

Star discrepancies for generalized Halton points sets

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Overview

Languages used

- C | Discrepancy calculation
- C++ | Unit simulations
- Python | Wrappers

Heuristics implemented

- Fully random search
 - Simulated annealing for local rand search
 - $(\mu+\lambda)$ Genetic search
-

MUCH DISCREPANCY

Wow

SUCH OPTIM

WOW

LOTS GRAPHS

Random Search

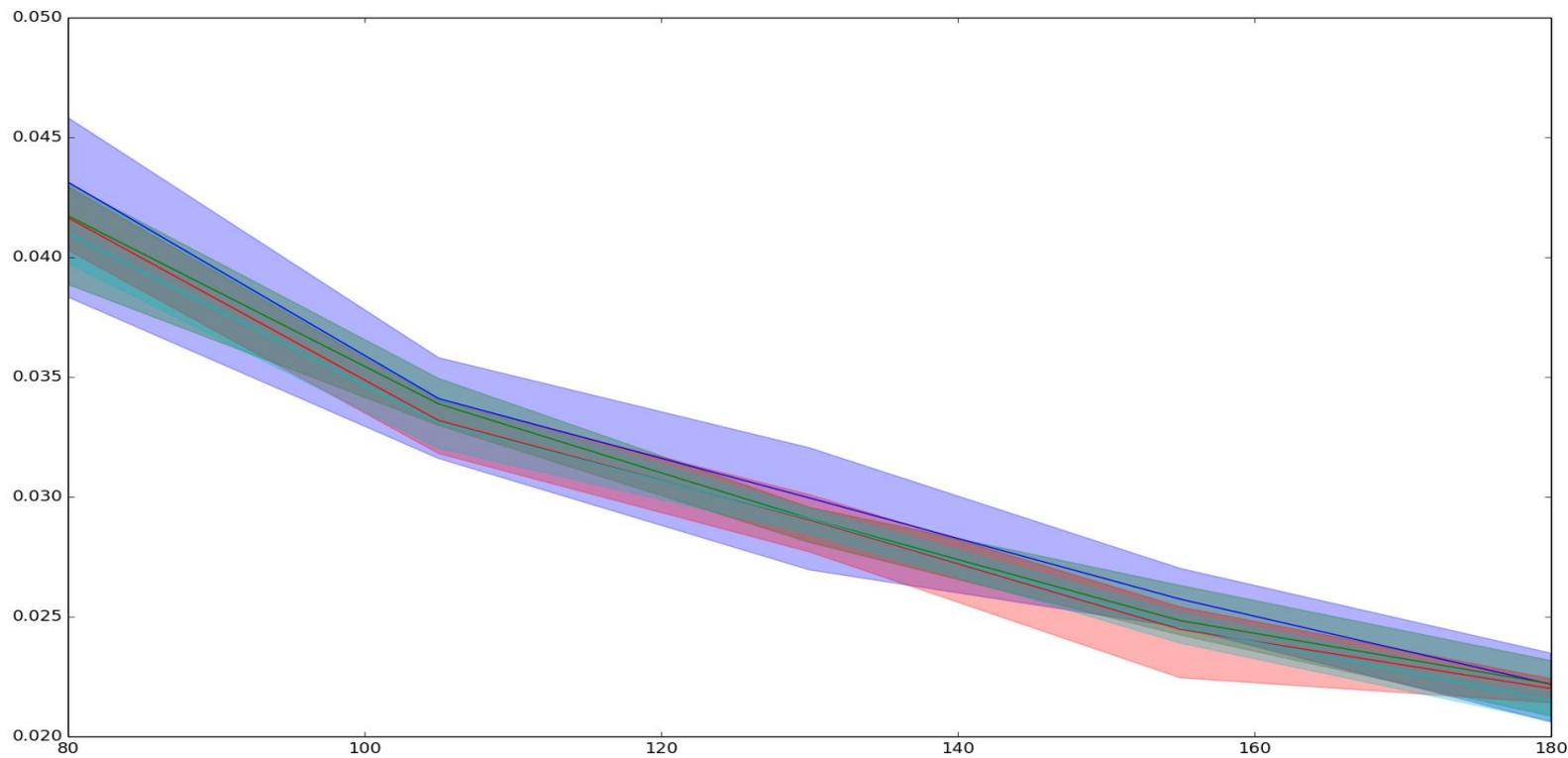
Overview

- Simplest search: regenerate the whole permutation at each iteration.
- The prime based is fixed
 $\{7, 13, 29, 3\}$
- Invariant $\text{pi}[0] = 0$ maintained + *KFY shuffle* called on $\text{pi}[1, \dots, n]$.

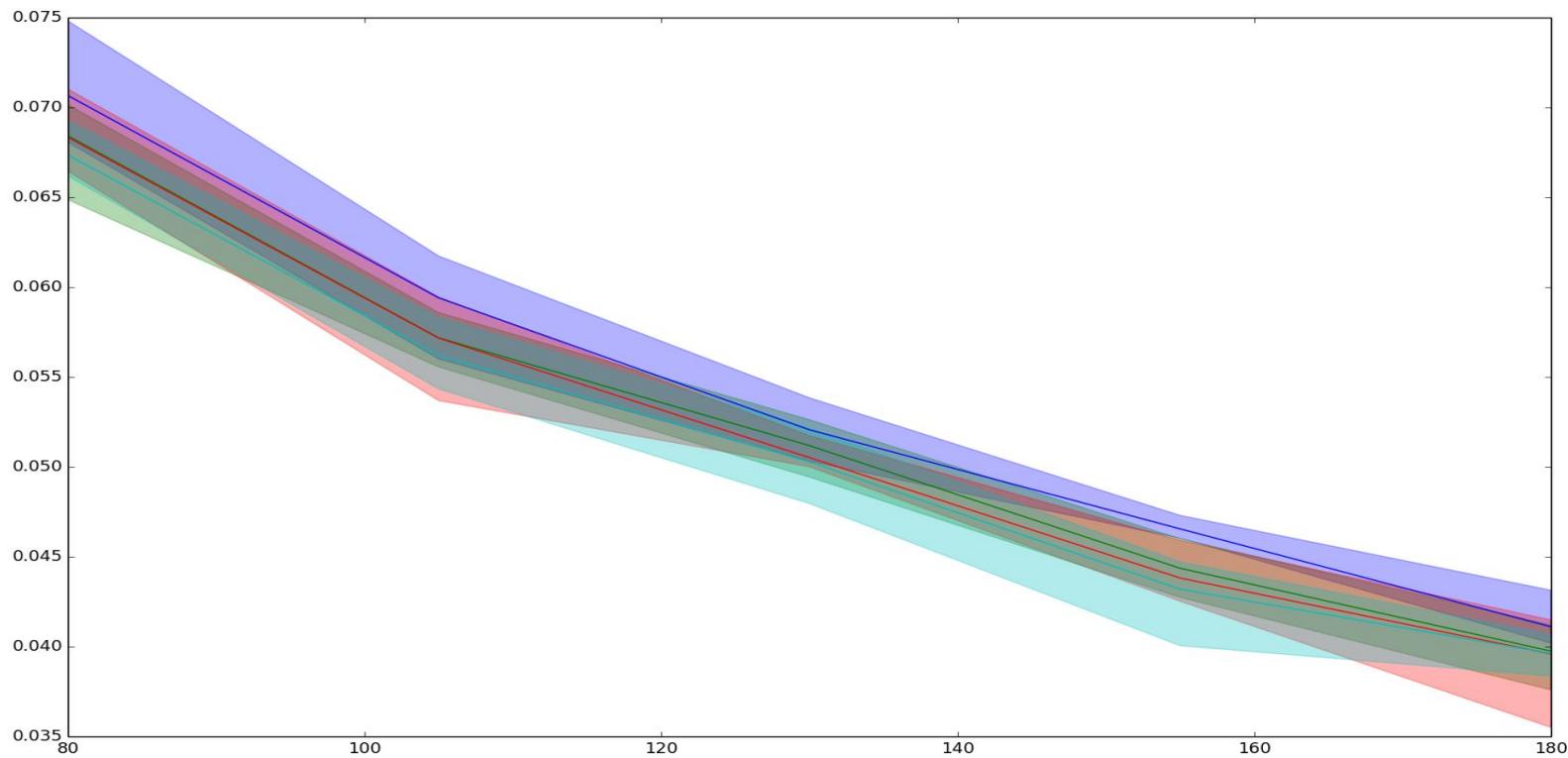
Knuth-Fisher-Yates Shuffle

1. *-- To shuffle an array a of n elements*
2. $A[0..n-1];$
3. **for** i **from** $n-1$ **downto** 1 **do**
4. $j \leftarrow$ random integer in $[0, \dots, i];$
5. $\text{swap}(A[j] , A[i]);$
6. **done**

Random Search | Stability (D=2)



Random Search | Stability (D=3)



Random Search Results

Large errors bands

Number of iterations > 1000 doesn't
give much better results

Simulated Annealing

What's that?

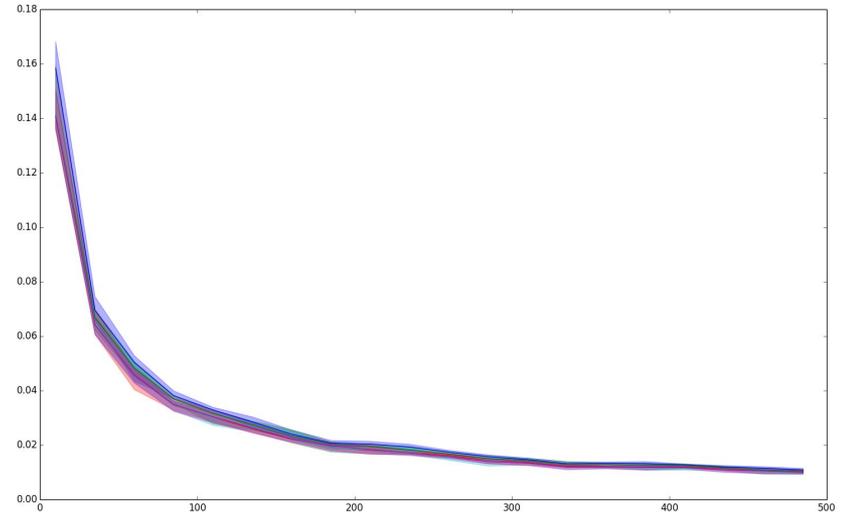
- Interprets slow cooling as a slow decrease in the probability of accepting worse solutions
- Accepting worse solutions is a fundamental property to avoid local minima.

Pseudo-Code

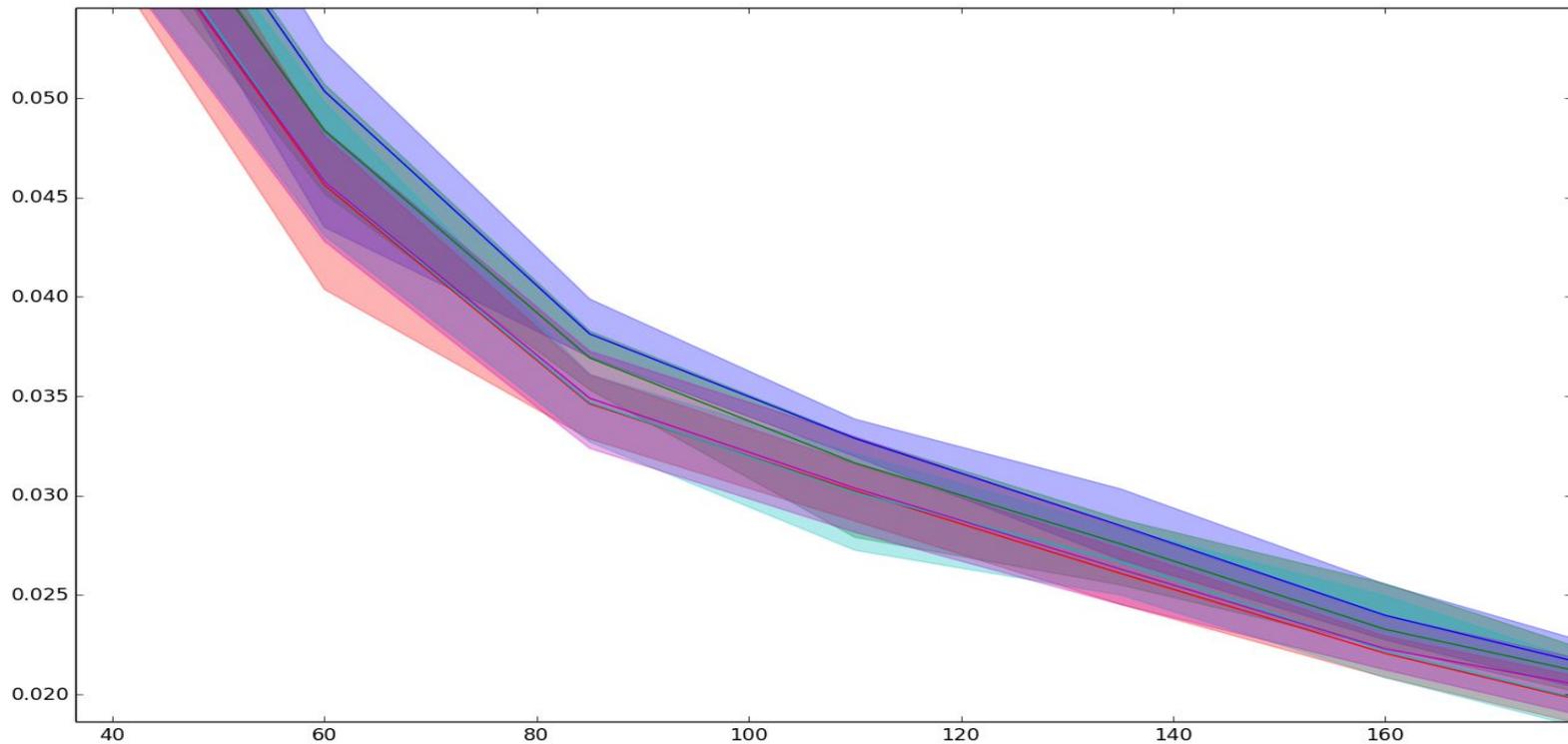
```
1.  $s \leftarrow s_0;$   
2. For  $k = 0$  to  $k_{\max}$  do  
3.    $s_{\text{new}} \leftarrow \text{neighbour}(s);$   
4.   If  $e^{(E(s)-E(s_{\text{new}}))/T} \geq \text{random}(0, 1)$  then  
5.      $s \leftarrow s_{\text{new}};$   
6.      $T \leftarrow T * \lambda; \quad // \lambda = 0.992$   
7.   done  
8. return  $s;$ 
```

Sim. Annealing Results

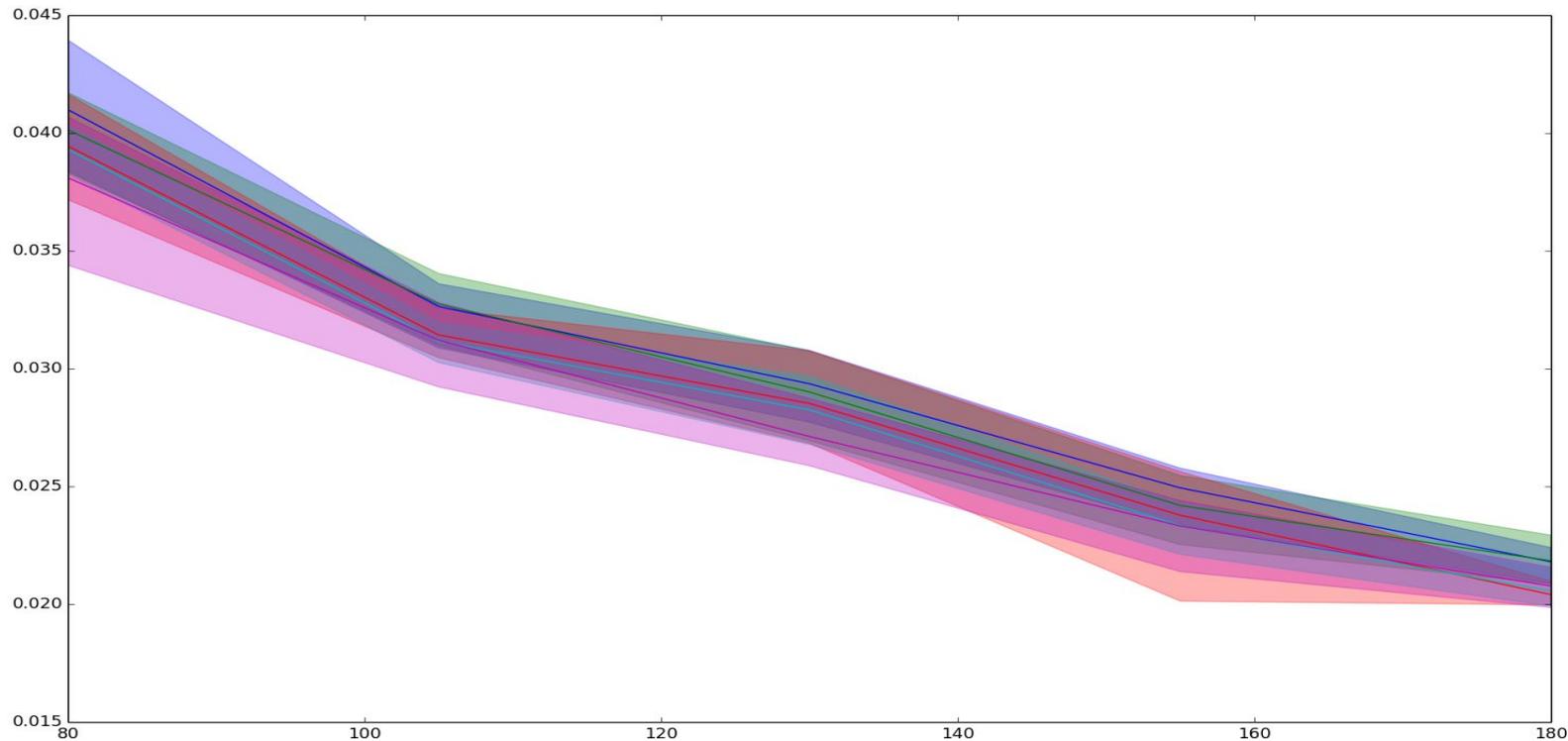
Dependance on initial temperature



Sim Annealing | Temperature (D=3)



Sim Annealing | Stability (D=2)



Sim. Annealing Results

Lowest temperature gives
best results
(saturates if < 0.001)

Number of iterations > 1000 doesn't
give much better results

Smaller error bands.

$(\mu+\lambda)$ Genetic Search

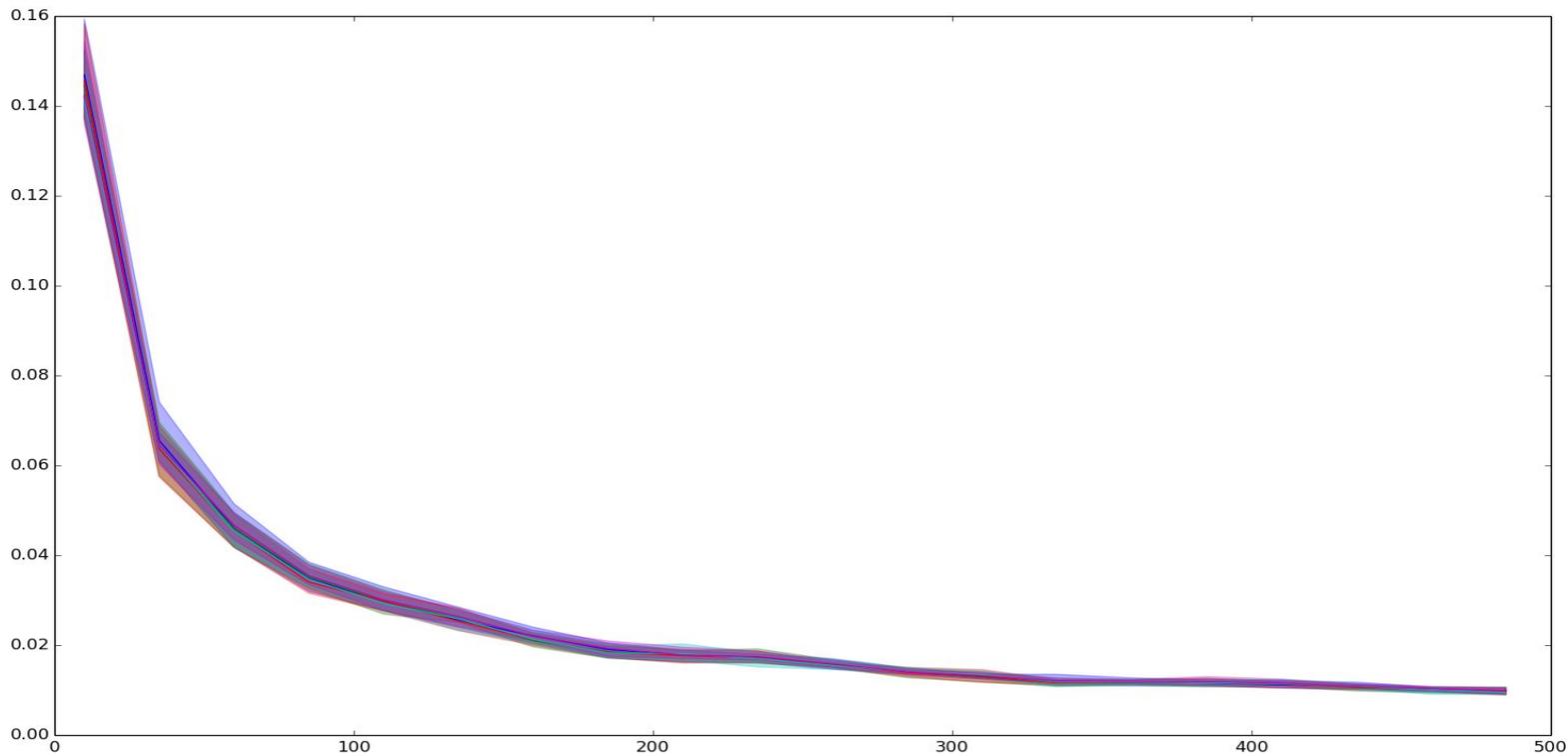
Overview

- (5,5) search implemented.
- Keep common values.
- Close to A or B.
- Don't modify more the end of the permutation than its start.

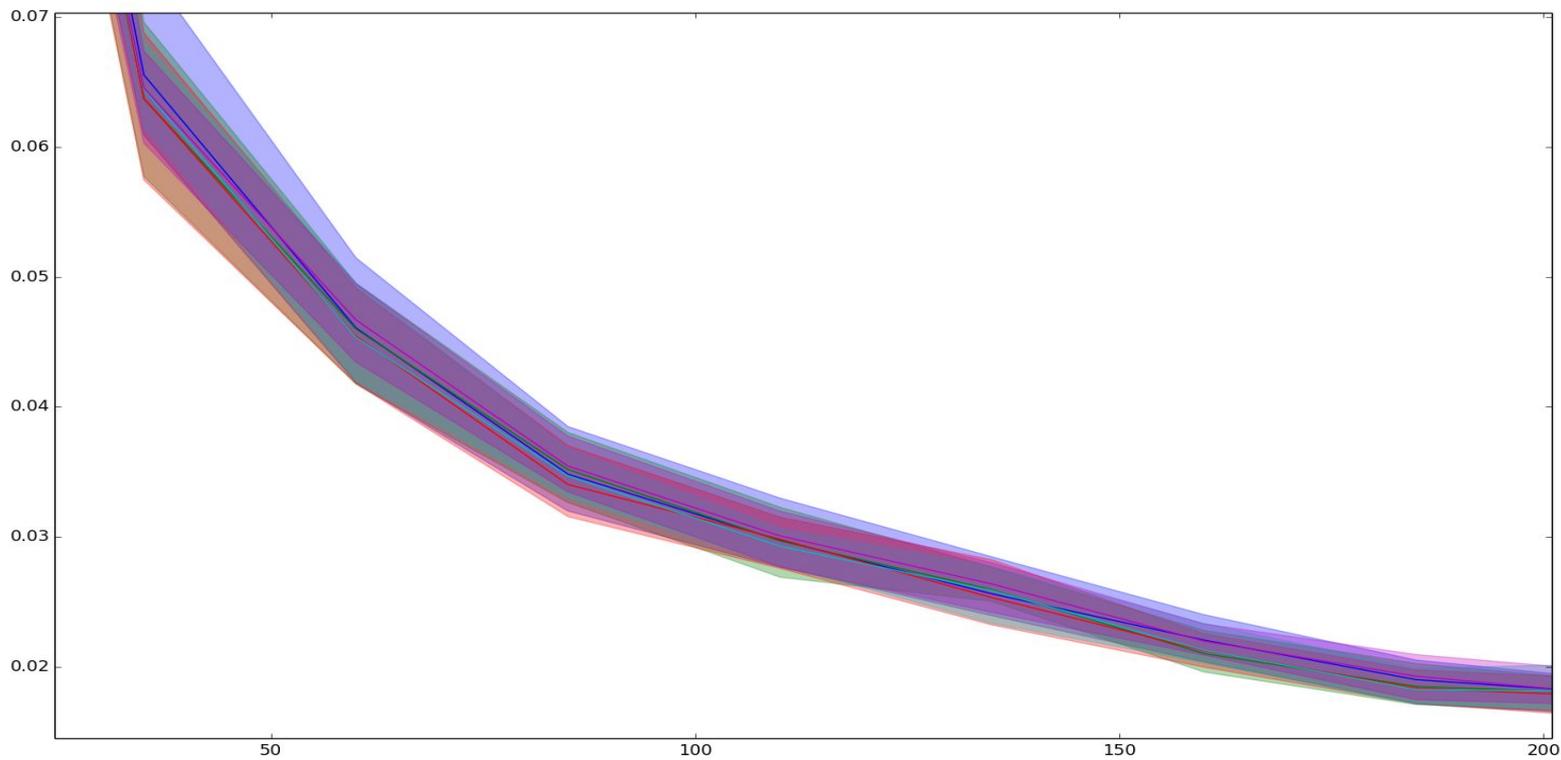
Crossover algorithm

```
1.  A[0..n-1]; B[0..n-1];
2.  pi ← KFY shuffle [1..n];
3.  availables ← ∅;
4.  for i from 1 downto n do
5.      if A[pi[i]] and B[pi[i]] already chosen then
6.          C[pi[i]] ← Random in availables;
7.      elif A[pi[i]] already chosen then
8.          C[i] ← B[pi[i]];
9.      elif B[pi[i]] already chosen then
10.         C[i] ← A[pi[i]];
11.     else
12.         swap A and B w.p. 1/2
13.         C[i] ← A[pi[i]];
14.         available ← available ∪ {B[pi[i]]};
15.     done
16.     availables ← availables \ {C[pi[i]]}
17. done
```

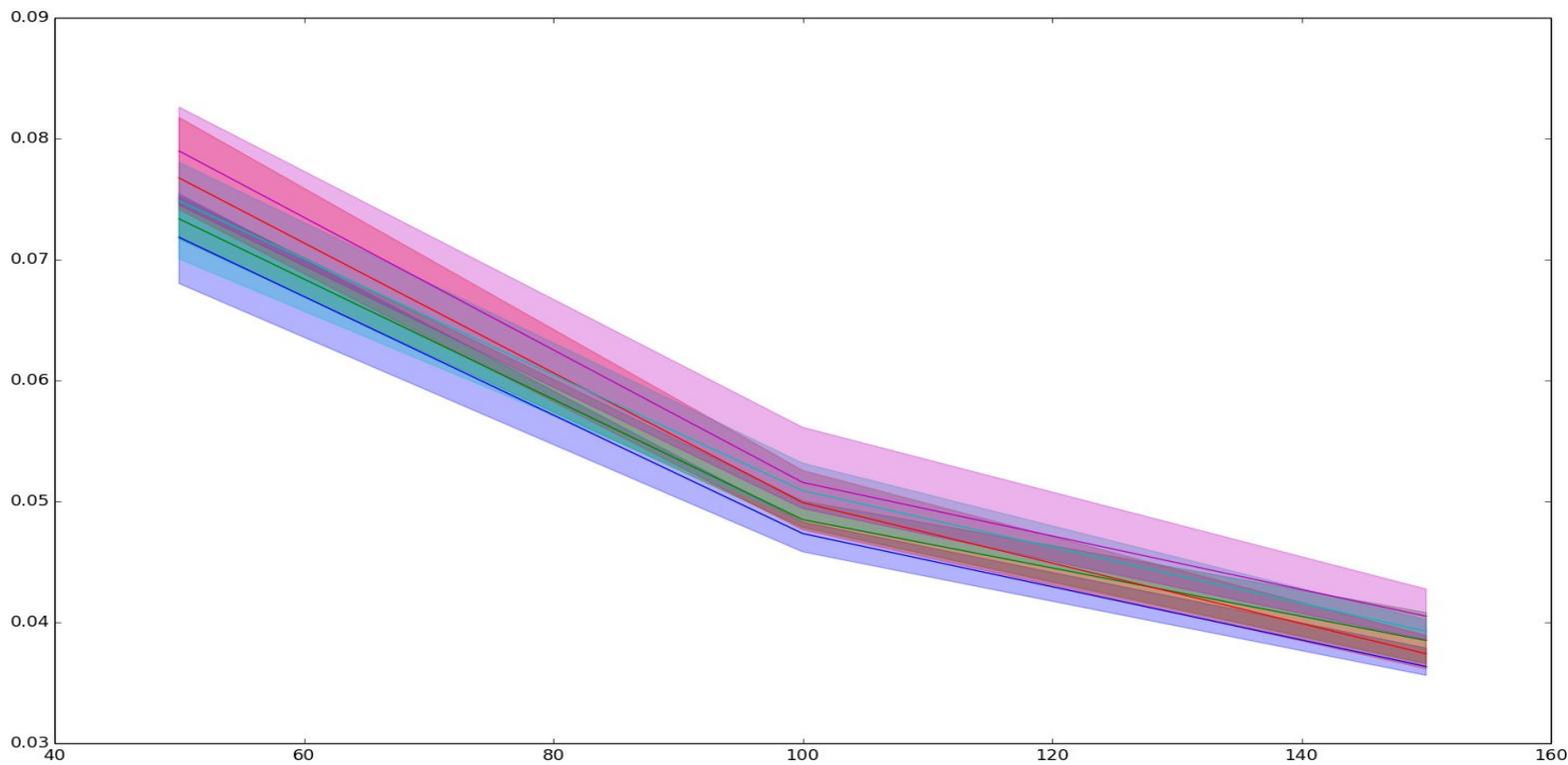
Genetic Search | p dependence (D=2)



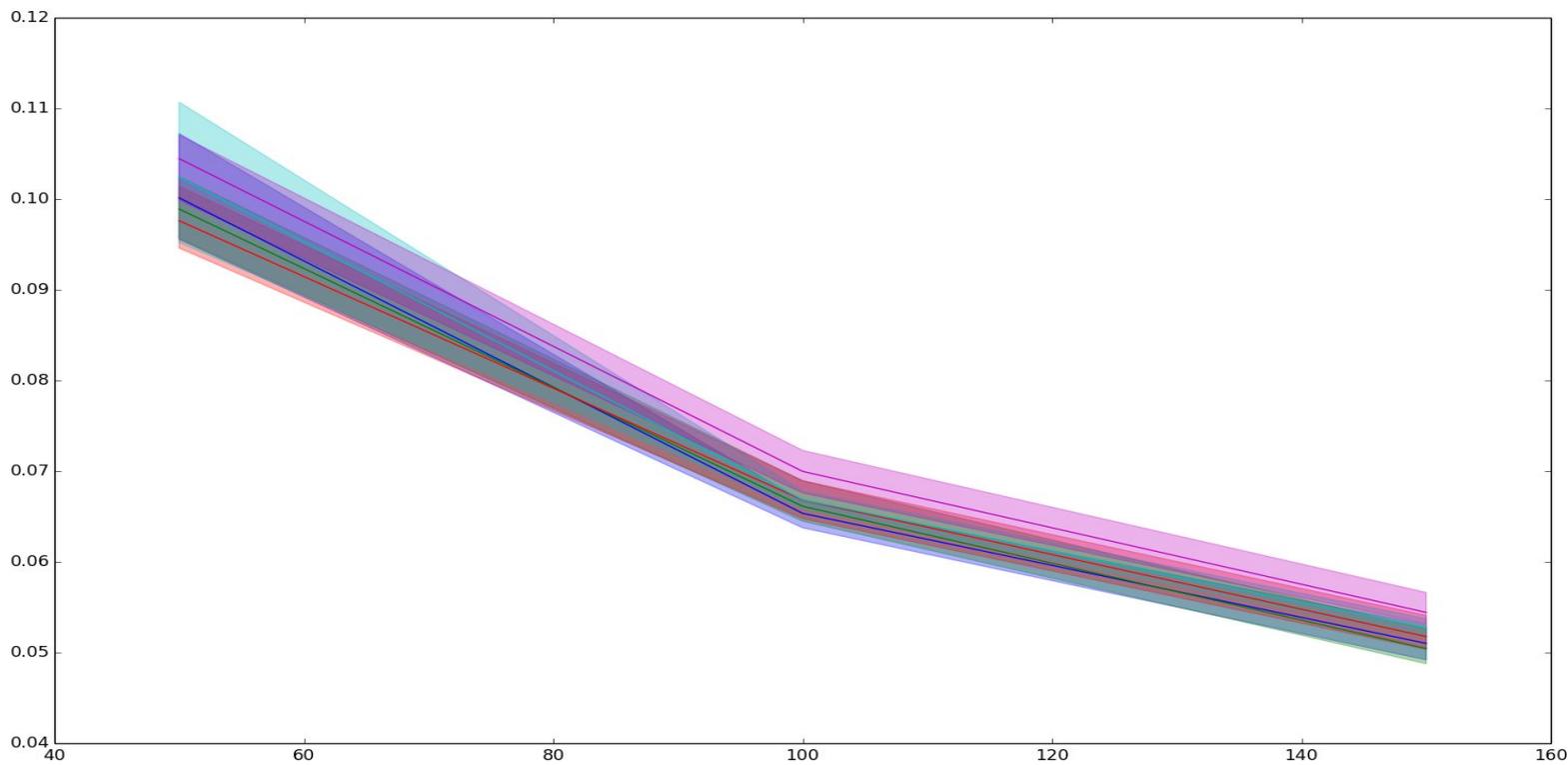
Genetic Search | p dependence (D=2)



Genetic Search | p dependence (D=3)



Genetic Search | p dependence (D=4)



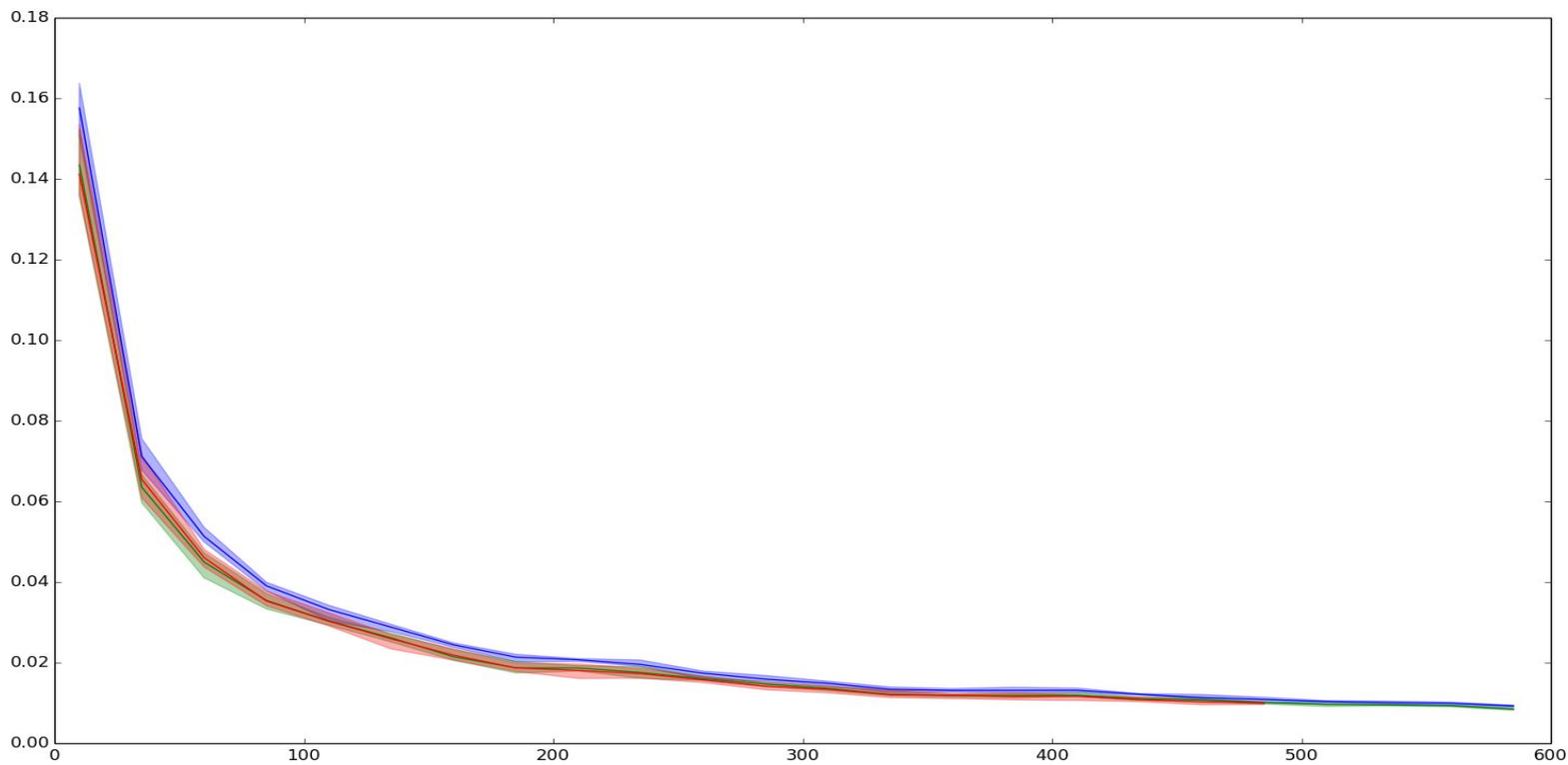
Genetic Search Results

Best results on average for
 $c=0.5/0.6$

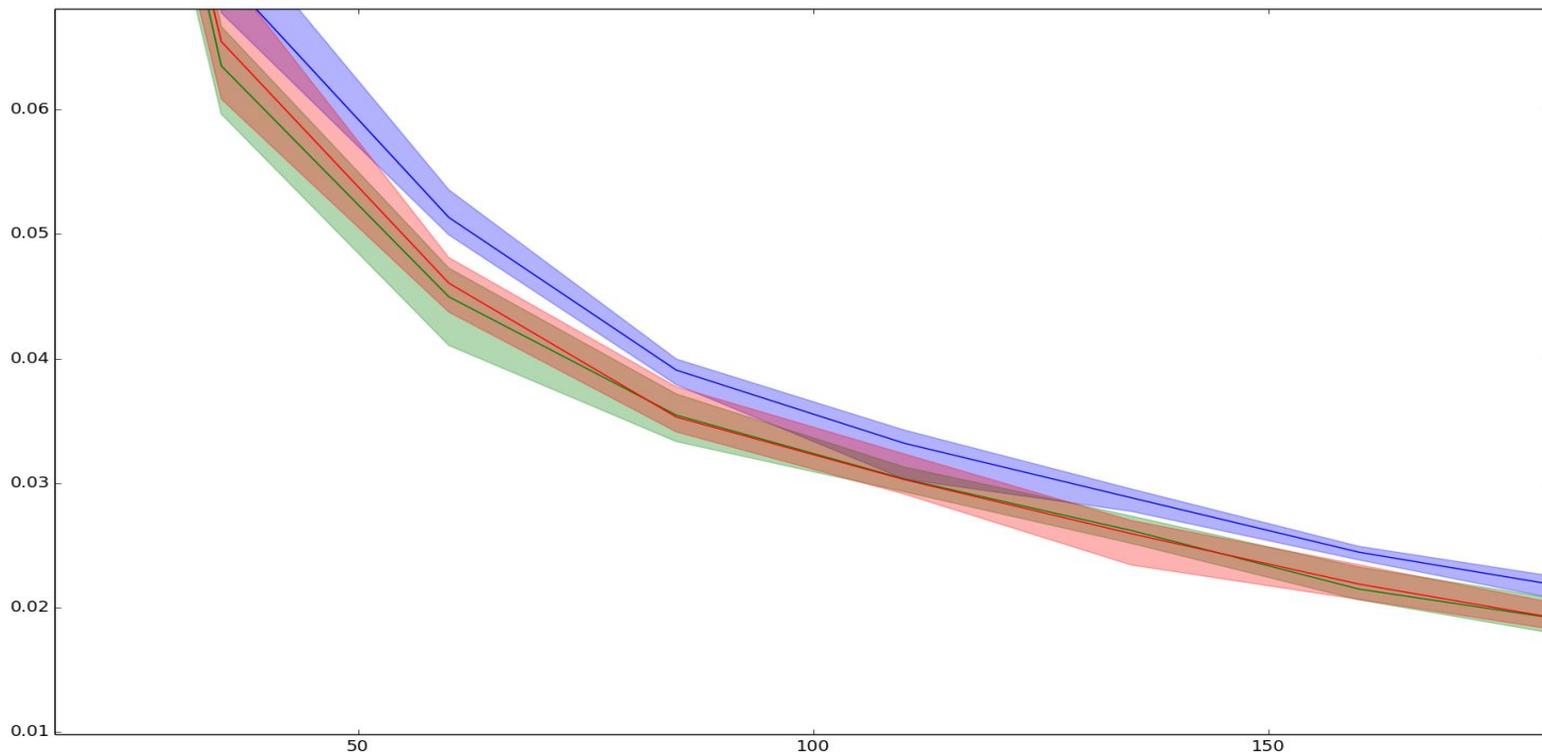
Number of iterations > 1000 doesn't
give much better results

Big errors bands on
low number of points.

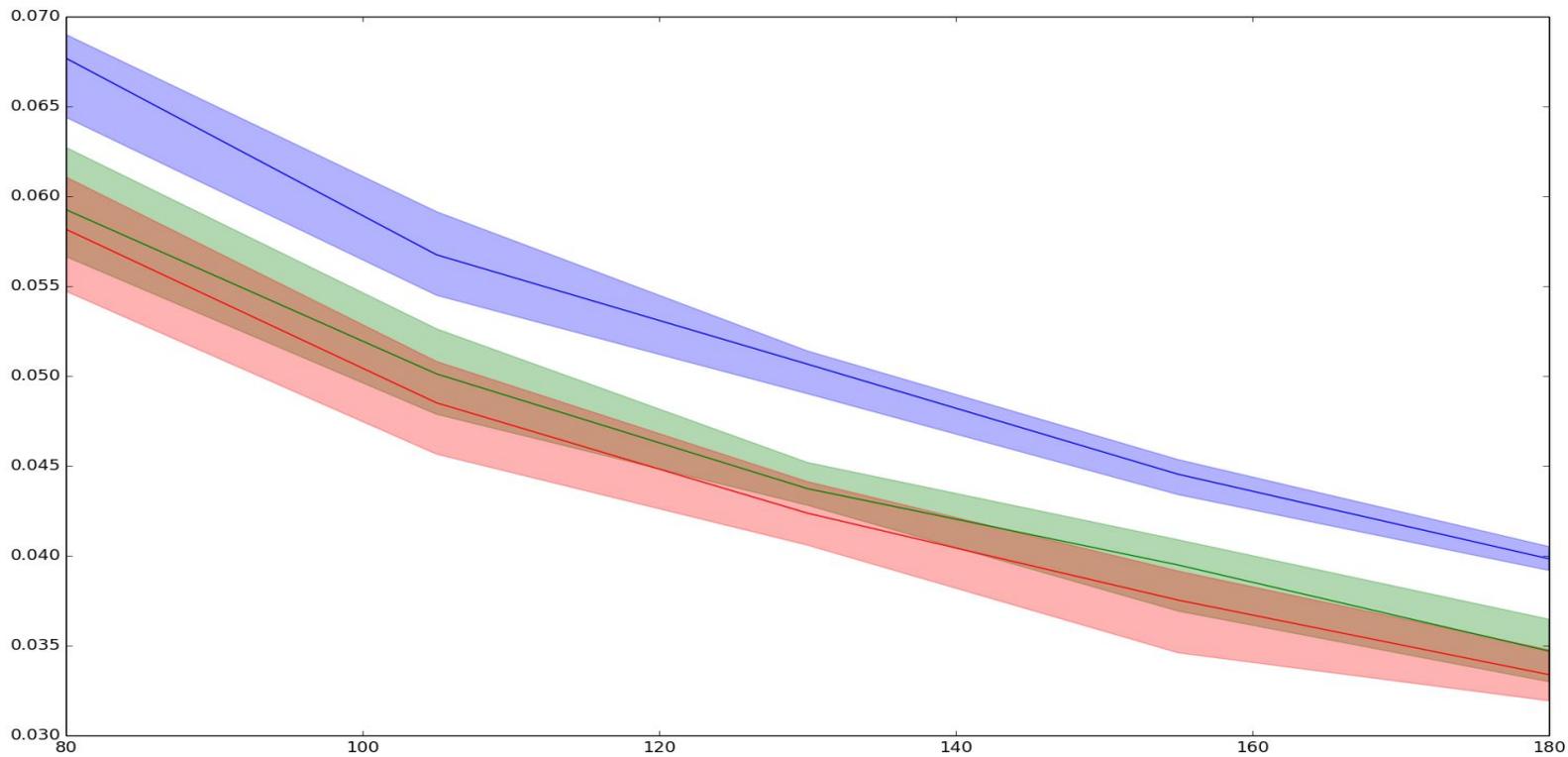
Wrap up all heuristics (D=2)



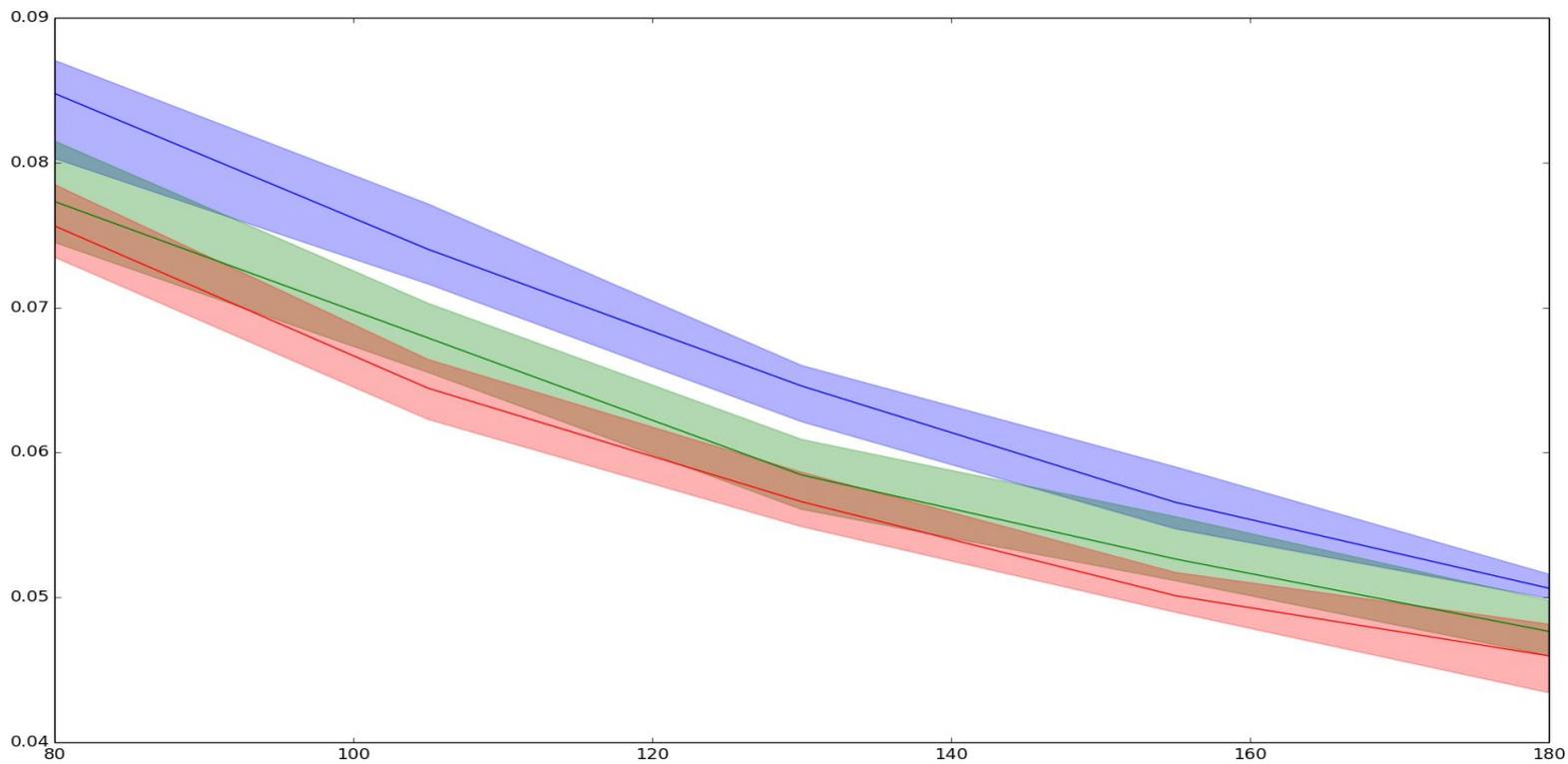
Wrap up all heuristics (D=2)



Wrap up all heuristics (D=3)



Wrap up all heuristics (D=4)



Wrap up

**“Intelligent” heuristics
are better than
fully random search**

**Genetic or S.A. is better
depending on the dimension.**
