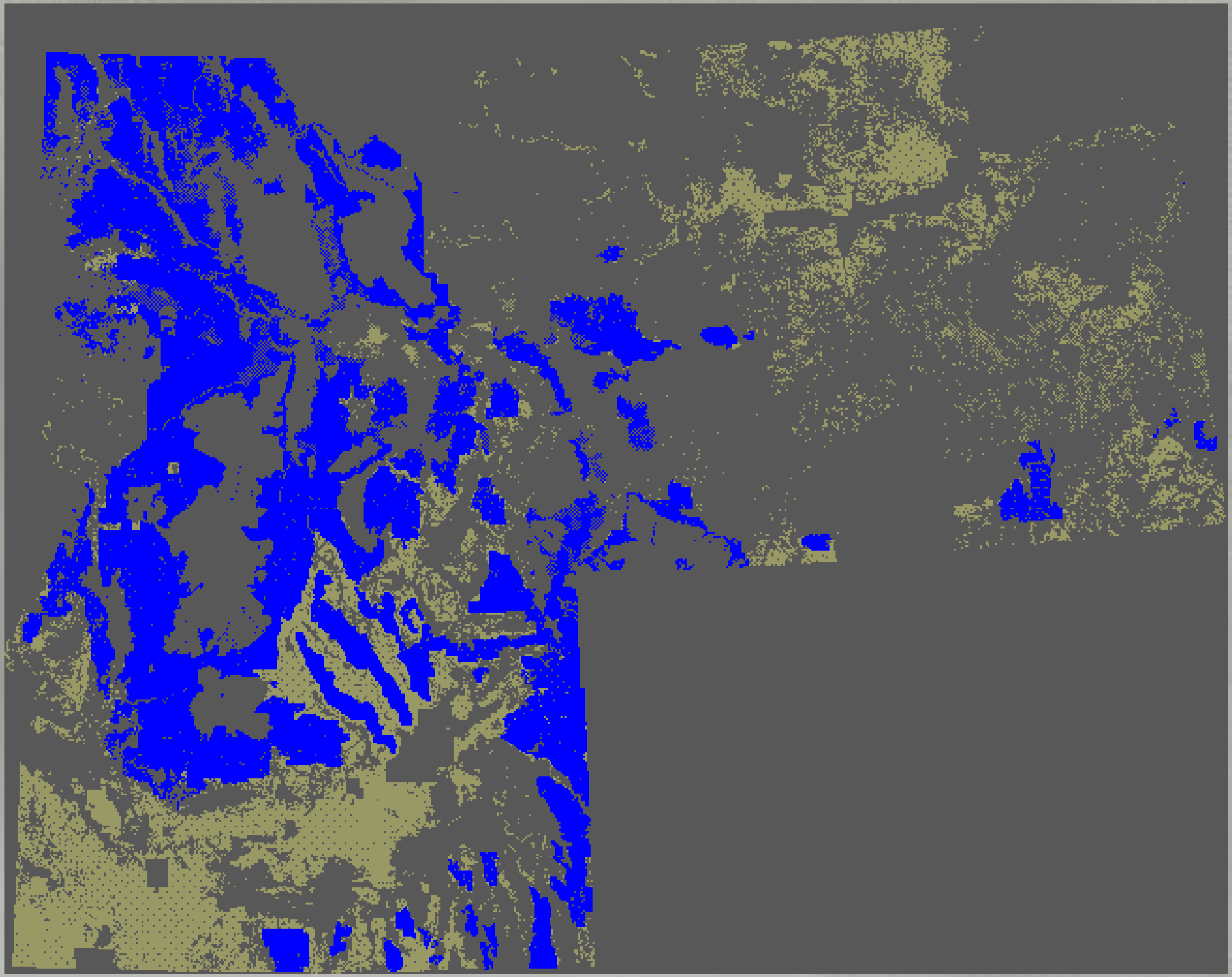
GA Encoding

top	Bottom	likelyInactive	likelyActive	veryLikely	somewhatLikely	verySomewhatLikely	unlikelyProb	ResourceThreashold
4	4	7	7	7	7	7	7	7

CHC Benefits

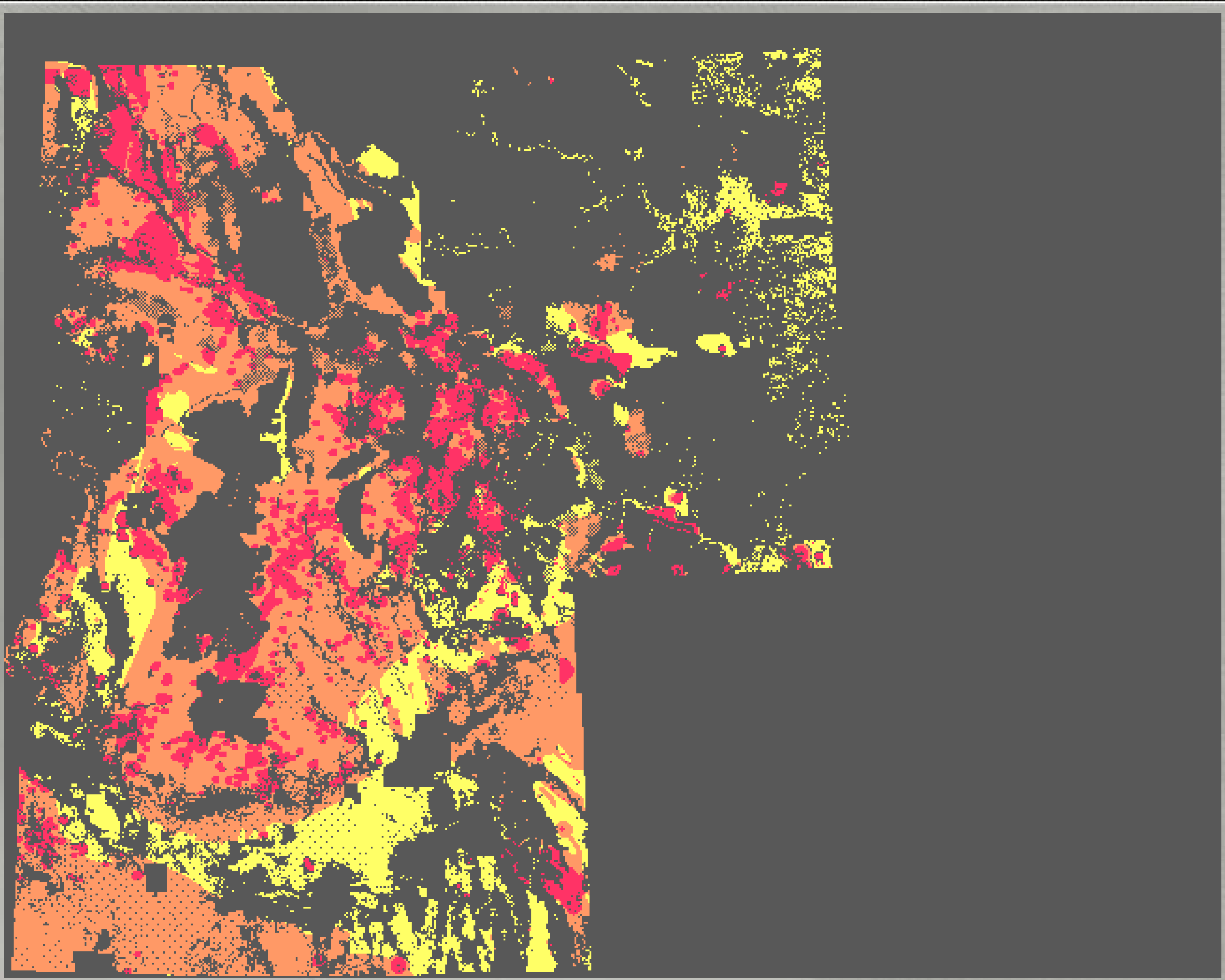
- Outperforms traditional GA as function optimizer
- Smaller population size needed to maintain same diversity as traditional GA
- Very effective for parameter optimization (Darrel Whitley)

Visualization of Data



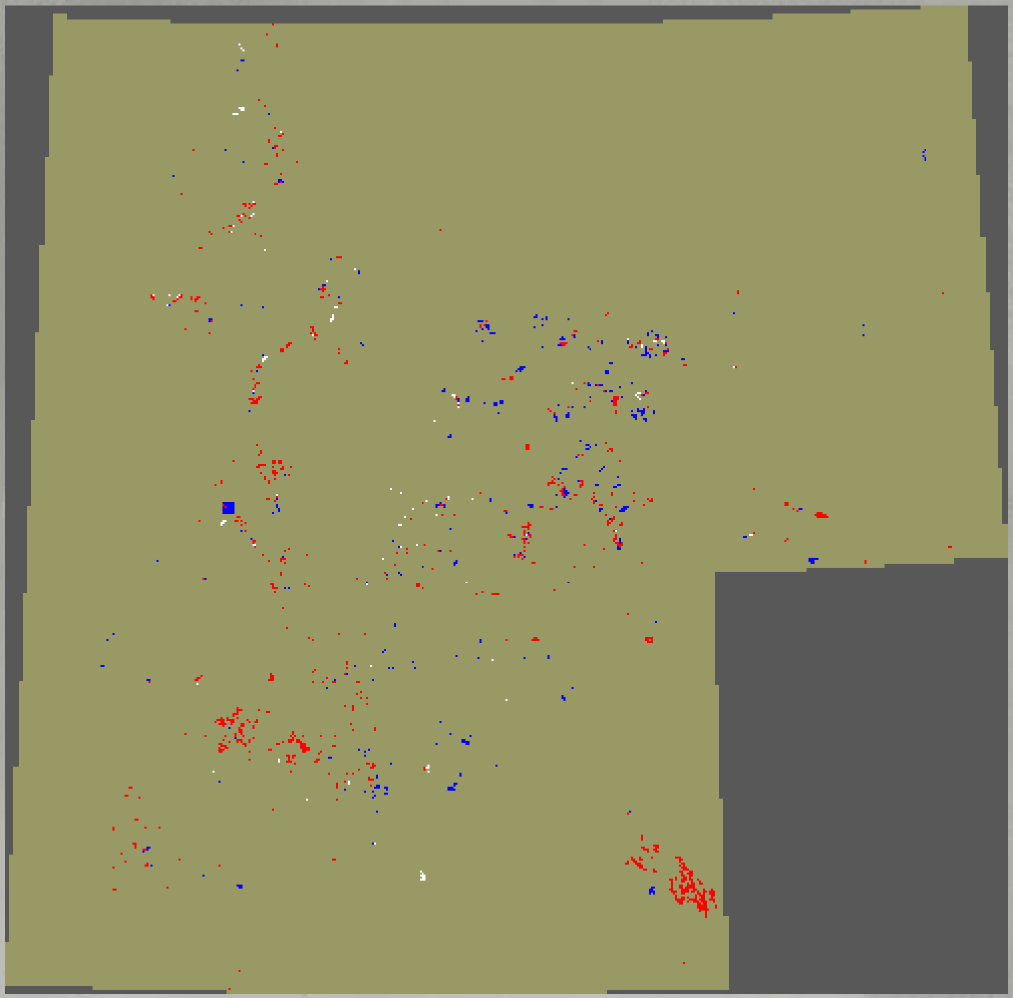
* Public Land

Visualization of Data



* Resources

Visualization of Data



*** CA Activity Model**

Evolution of the project

- **TCSC: Total Cell State Count**

$$\text{Minimize } \; g = \sum_{j=0}^{\text{nyears}} \sum_{i=0}^{\text{nstates}} \left(100 \times \frac{\mid M_{ij} - O_{ij} \mid}{M_{ij} + O_{ij}} \right)$$

  - Mij : predicted number of cells in state i in year j
  - Oij : actual number of cells in state i in year j
  - 4 Types of Cells:
    - Alive
    - Dead
    - Just Born
    - Just Died

Evolution of the project

- **Kappa statistic**
  - *Kappa is a measure of agreement normalized for chance agreement*

$$K = \frac{P(A) - P(E)}{1 - P(E)}$$

  - ***Where P(A) is the percentage agreement (e.g., between your classifier and ground truth) and P(E) is the chance agreement. K=1 indicates perfect agreement, K=0 indicates chance agreement.***

Evolution of the project

- **NSCP: Number of Spatially Correct Predictions**

$$\sum_{j=0}^{nyears} \sum_{i=0}^{nstates} w_i M_{ij}$$

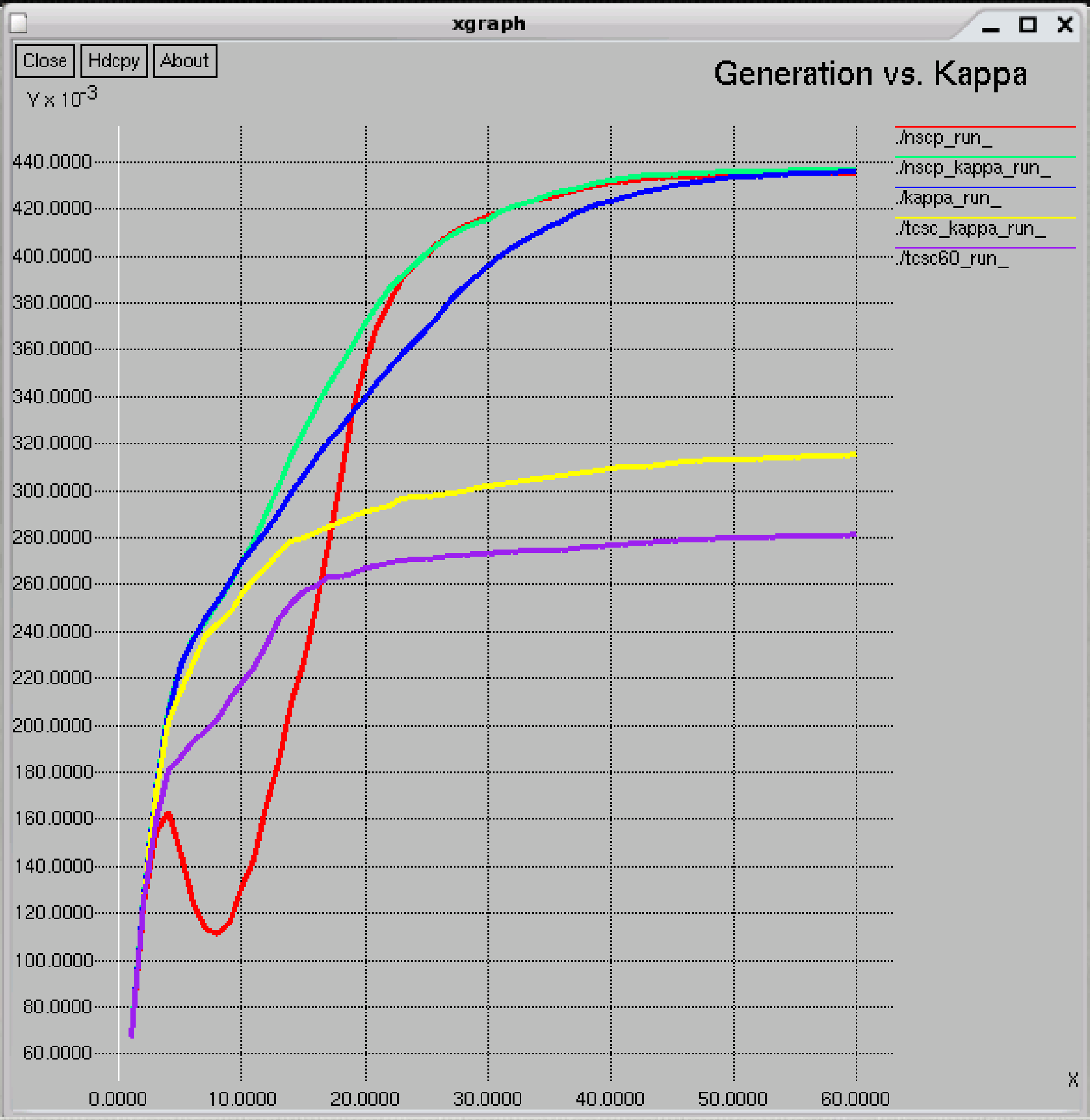
- M_{ij} : NSCP in state i in year j
- w_i : weight of state i

Results

- **Different Evaluation methods tested**
  - Population : 60
  - Generations : 60
  - Crossover Rate : 0.99
  - Mutation : 0.05
  - Runs : 10 with different seeds

  - 4 Million Computations * 60 * 60 =
  - 14.4 Billion Computations
  - On average, 0.3 seconds / evaluation

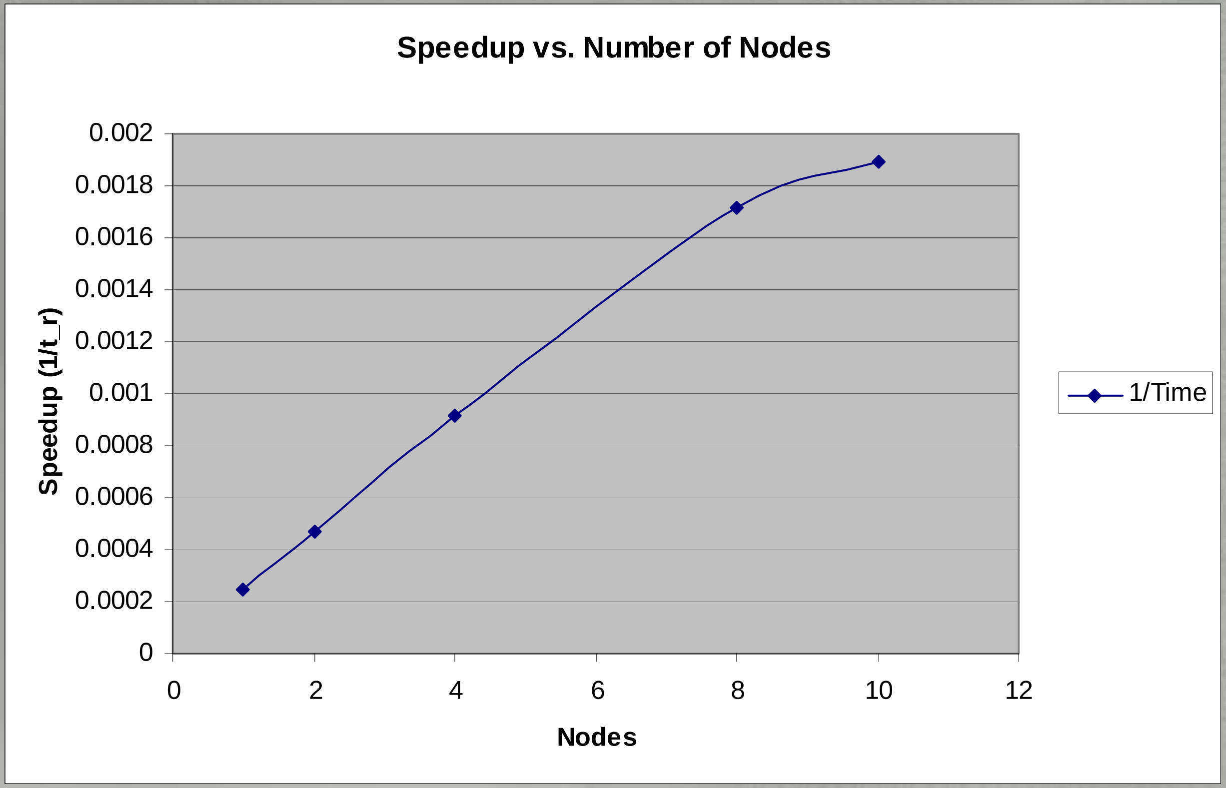
Results


xgraph
Close
Hdcpy
About
Generation vs. Kappa
Y x 10-3
./nscp_run_
./nscp_kappa_run_
./kappa_run_
./tcsc_kappa_run_
./tcsc60_run_
440.0000
420.0000
400.0000
380.0000
360.0000
340.0000
320.0000
300.0000
280.0000
260.0000
240.0000
220.0000
200.0000
180.0000
160.0000
140.0000
120.0000
100.0000
80.0000
60.0000
0.0000
10.0000
20.0000
30.0000
40.0000
50.0000
60.0000
X

Results

- Kappa results for fitness defined by
  - **TCSC**
    - Avg : 0.2814
  - **Kappa**
    - Avg : 0.4362
  - **TCSC** and **Kappa**
    - Avg : 0.3154
  - **NSCP**
    - Avg : 0.4356
  - **NSCP** and **Kappa**
    - Avg : 0.4366

Parallel GA



Speedup vs. Number of Nodes
0.002
0.0018
0.0016
0.0014
0.0012
0.001
0.0008
0.0006
0.0004
0.0002
0
Speedup (1/t_r)
0
2
4
6
8
10
12
Nodes
1/Time

Conclusion

- 0.437 = Absolute Barrier
- Using Kappa Statistic in evaluation improves performance in both NSCP and TCSC
- Using NSCP results in reaching higher Kappa values more quickly
- Unfortunately NSCP was not able to break the 0.437 barrier

Future Work

- Evolve different rules for different sub-regions of the grid
- Encode and evolve rules instead of just rule parameters
- Explore different measurements of “success”
- Visualize Results