

Search space optimisation for procedural content generators

Harald De Bondt

Problem statement

- Content creation problem
 - Unscalable
 - Expensive
- Procedural Content Generation (PCG)
 - Automation
 - Variety
 - Replayability
- Research problem in PCG
 - Controllability
 - Intuitive configuration
 - Expressiveness
 - Avoid bias due to implementation



Related work

Controllability in PCG

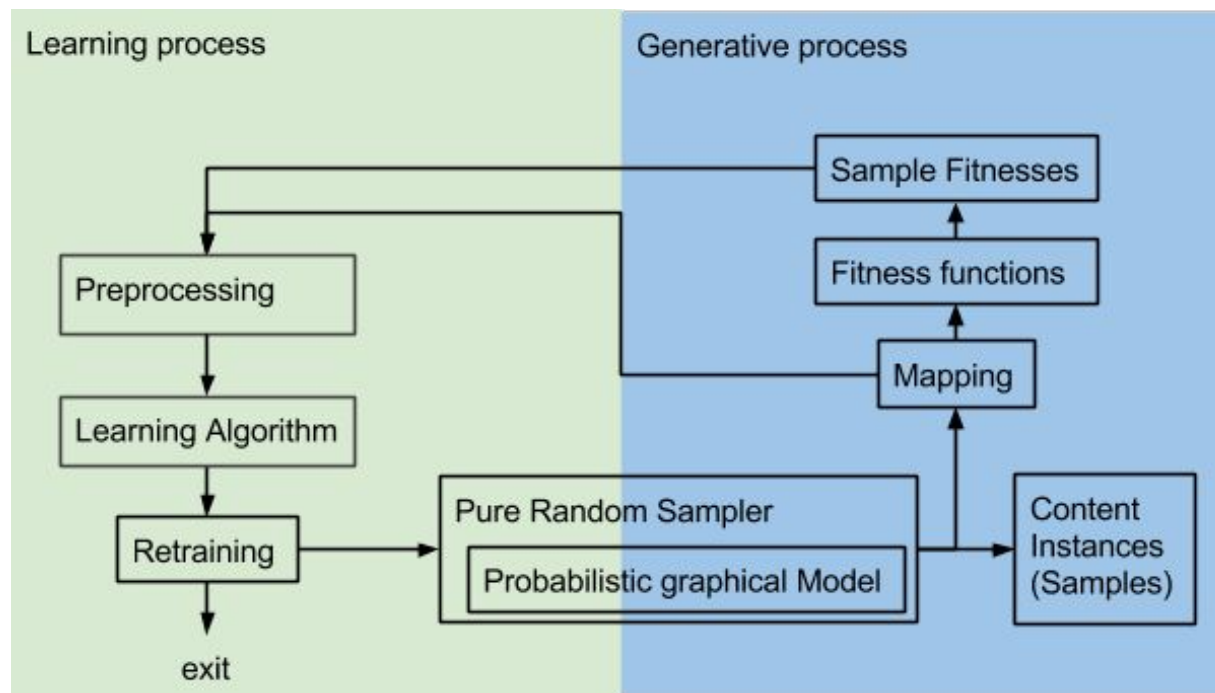
- Expressiveness ↔ Controllability
- Control types: Bottom-up vs top-down
 - How vs what is generated
 - Feed-forward vs iterative
 - Local control vs global
- Examples
 - Constructive
 - Declarative
 - Search-based
 - Probabilistic
 - Learning

[-] Ramp	
Ramp Output	Z
Ramp size	567.6 nm
Z scan start	567.6 nm
Ramp Rate	1.03 Hz
Forward velocity	1.17 µm/s
Reverse velocity	1.17 µm/s
X Offset	0.000 nm
Y Offset	0.000 nm
Number of samples	512
Spring Constant	42.00 N/m
Plot Units	Metric
Display Mode	Both
X Rotate	0.00 °
Z Closed Loop	On
[-] Mode	
Trigger mode	Relative
Data Type	Deflection Error
Trig threshold	55.00 nm
Start mode	Calibrate
End mode	Retracted
Z step size	0 nm
Auto start	Disable
Surface delay	0.00 s
Retracted delay	0.00 s
XY move on surface	Enabled

Methodology

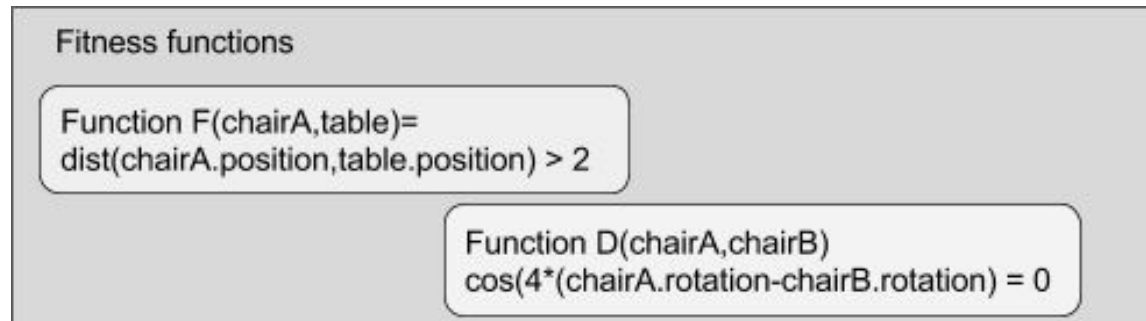
- Maximise expressiveness
 - Uniform sampling from optimised model \leftrightarrow optimised search algorithm

Two processes

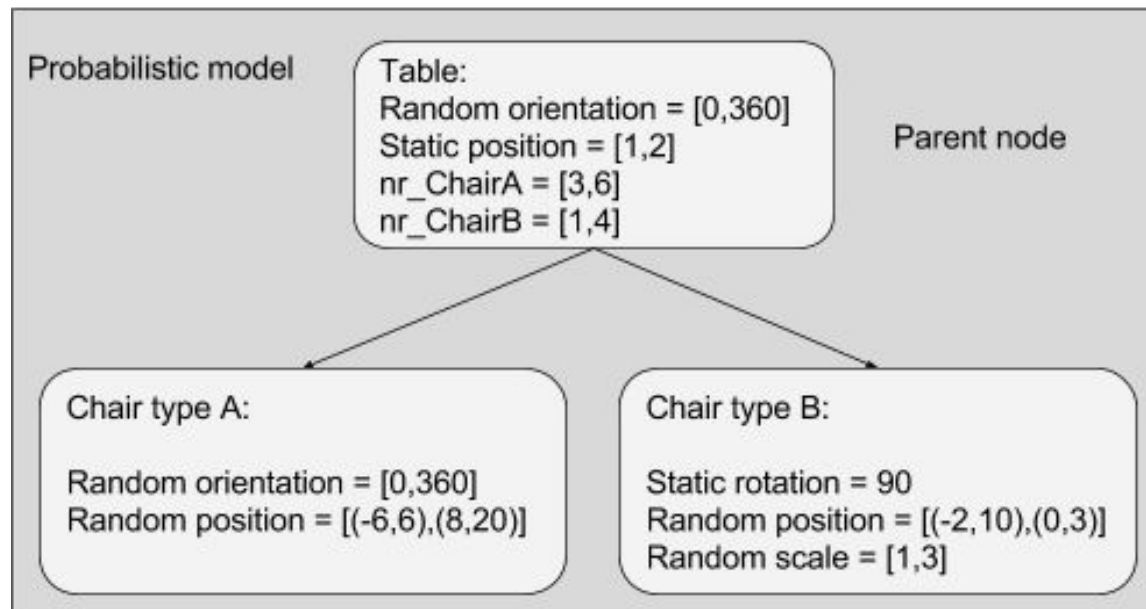


Generative process: Initialization

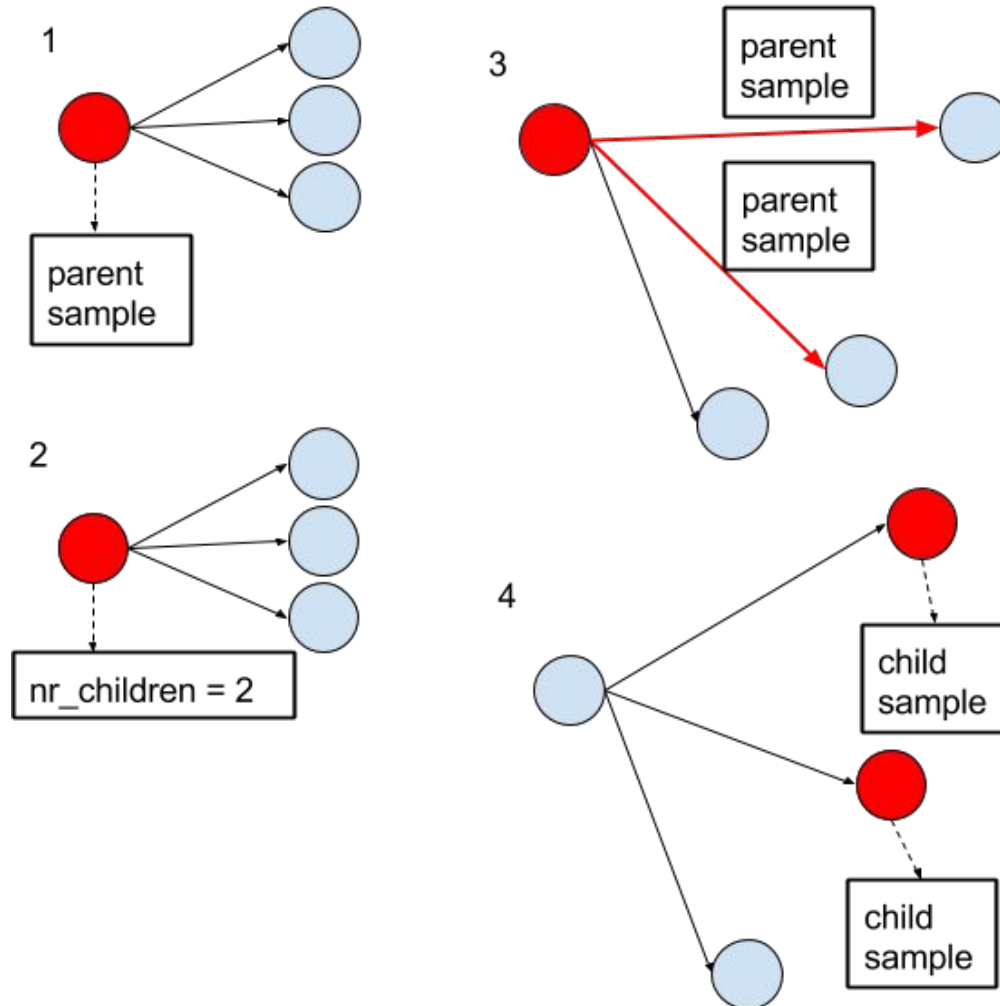
Top-down



Bottom-up



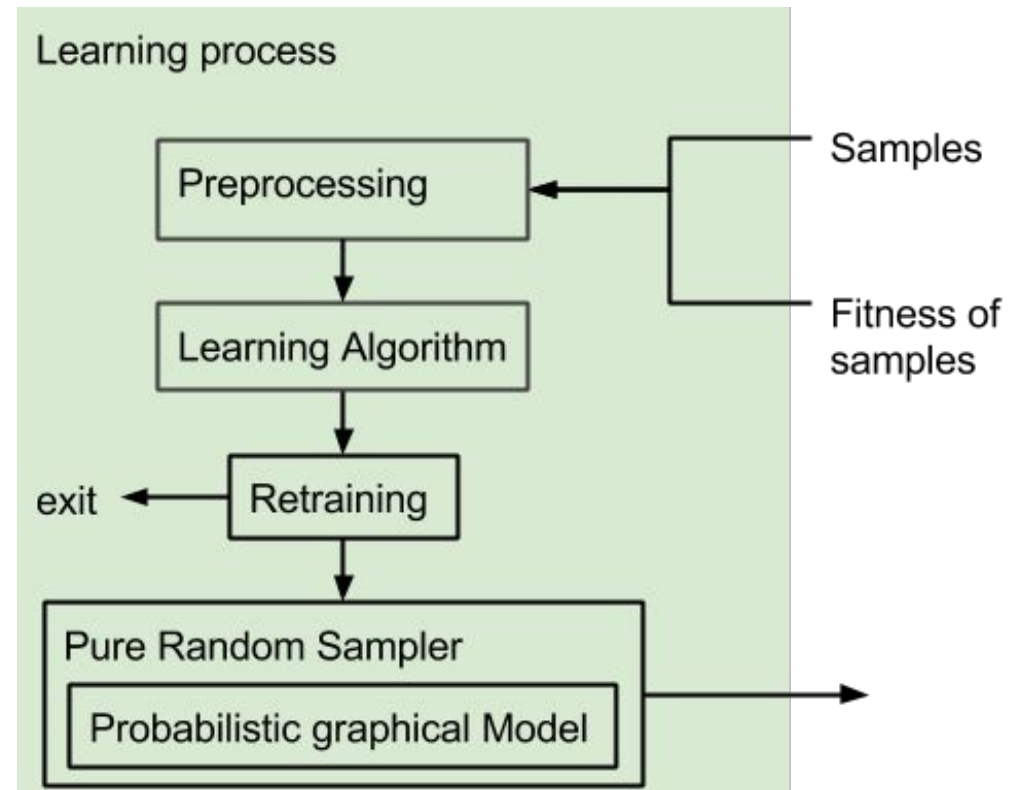
Generative process: Sampling (uniform)



Learning process

NG AND
ECTURE

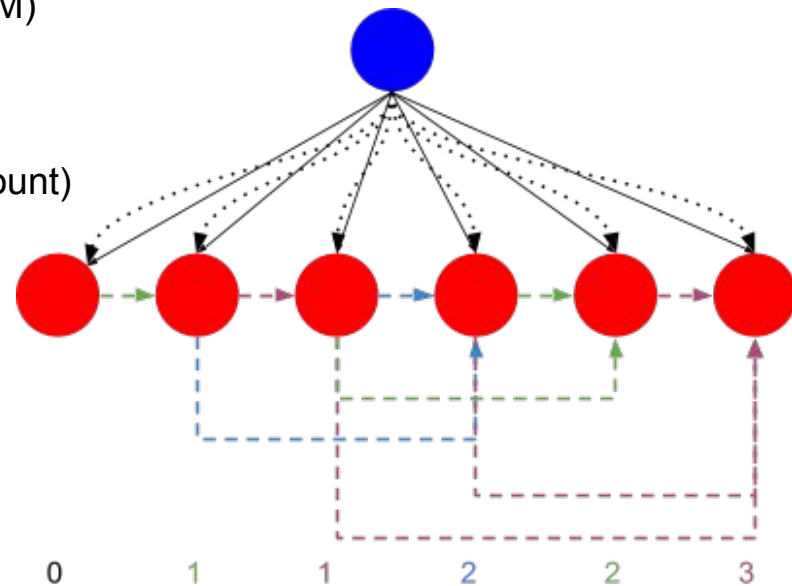
- Optimisation of the generative process → learning problem (synthetic data)
- Components
 - Preprocessing
 - Retraining
 - Probabilistic model
 - Learning Algorithm



Learning process: components

Probabilistic model

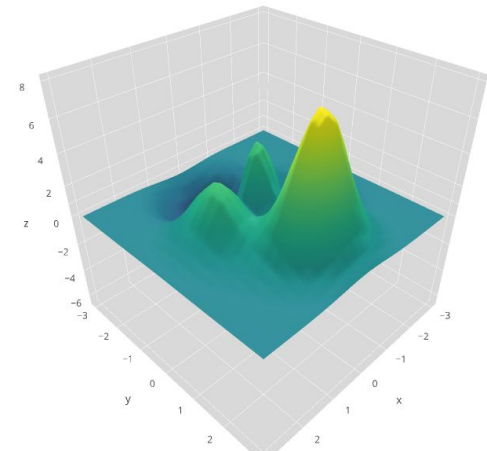
- Probabilistic model compatible with generation process
 - Hierarchical Gaussian Mixture Models (GMM)
 - Conditional relation
 - Parent and child
 - Child and it's siblings
 - Multiple-instance learning (varying object count)
- Optimisations
 - Variable sibling order
 - Marginalisation



Learning process: components

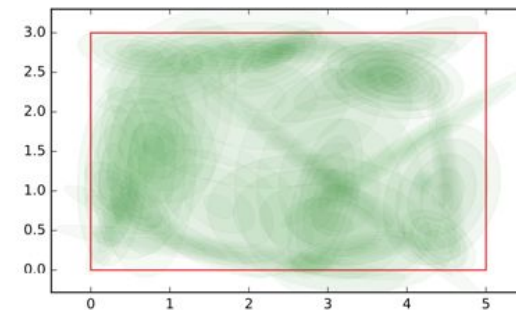
Learning algorithm

- Supervised learning
 - Fit GMM based on sample and fitness data
 - EM algorithm (unsupervised)
- Incorporate fitness in EM
 - Weighted density estimation (WDE)
 - Likelihood \sim fitness
 - Regression $\rightarrow P(\text{Variables}|\text{Fitness})$



Evaluation and discussion

- Measuring expressiveness is open problem [1]
- Elaborate evaluation of simplified case (2 dimensional)
 - Expressiveness relative to fitness
 - Sampling Performance using heatmaps
- Simplified evaluation of multiple cases (>3 dimensional)
 - Visualized expressiveness
 - Sampling Performance using Average Fitness Gain
 - Runtime complexity/computational time



Simplified case: Expressiveness results



		Predicted condition	
	Total population	Predicted condition positive	Predicted condition negative
True condition	Condition positive	True positive: 89 %	False negative: 11 %
	Condition negative	False positive: 15 %	True negative: 85 %

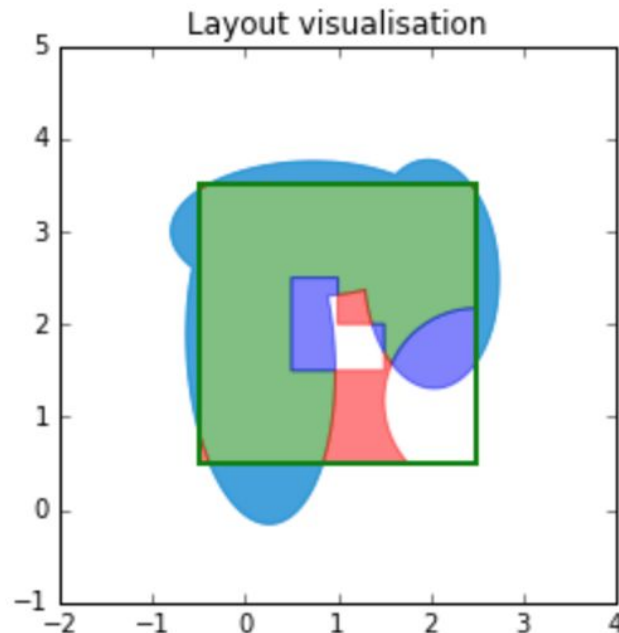


Fig. 5. GMM surface area coverage

Simplified case: Sampling performance results

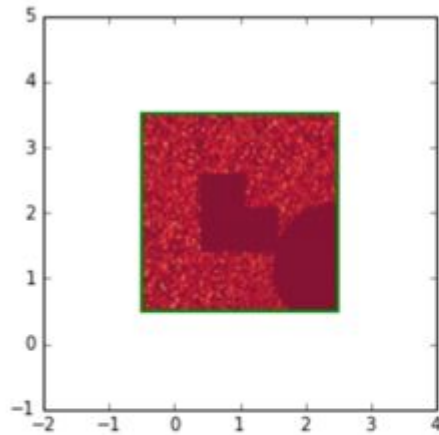


Fig. 3. Heat-map for naive sampling

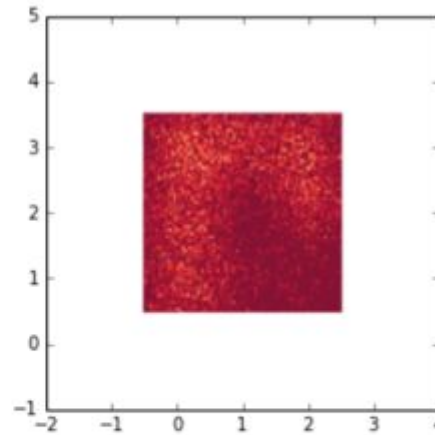


Fig. 4. Heat-map for sampling from trained model

Average acceptance rate:
Naive: 70%
Optimised: 86%



Multiple cases

- Evaluation of 15 parameters in the methodology
- Generality: 5 separate fitness functions
 - Functions derived from constraints in architectural context [1]

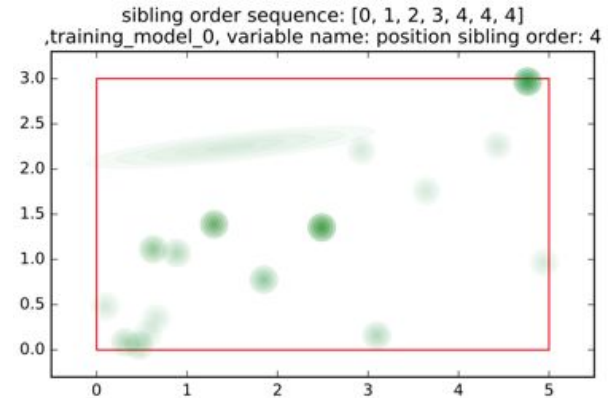
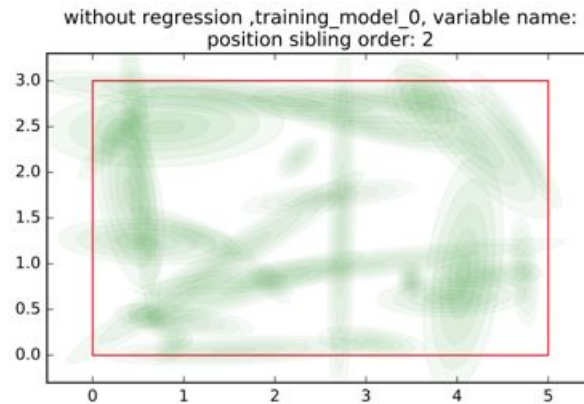
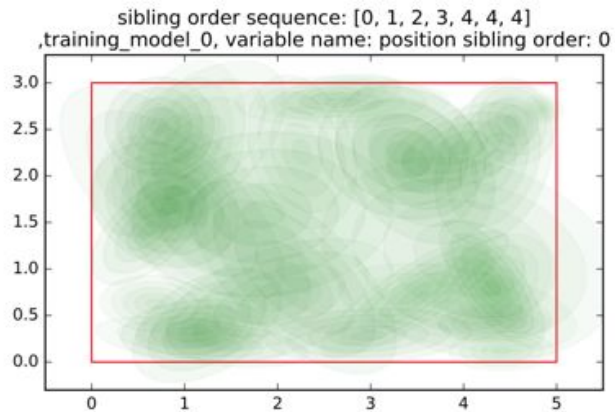
	Hierarchical relation	Analytic family
Minimum polygon overlap	pairwise	geometric
Target surface ratio	absolute	geometric
target distance	pairwise	distance based
Minimum centroid difference	absolute	geometric/distance based
Closest side alignment	pairwise	goniometric/geometric

[1] P. Merrell, E. Schkufza, Z. Li, M. Agrawala, and V. Koltun, "Interactive furniture layout using interior design guidelines," ACM Trans. Graph., vol. 30, no. 4, p. 1, 2011.

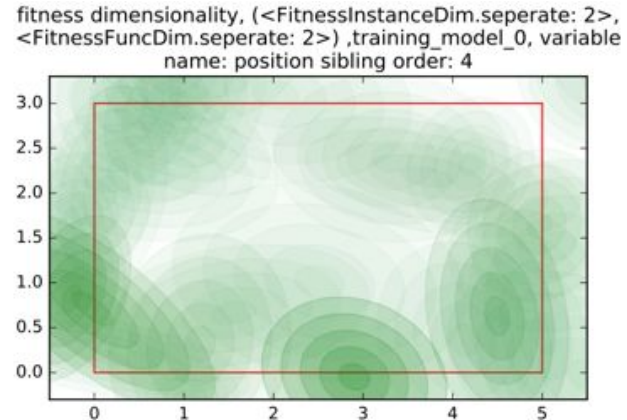
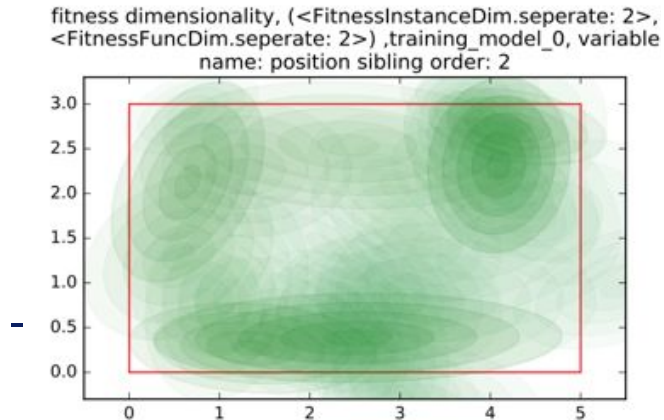
Multiple cases: Visualized expressiveness



With weighted density estimation



With regression



Multiple cases: Results Summary

- Most significant parameters
 - Number of training samples ↑
 - Increase expressiveness and sampling performance ↑
 - Marginalisation ↑
 - Reduce computation time ↓
 - Expressiveness
- Optimised fitness functions ($\frac{3}{5}$)
 - Minimum polygon overlay: 100%
 - Target distance: 22%
 - Minimum centroid difference: 45%

Conclusion and Future work

- Novel expressiveness metric
- New approach as alternative for current PCG solutions
 - Combines top-down and bottom-up control
 - Automatic search space optimise
 - Minimal decrease in expressiveness
- Optimisation not significant enough
- Possible paths for future research:
 - Evaluate more complex fitness functions
 - Train on data from optimised search algorithm
 - E.g Markov chain Monte Carlo
 - A more elaborate probabilistic model
 - Learn hierarchical structure from the data