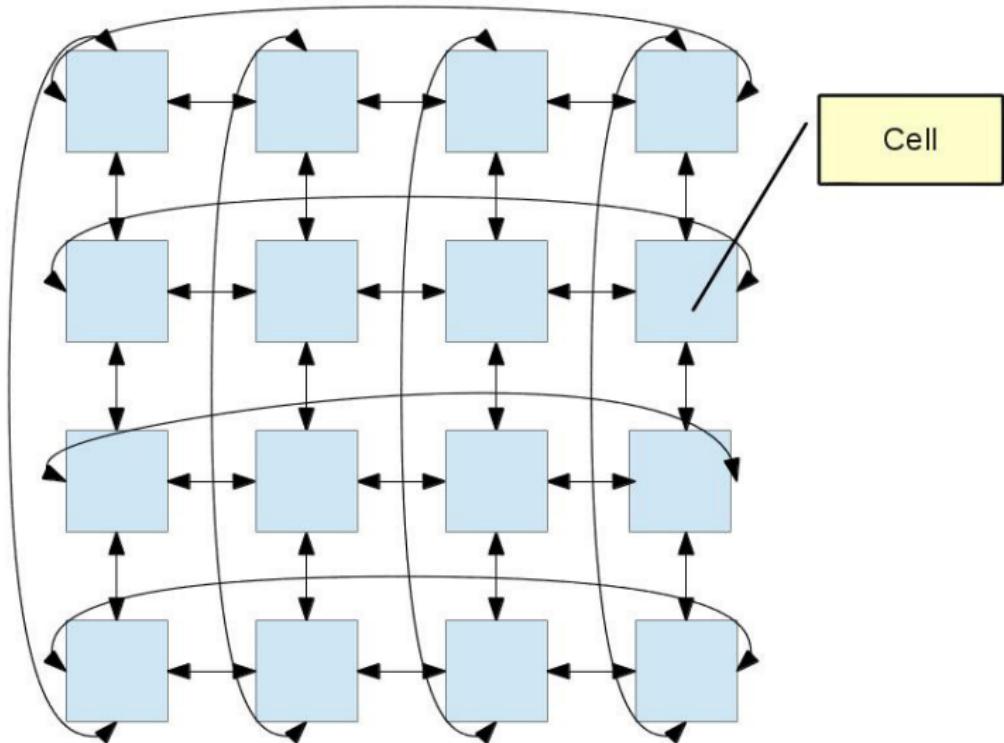


# Benchmarking Cellular Genetic Algorithms on the BBOB Noiseless Testbed

Neal Holtschulte

July 6, 2013

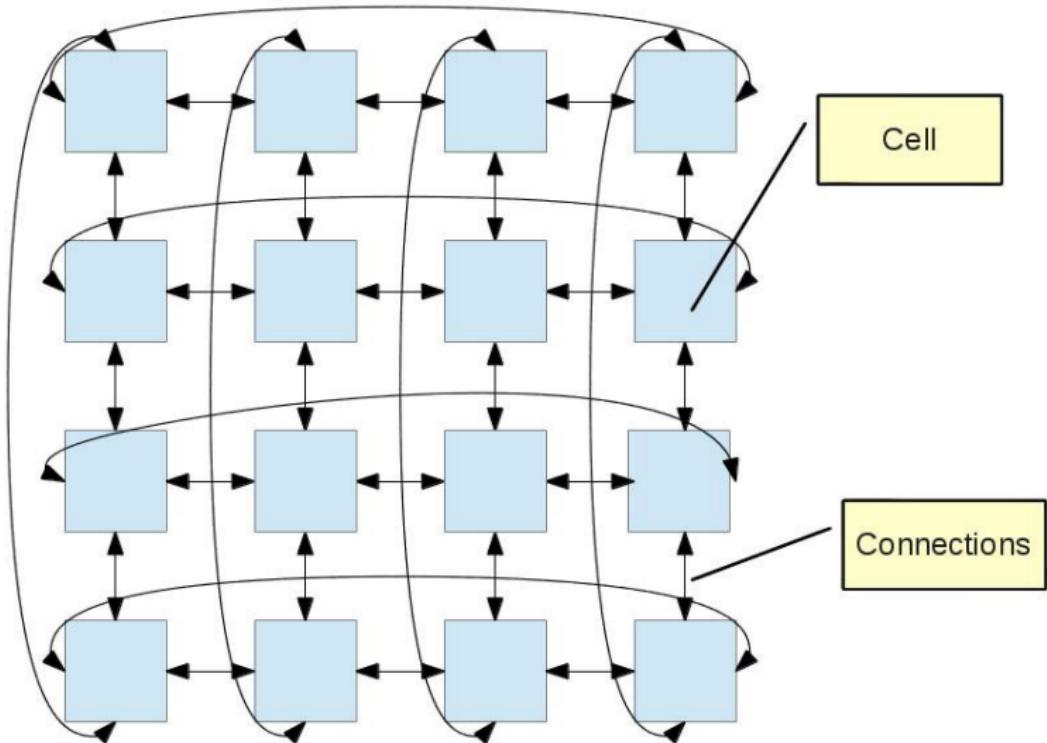
# Cellular Genetic Algorithm



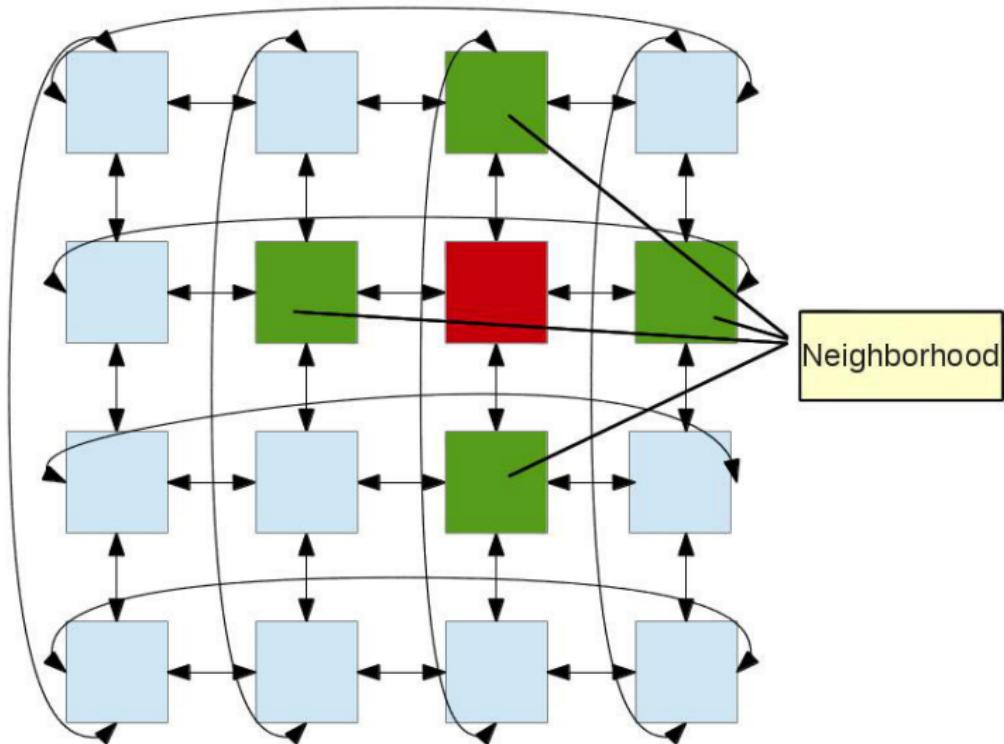
# Cellular Genetic Algorithm



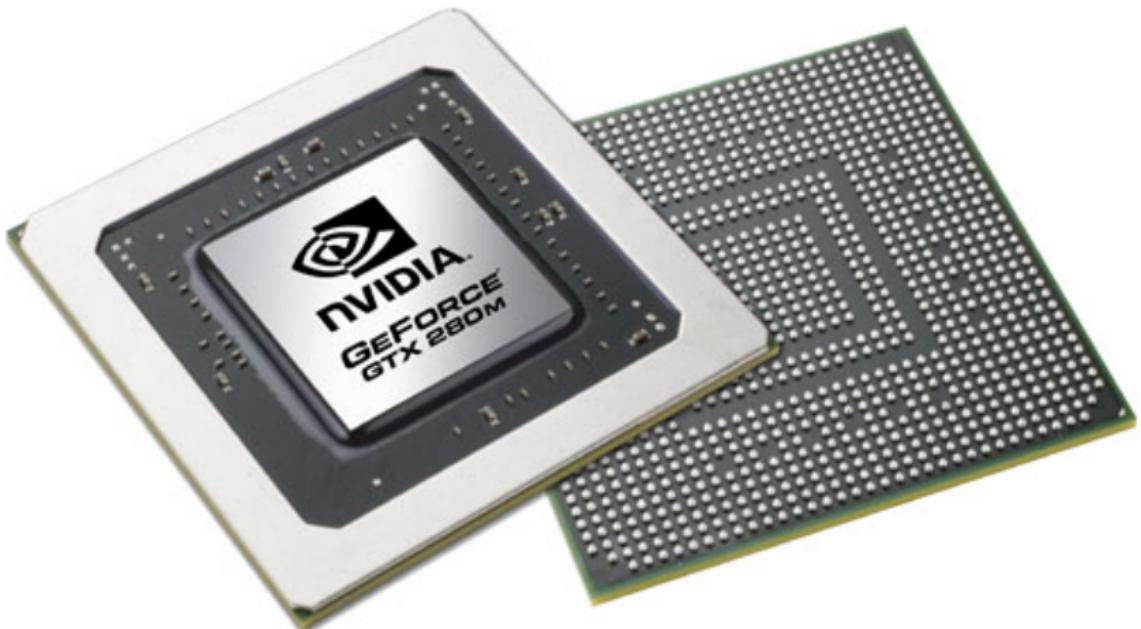
UNM



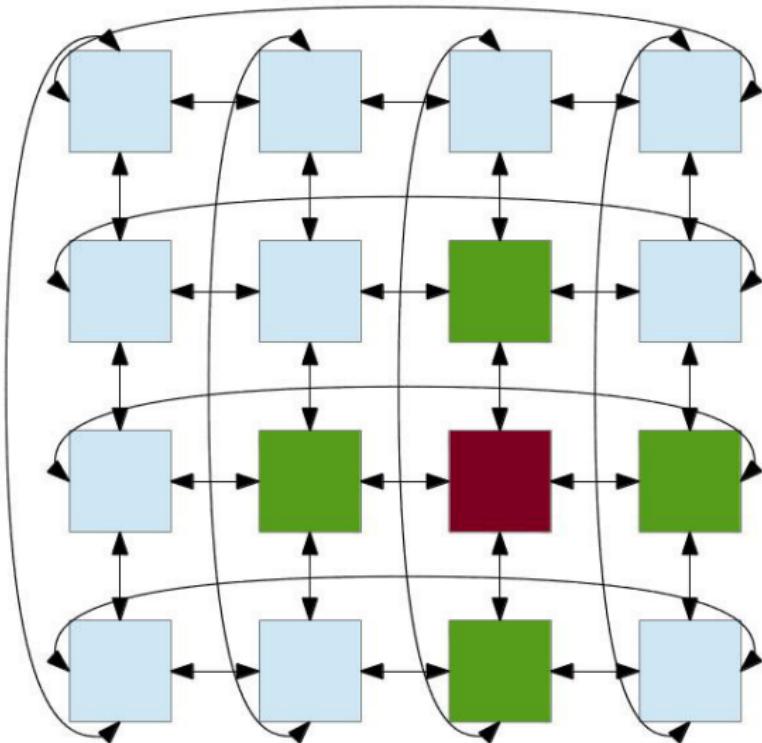
# Cellular Genetic Algorithm



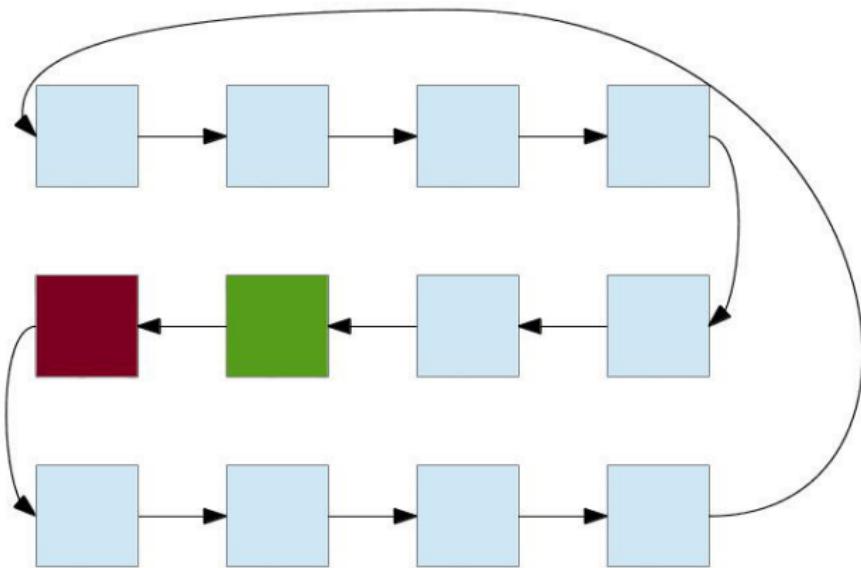
# Hardware-motivated topology



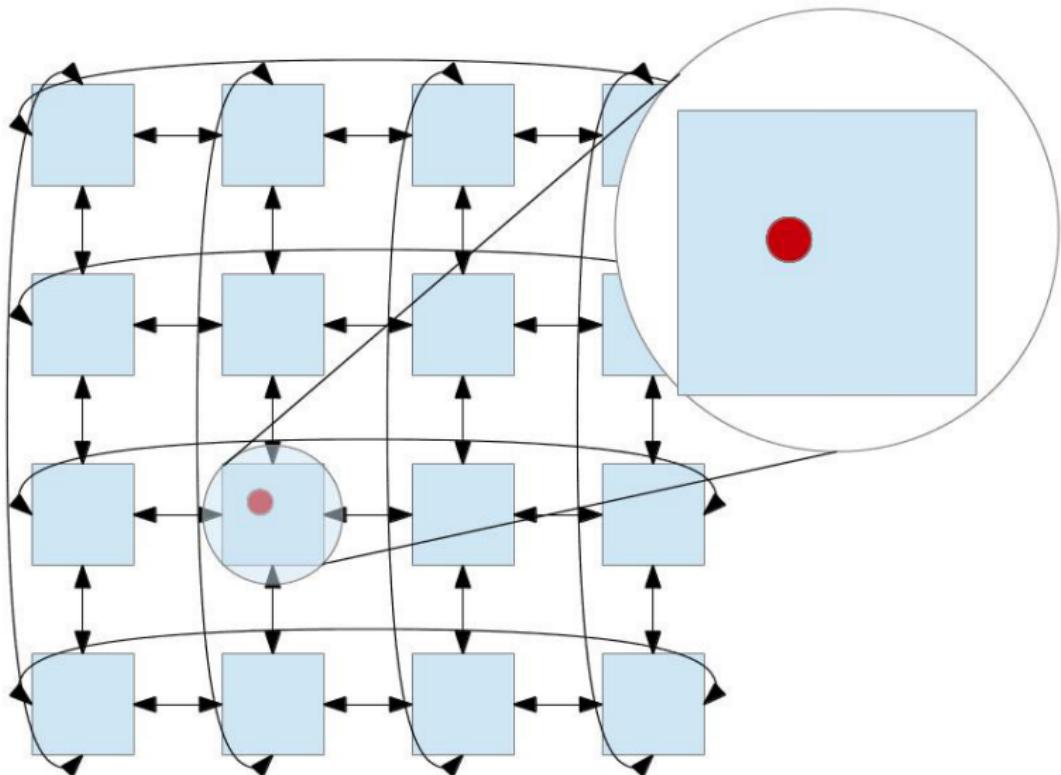
# Neighborhoods



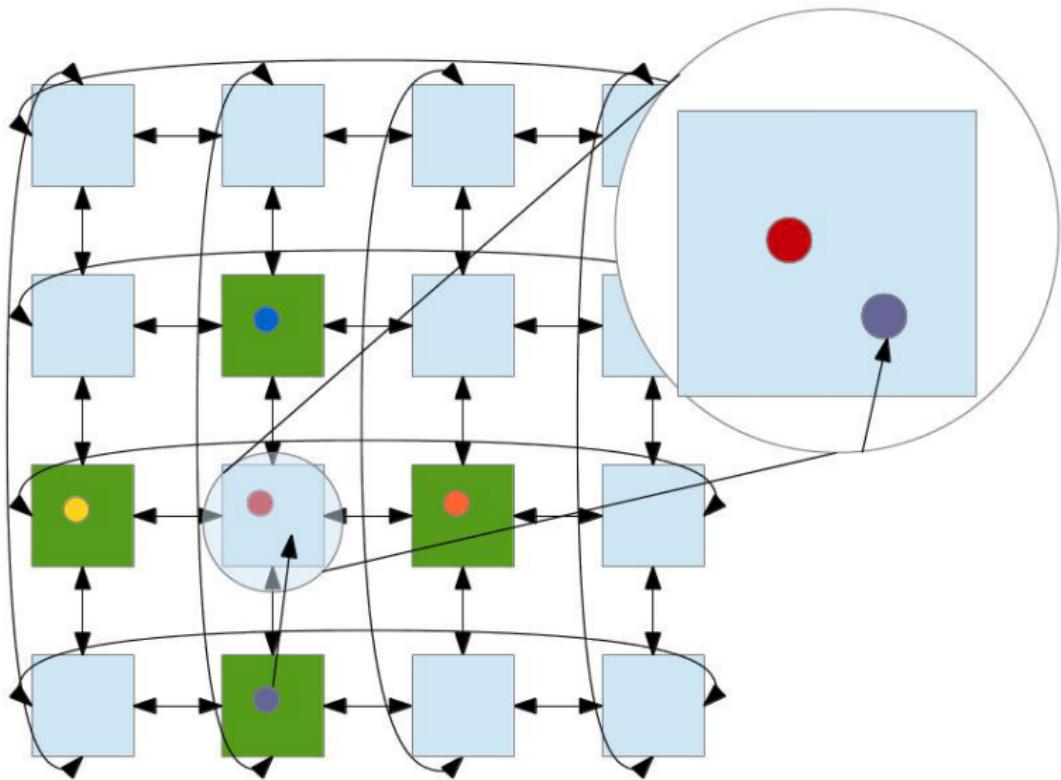
# Neighborhoods



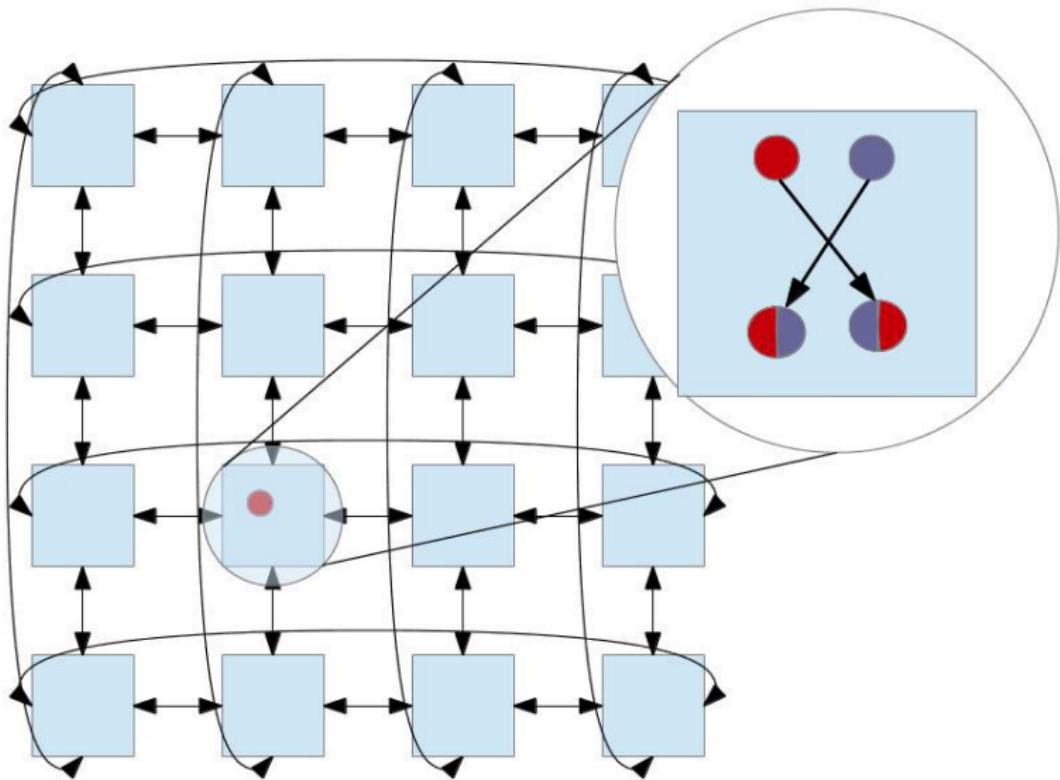
# One generation at one node



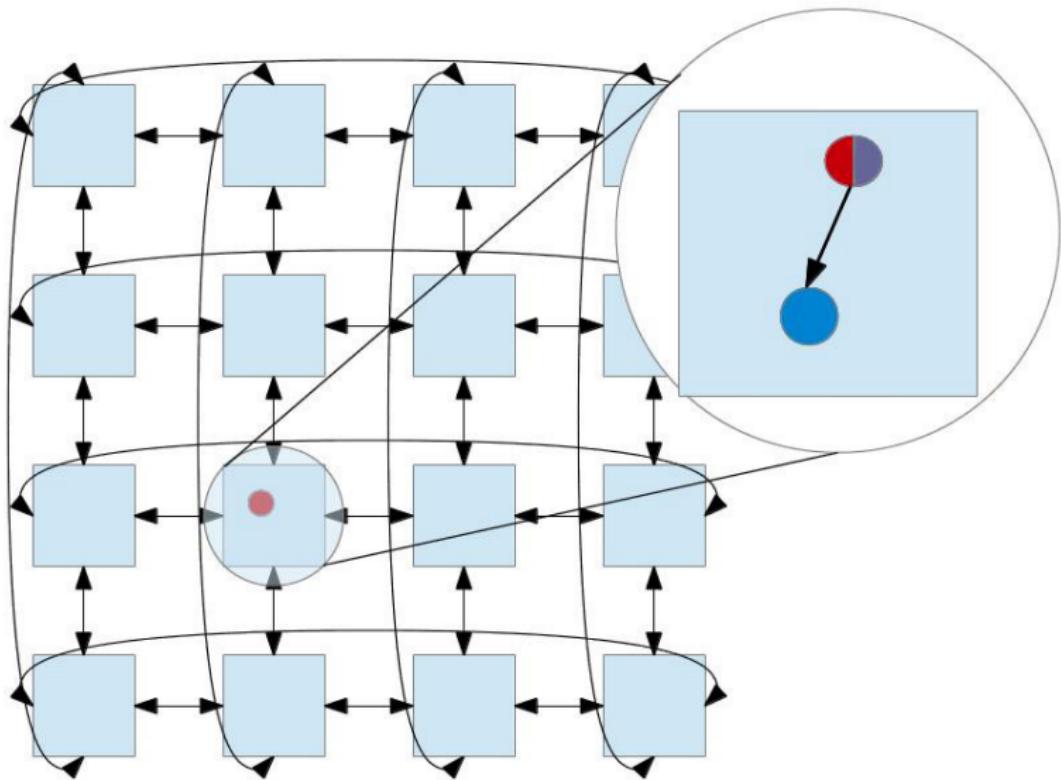
# Migration



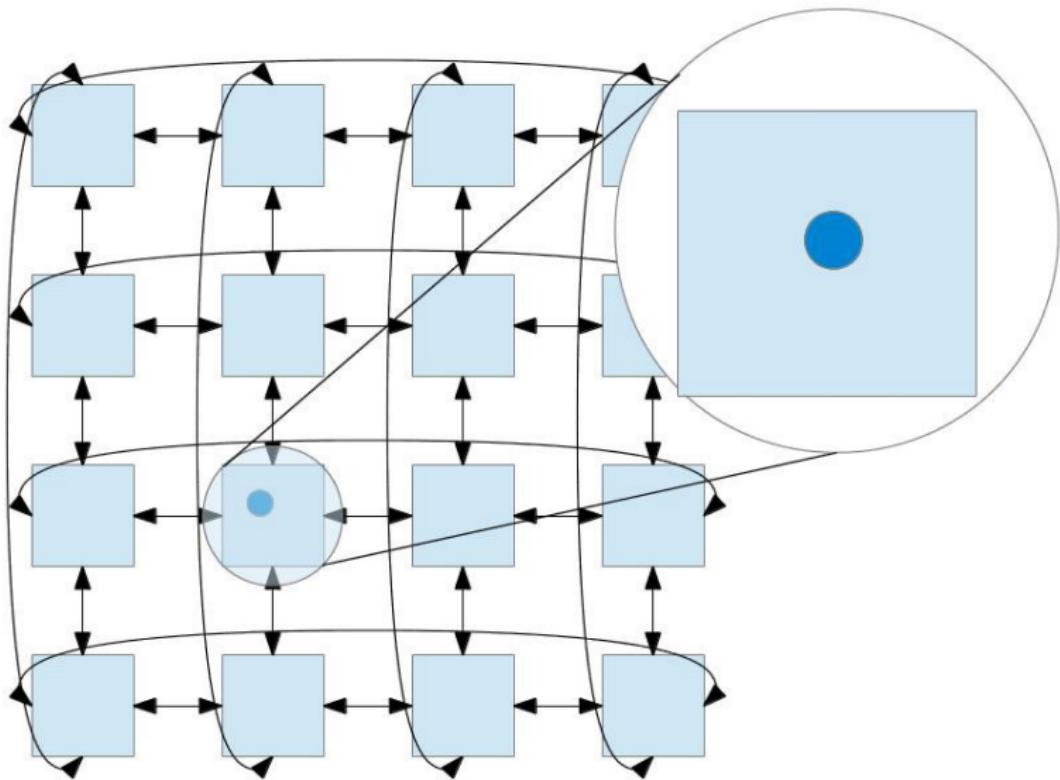
# Crossover



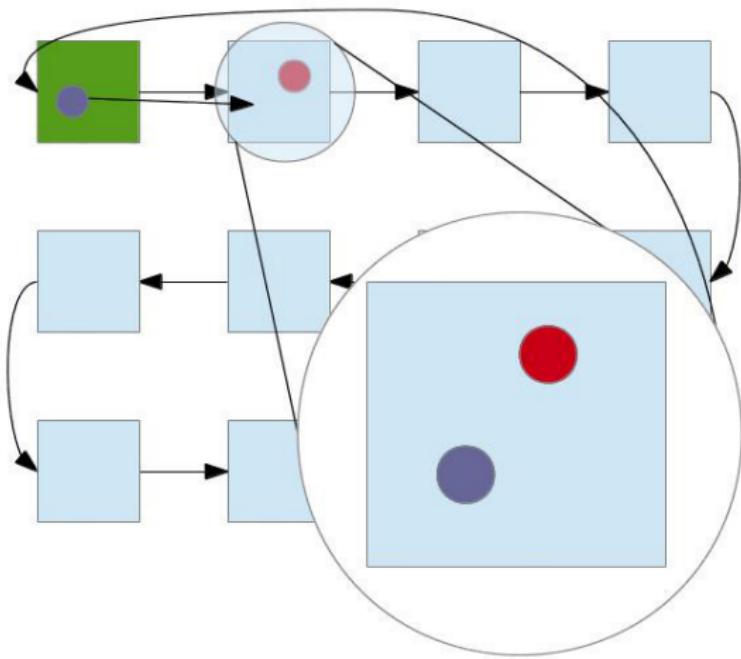
# Mutation



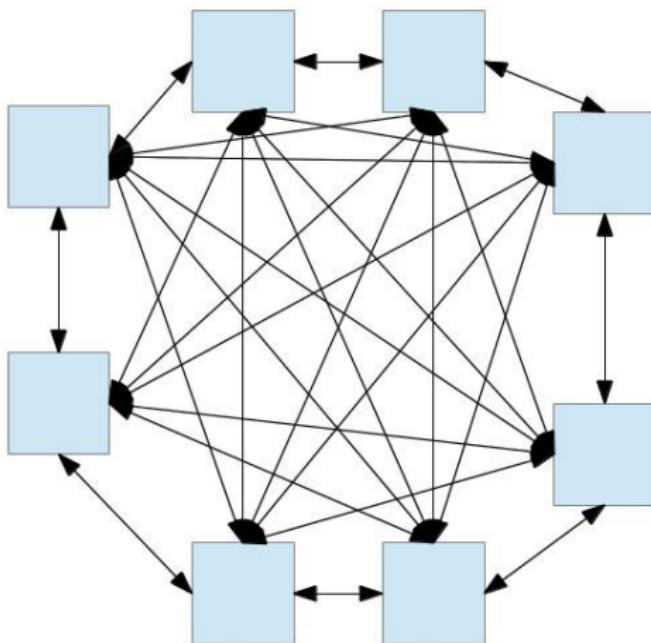
# Update



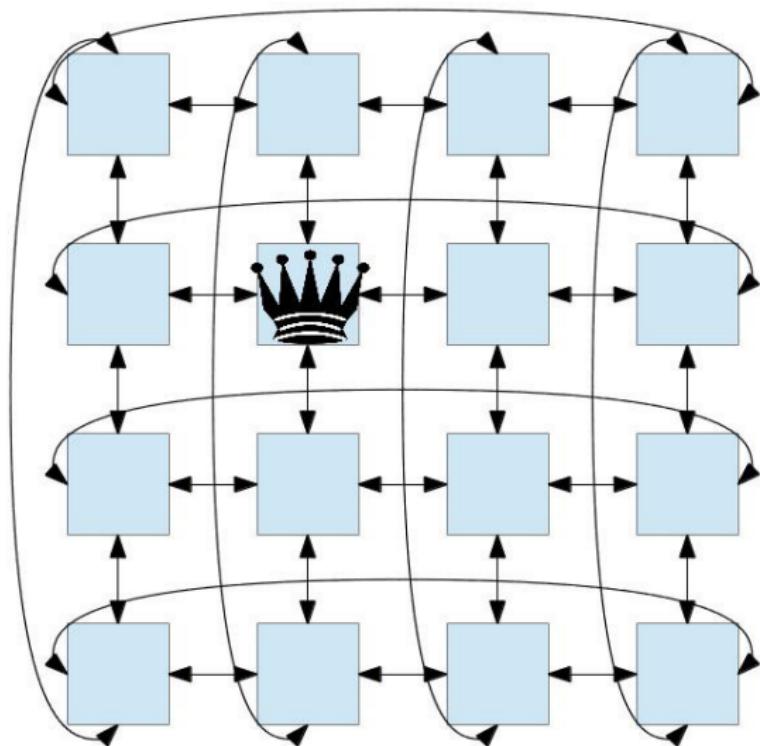
# Migration in a Ring CGA



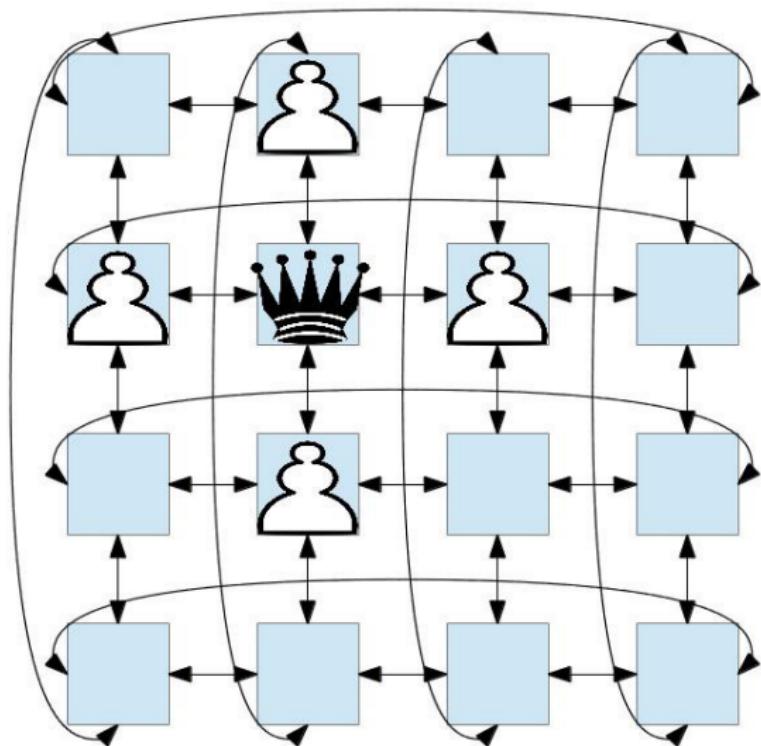
# Conventional GA Population



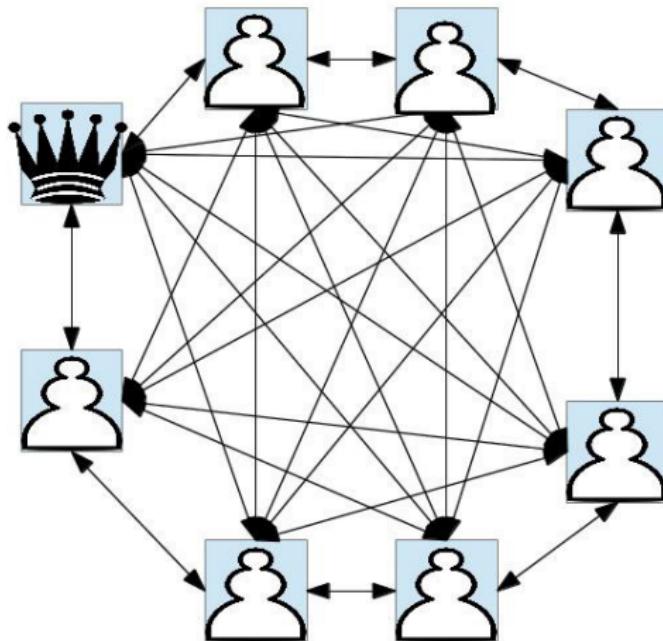
# Explore vs. Exploit



# Explore vs. Exploit



# Explore vs. Exploit



So you want to use a GA on  
your distributed hardware.



Which GA should you use?

# Questions



- ▶ Which CGA topology is better? Grid or ring?

# Questions



- ▶ Which CGA topology is better? Grid or ring?
- ▶ How does CGA compare to classic GA or random search?

# Questions



- ▶ Which CGA topology is better? Grid or ring?
- ▶ How does CGA compare to classic GA or random search?
- ▶ How does CGA compare to a state-of-the-art GA? (Tran and Jin)

# Questions



- ▶ Which CGA topology is better? Grid or ring?
- ▶ How does CGA compare to classic GA or random search?
- ▶ How does CGA compare to a state-of-the-art GA? (Tran and Jin)
- ▶ How much does operator choice affect performance?

# Experimental Design



- ▶ Algorithms: CGA, GA, random search
- ▶ Population Sizes: 16, 49, and 100
- ▶ Mutation rate: 1/dimensionality
- ▶ Mutation Op: Gaussian with 20% variance
- ▶ Crossover rate: 90%
- ▶ Crossover Op: Two point crossover
- ▶ Evaluation limit:  $50,000 * \text{dimensionality}$

# Two-point Crossover

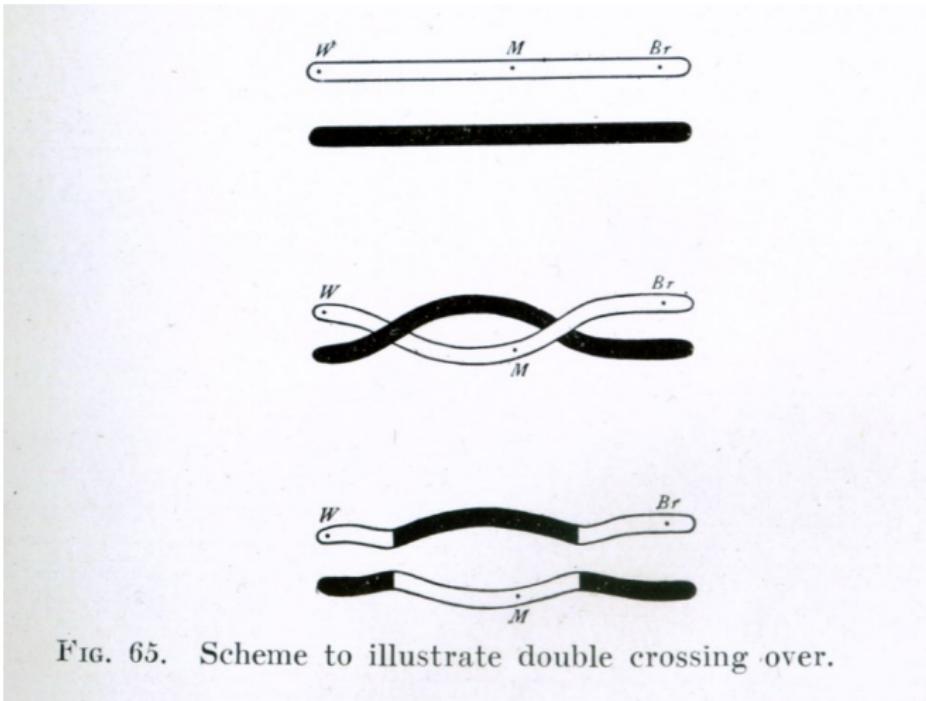
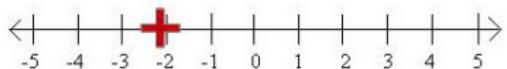


FIG. 65. Scheme to illustrate double crossing over.

# Gaussian Mutation



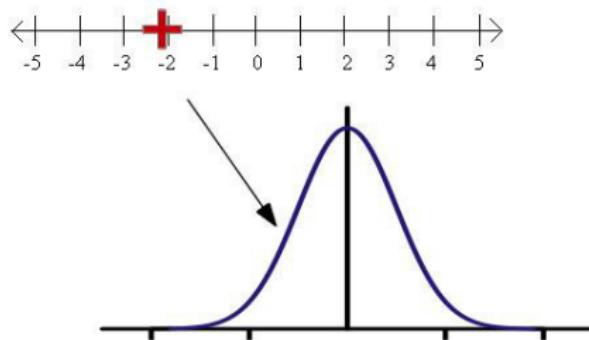
Value to be mutated



# Gaussian Mutation



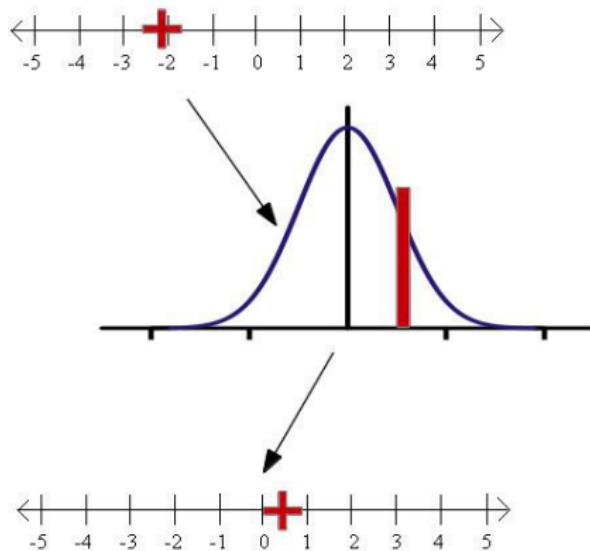
Sample from a normal distribution



# Gaussian Mutation



Add the sampled value to the value to be mutated



# Evaluated algorithms



- ▶ Cellular Genetic Algorithm
  - ▶ Grid
  - ▶ Ring
- ▶ Standard Genetic Algorithm
- ▶ Random search

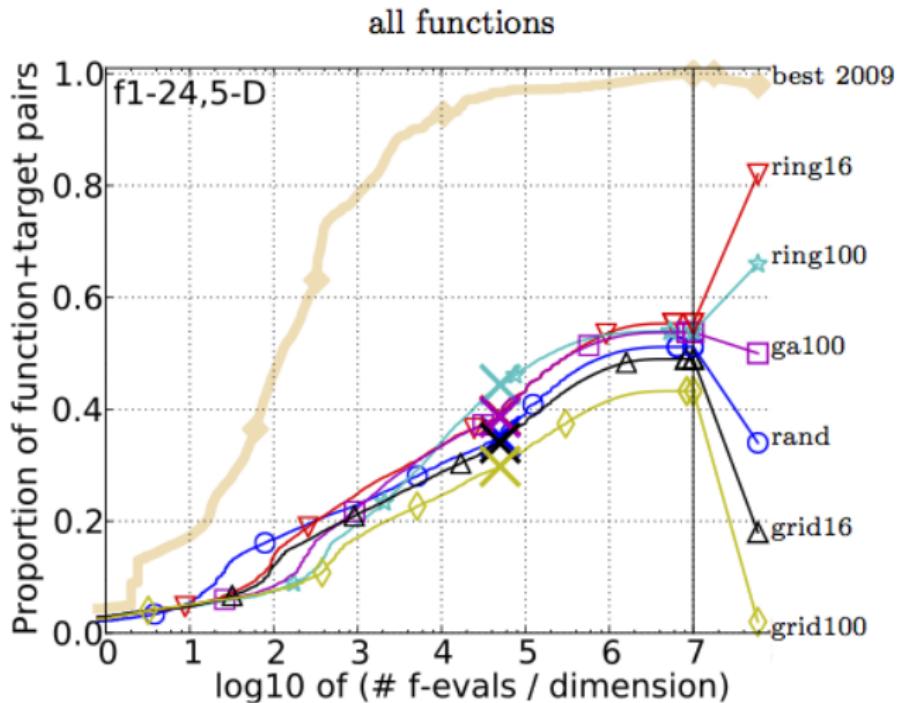
# Which CGA topology to use?



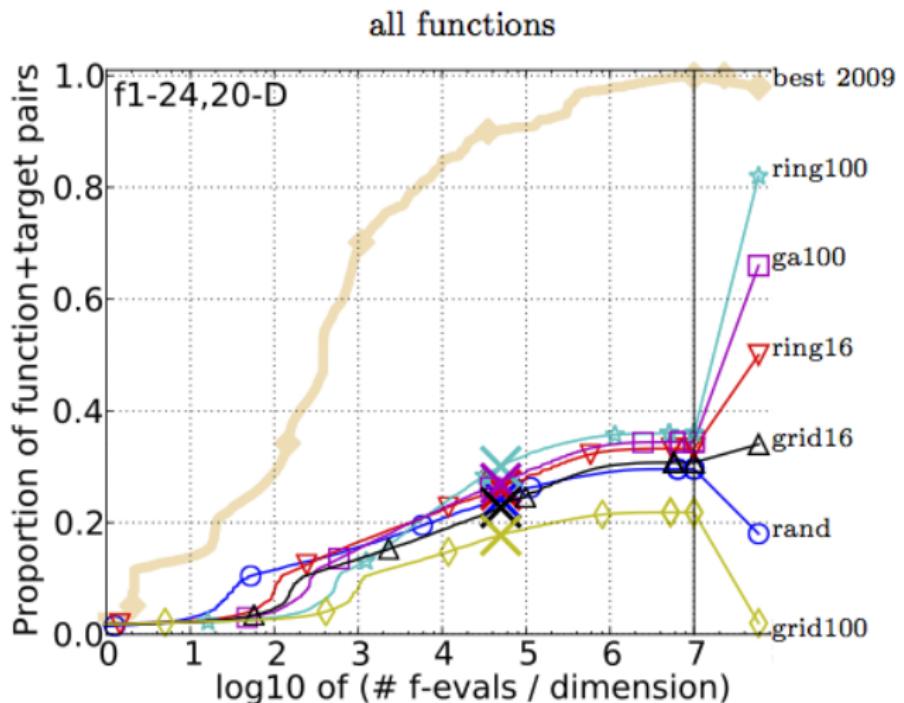
## Use Ring



# 5-D All Functions



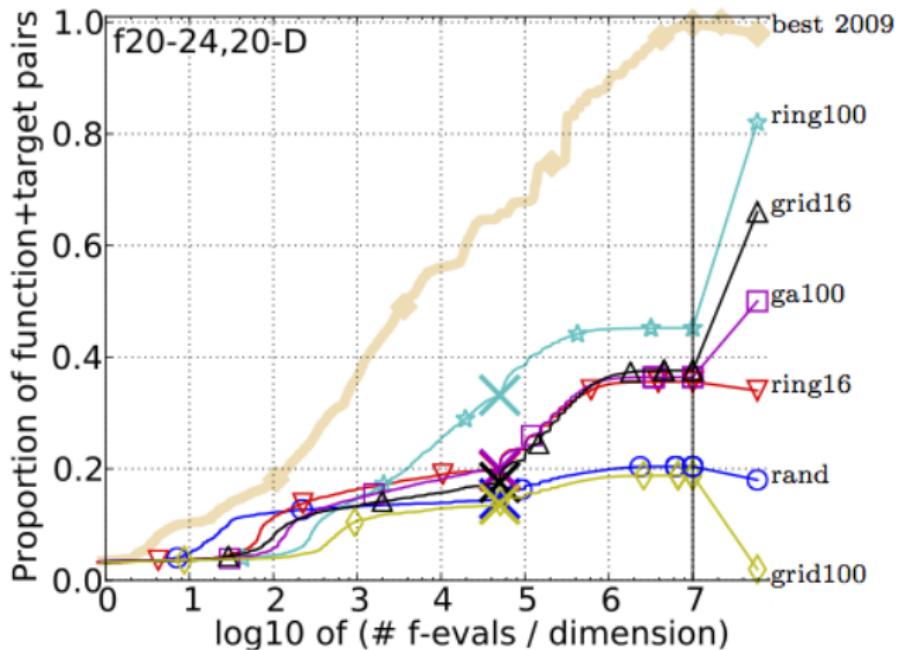
# 20-D All Functions



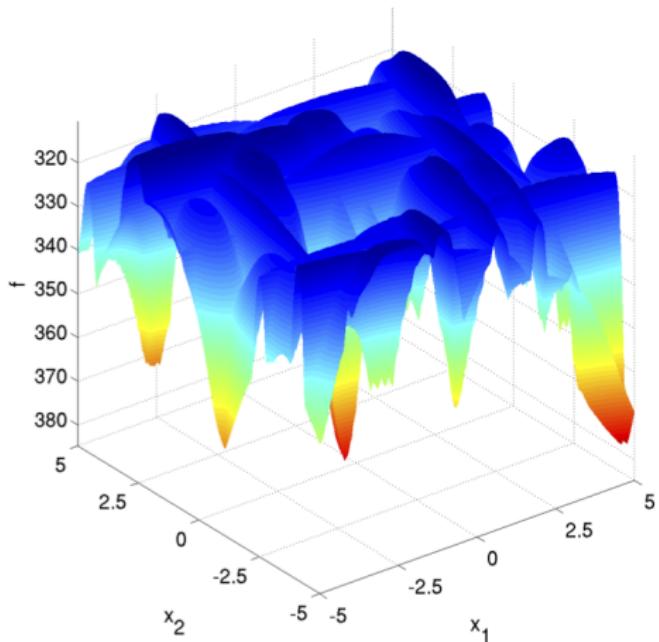
# 20-D Weakly Structured



weakly structured multi-modal fcts

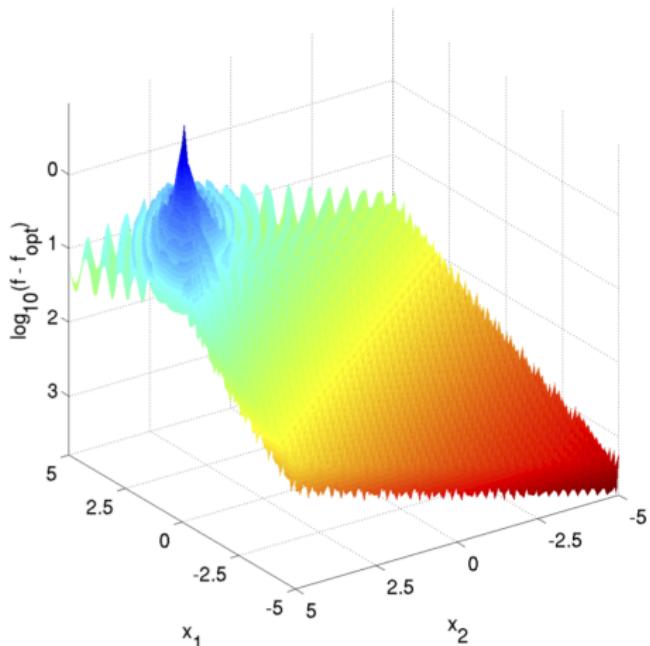


# Brief aside: What is Weakly Structured?



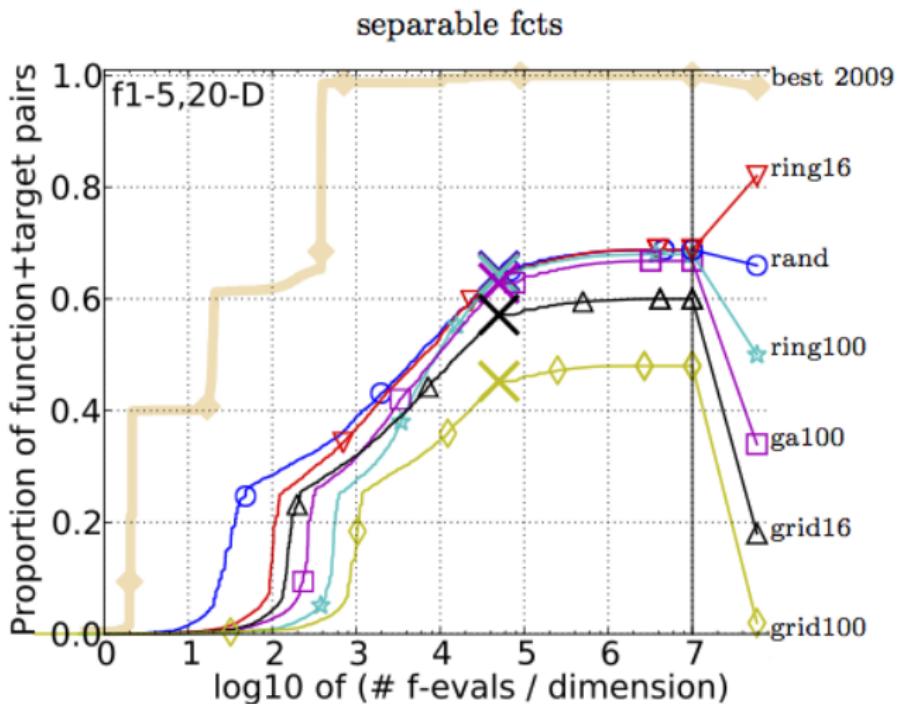
Gallagher's Gaussian 101-me Peaks Function

# Brief aside: What is Weakly Structured?



Schaffers F7 Function

# 20-D Separable



# Apples to Apples



Real-coded genetic algorithm benchmarked  
on noiseless black-box optimization testbed

by Thanh-Do Tran and Gang-Gyoo Jin

GECCO 2010

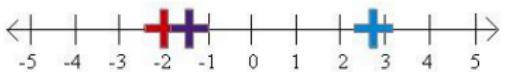
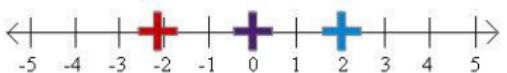
Population Size	100
Crossover rate	0.95
Tournament size	2
Mutation rate	0.05, 0.1, 0.2
Restart trigger A	After a fixed number of iterations
Restart trigger B	Based on lack of improvement in population fitness

# Restarts



Mutation rate	0.05, 0.1, 0.2
Restart trigger A	$\text{floor}(100 + 3800D\sqrt{D})$ iterations
Restart trigger B	best population fitness varying less than $10^{-12}$ in $(50 + 25D)$ generations

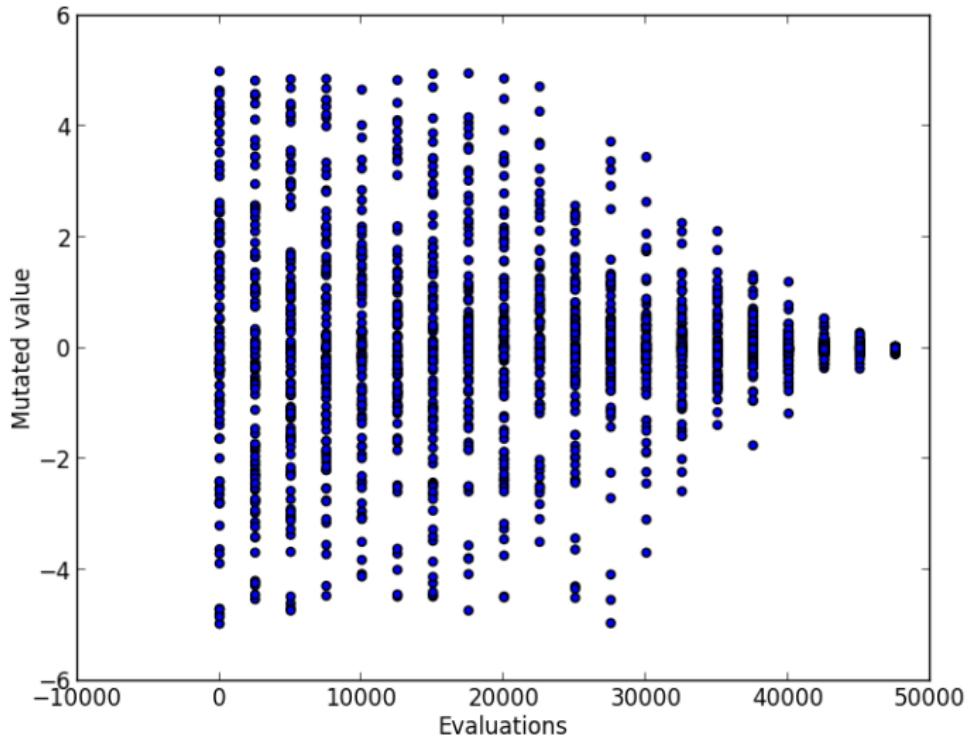
# Arithmetic crossover



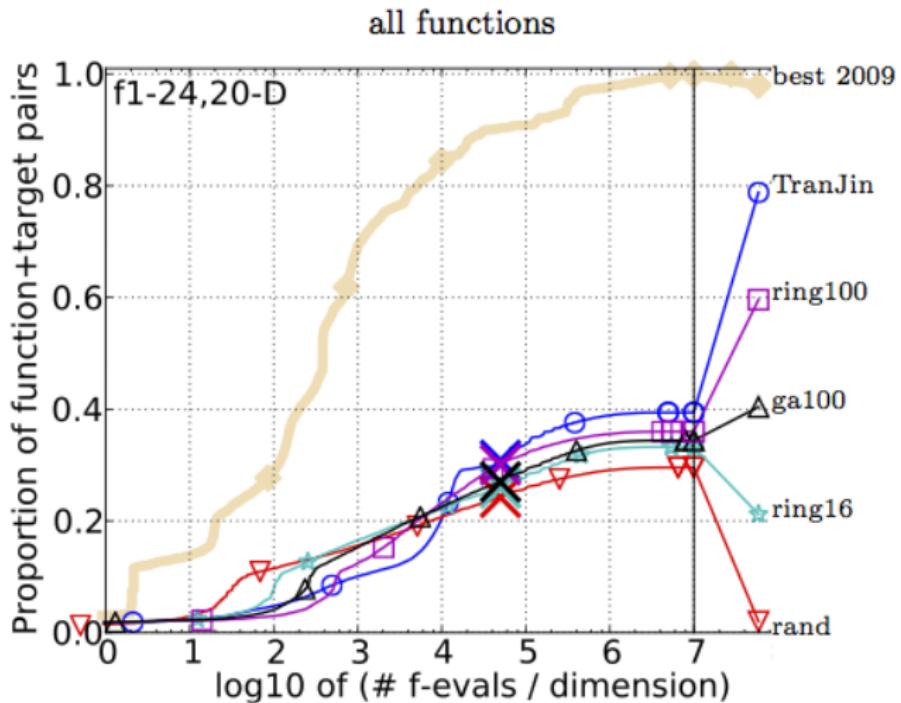
This operator is a modification of  
Michalewicz non-uniform mutation from:

An adaptive range mutation operator for  
real-coded genetic algorithms  
by Kevin Austin and Peter Jacobs  
2001

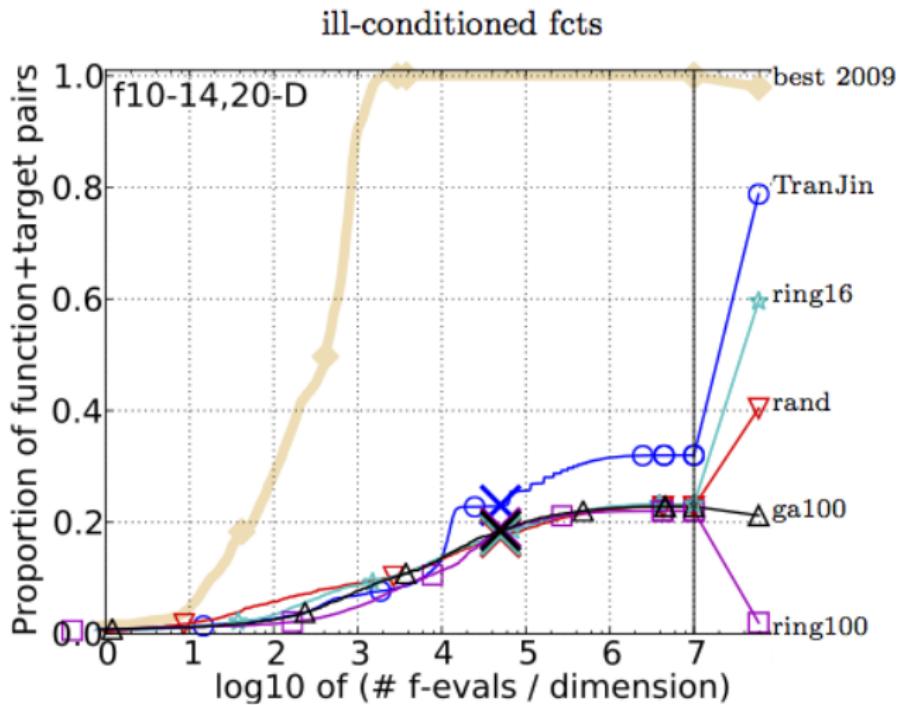
# Adaptive range mutation



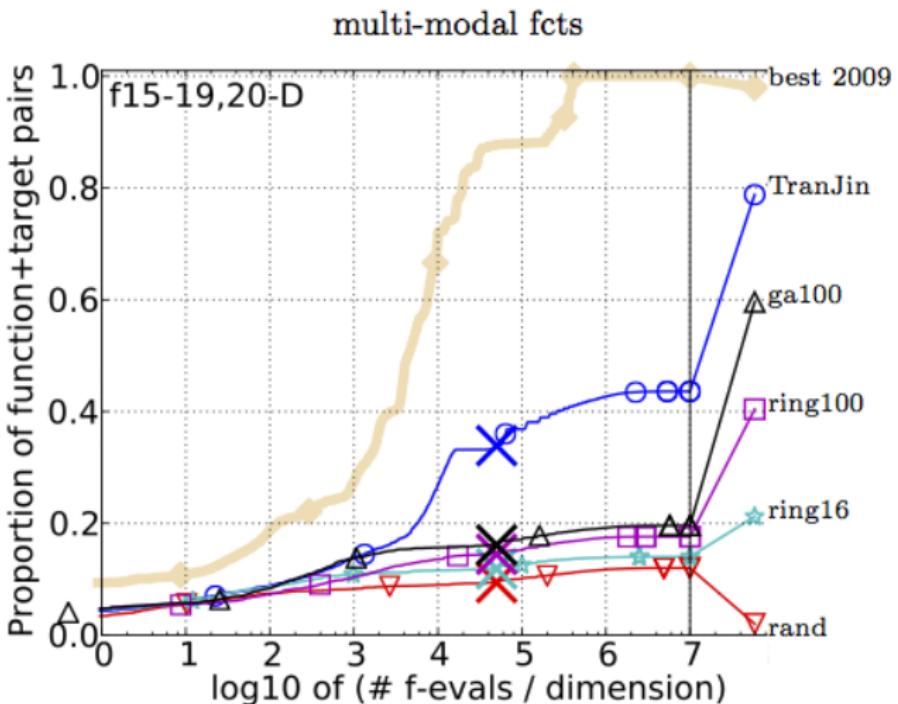
# CGA compared unfavorably overall (20-D)



...particularly on  
ill-conditioned (20-D)



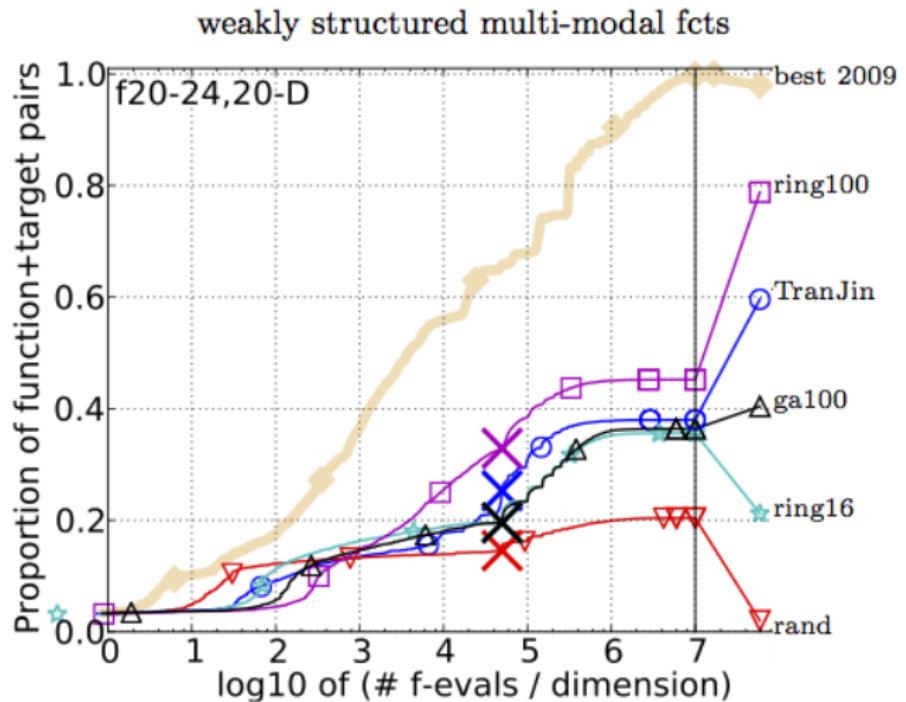
# ...and multi-modal functions (20-D)



# CGA outperformed RCGA on weakly structured functions (20-D)



UNM



# Interesting operator



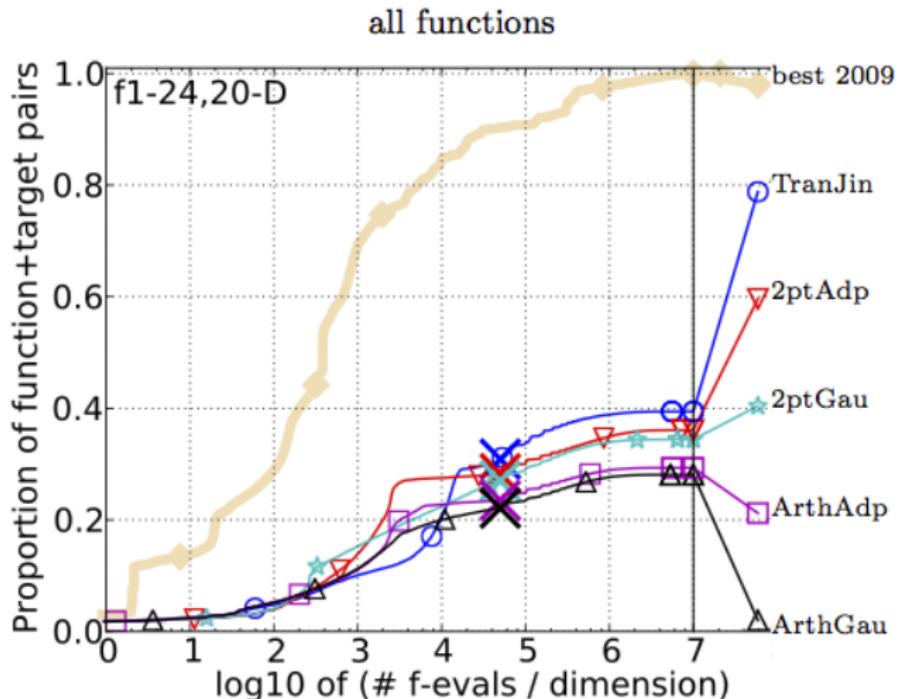
# Operator comparison



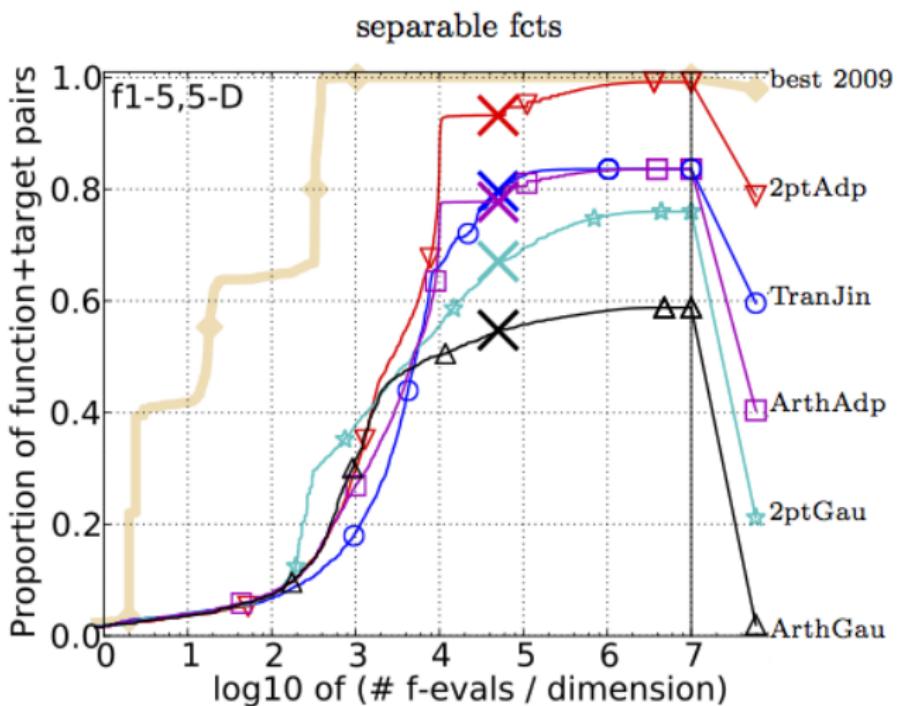
Algorithm name	Crossover Operator	Mutation Operator	Restarts
2ptAdp	2-point	Adaptive	no
2ptGau	2-point	Gaussian	no
ArthAdp	Arithmetic	Adaptive	no
ArthGau	Arithmetic	Gaussian	no
TranJin	Arithmetic	Adaptive	yes

Population size 100

# 20-D All Functions

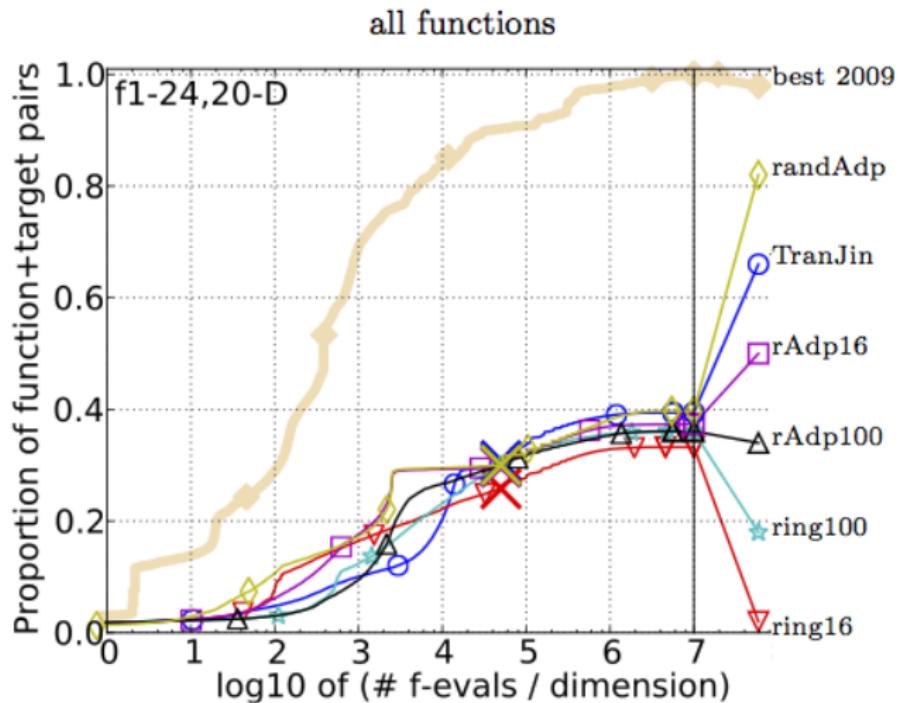


# 5-D Separable



So what happens if we bolster ring CGA with adaptive range mutation?

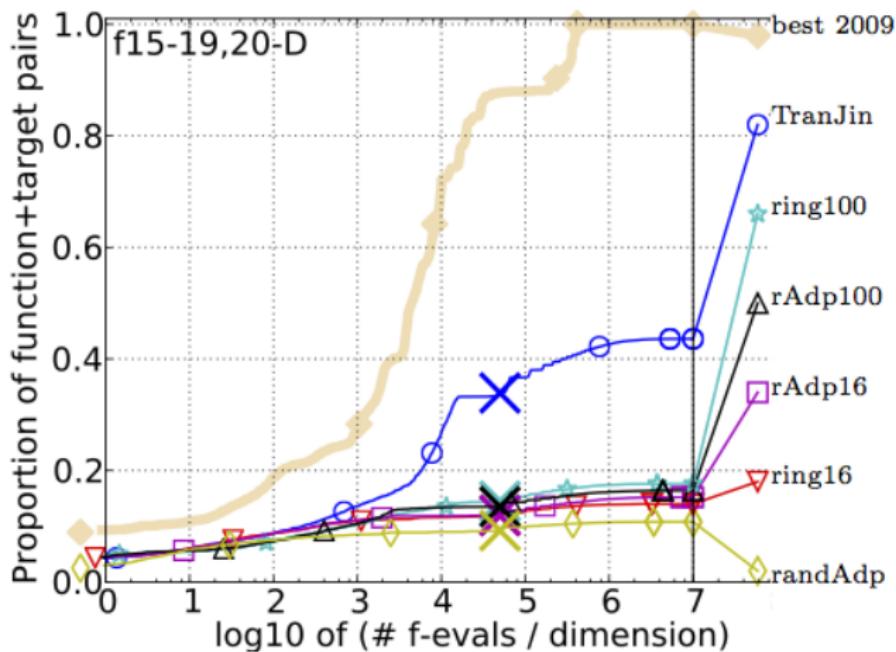
# 20-D All functions



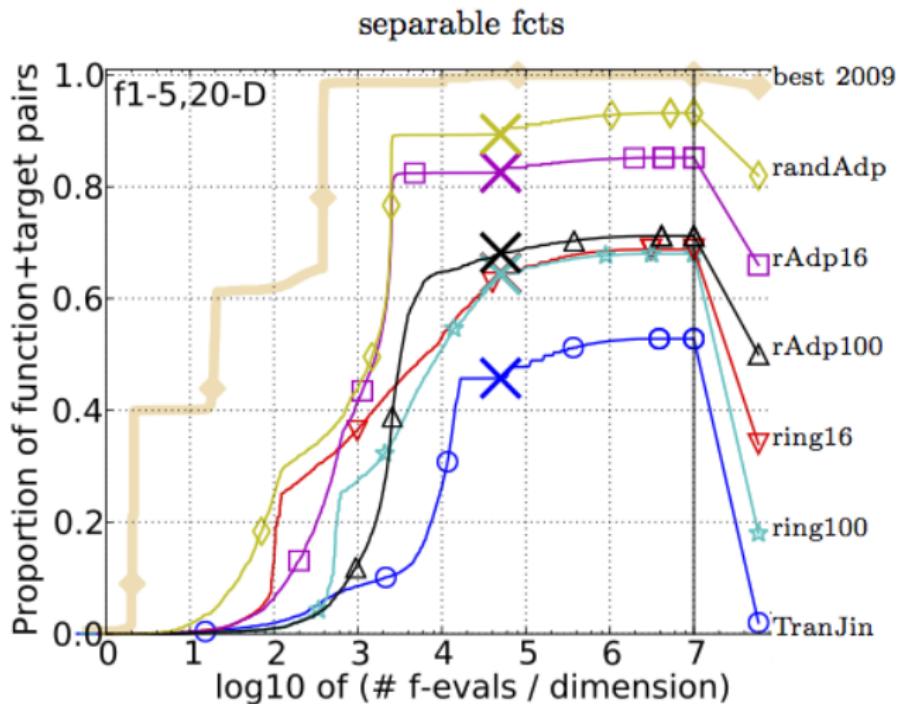
# 20-D Multi-modal



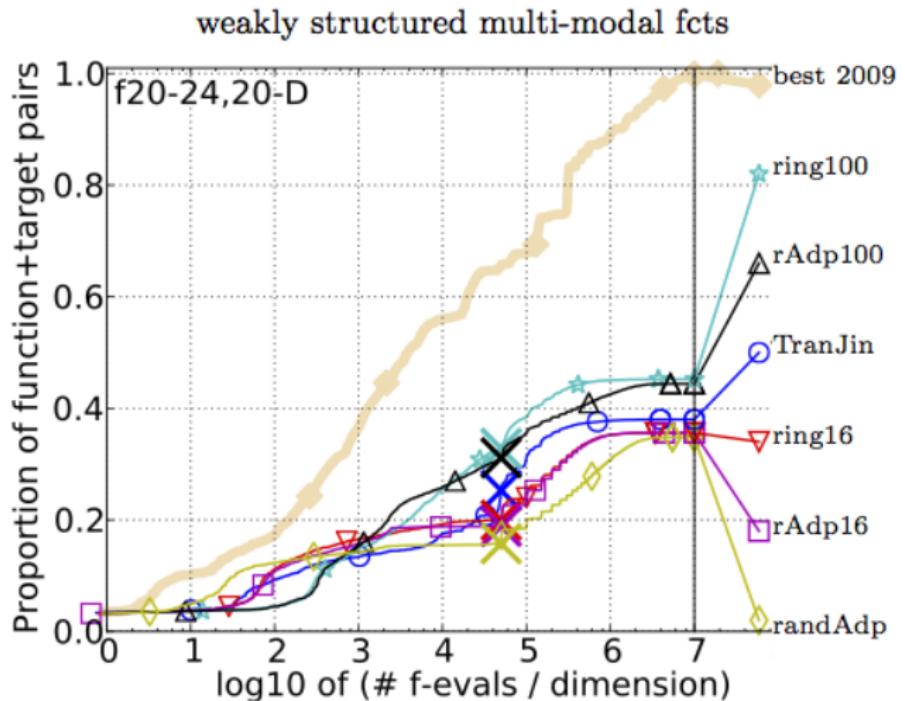
multi-modal fcts



# 20-D Separable



# 20-D Weakly structured



# Conclusion



Which algorithm is best?



Which algorithm is best?



It depends on the function to be optimized.

# Conclusion



Random search can be highly effective on separable functions.

# Conclusion



Single-population, panmictic GAs are competitive with grid CGAs run on a single core.

# Conclusion



Adaptive range mutation is an effective mutation operator for closing the distance to the optimal solution.

Arithmetic crossover is not particularly effective on these benchmarks.

# Conclusion

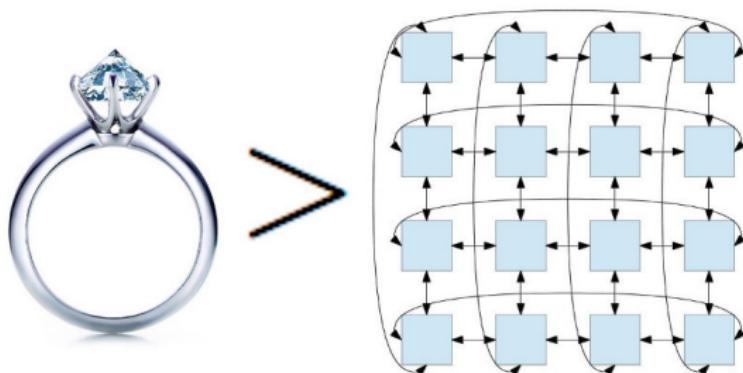


Ring CGA outperforms single-population GAs on weakly-structured, multi-modal functions most likely due to the Ring CGA's greater emphasis on exploration over exploitation.

# Conclusion



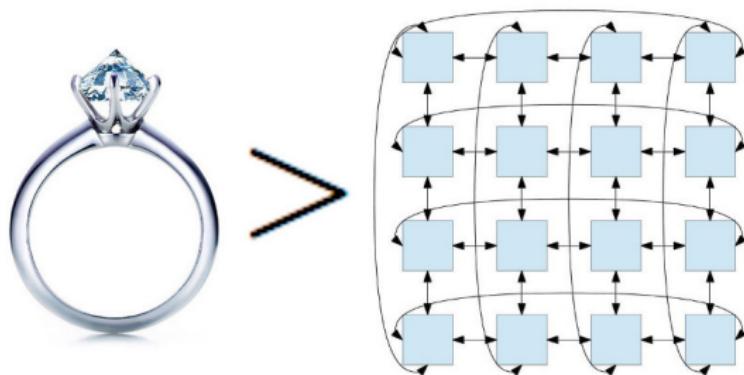
Ring CGAs outperform Grid CGAs.



# Conclusion



Ring CGAs outperform Grid CGAs.



Bonus! Lower communication overhead

Thank you for your time.

Questions?