Learning Arbitrary RDF Dataset Enrichment Graphs Using Pre- & Postcondition Broadcasting

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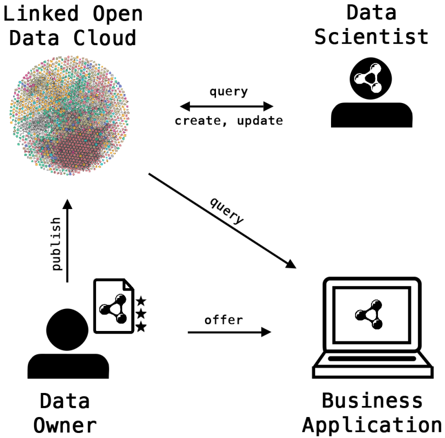
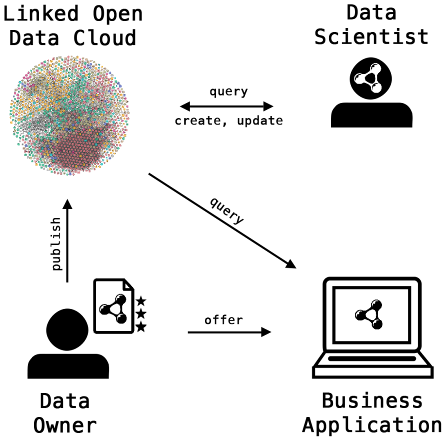
Outline



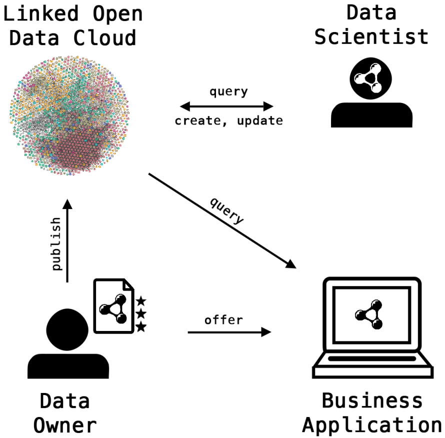
- Publishing 5-Star Linked Open Data (LOD)



- Publishing 5-Star Linked Open Data (LOD)
- Flexible distribution of datasets to customers

Motivation

Linked Data Integration



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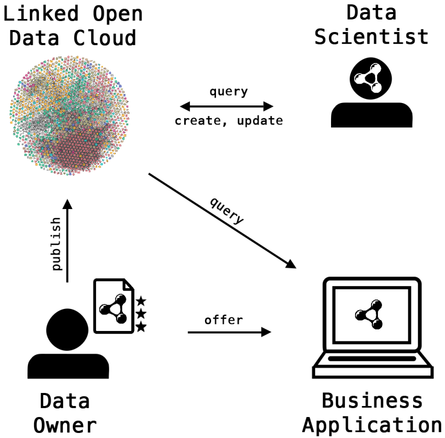

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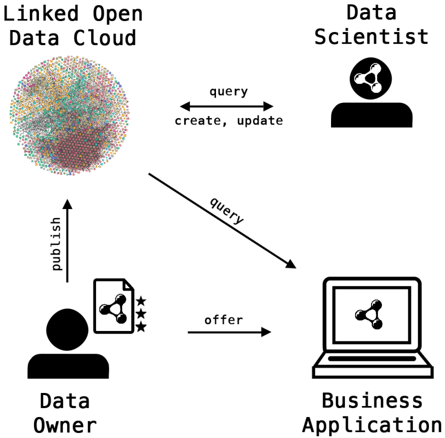

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- Flexible distribution of datasets to customers
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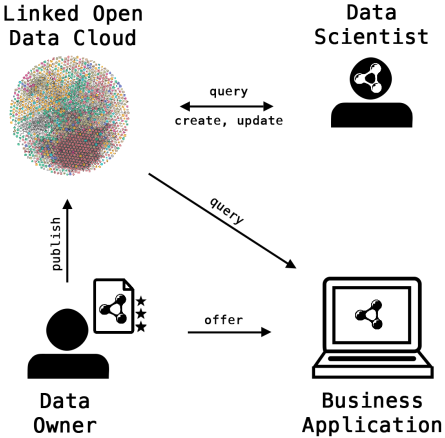
- Integrating LOD into business applications

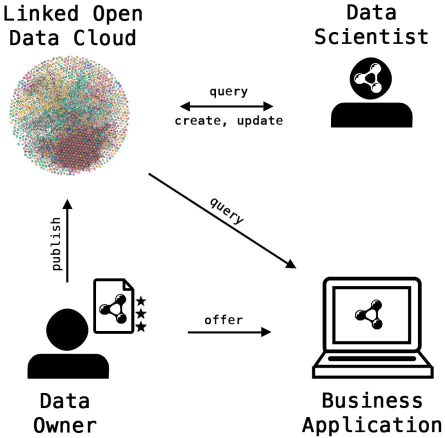


Linked Open Data Cloud
Data Scientist
query
create, update
query
publish
offer
Data Owner
Business Application

- Lifting

Motivation

Linked Data Integration Steps



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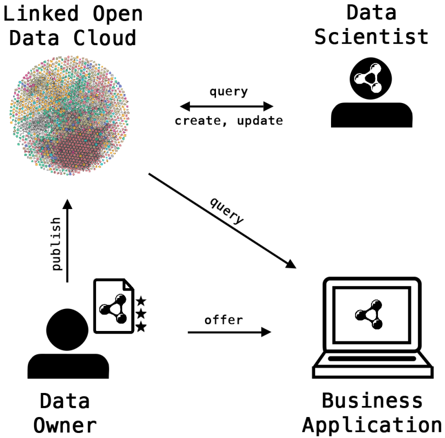

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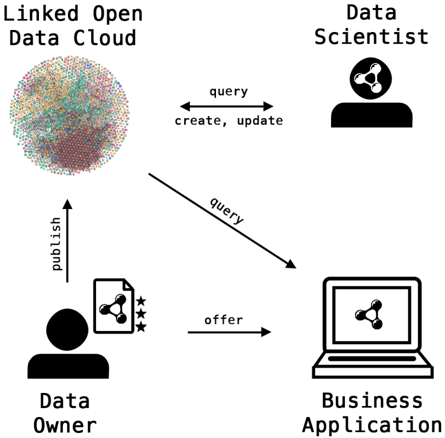

- Lifting
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- **Enrichment**
  →RDF Dataset Enrichment Framework (DEER)

Motivation

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- Generalistic framework for RDF dataset enrichment

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RDF Dataset Enrichment Framework (DEER)

- Generalistic framework for RDF dataset enrichment
- Goal: accessible easy enrichment for non-experts
- Enrichment represented as pipelines
- Most enrichment functions need configuration
- → Requires expert knowledge ↯
- → Try to use machine learning

Motivation

ML Algorithm in original DEER

- Training data: RDF Datasets Source (S) and Target (T)
- Fitness Function: F_1 score over triples
- Iterative construction with an upward refinement operator
- Good theoretical properties (finite, proper, complete, not redundant)

- But several incorrect implicit assumptions

Motivation

Analysis of Existing ML Algorithm in DEER

- But several incorrect implicit assumptions
  - Sequential chaining is sufficient for arbitrary enrichment $\lightning$

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- $\rightarrow$ Objective of this thesis: develop new approach (DEER2)

- Design goals: DEER2 should

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Derived Goals & Research Questions

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- Research questions w.r.t. learning algorithm:
  - **(Q1)** What is the optimal set of hyperparameters?
  - **(Q2)** How does our approach perform on real world datasets?

$$\mathbb{O}_{(0,1)} \longrightarrow \mathbb{O}_{(1,1)} \longrightarrow \mathbb{O}_{(1,0)}$$

Definition **Dataset Operator**

$$\mathbb{O}_{(n,m)} : \mathscr{D}^n \times \mathscr{D} \to \mathscr{D}^m$$
$$\left(\left(D_1^{(\text{in})}, \ldots, D_n^{(\text{in})}\right), P\right) \mapsto \left(D_1^{(\text{out})}, \ldots, D_m^{(\text{out})}\right)$$

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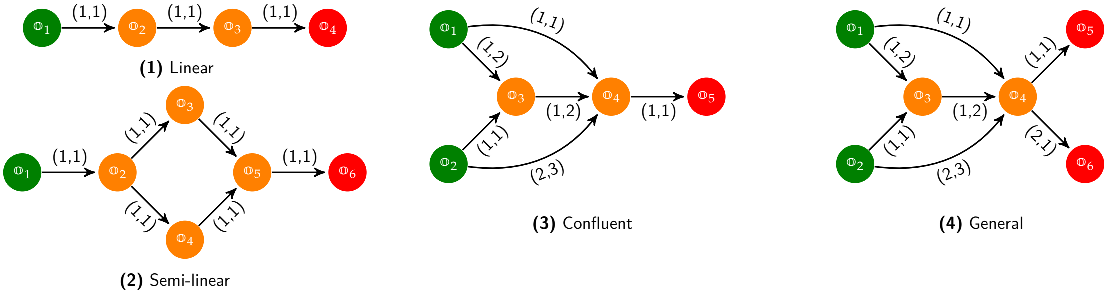
- $\mathbb{O}_{(n,1)}$ is called a **confluent enrichment operator**.



Definition **Enrichment Graph**

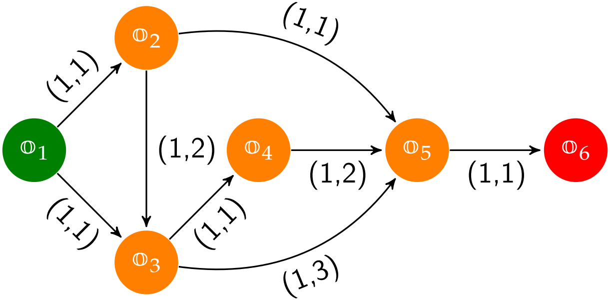
Let $G = (\mathbf{V}, \mathbf{E}, \mathbf{L}, \Phi, \Psi)$ be a directed acyclic labeled multigraph.

$$\mathbf{L}\colon E \to 2^{(\mathbb{N}\times\mathbb{N})} \qquad \Phi\colon \mathbf{V} \to \mathbb{O} \qquad \Psi\colon \mathbf{V} \to \mathcal{D}$$

$$e = (u,v) \mapsto \{(i_1, j_1), \ldots, (i_n, j_n)\} \qquad v \mapsto \mathbb{O}_{(n,m)} \qquad v \mapsto P$$

Approach

Enrichment Tables - An Efficient Representation for Learning



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5:	$\mathbb{O}_5$	P_5	3	2	4	3

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- Learn enrichment table using Genetic Programming (GP) and Multi-Expression Programming (MEP)
- Use linear combination of F_1 measure on subjects, predicates, objects and whole triples as fitness function

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  - Insert $\lambda - \mu$ individuals into p_n using tournament selection on p_c
  - Apply mutation to each individual $\mathbb{T} \in p_n$ with probability σ
  - For each row $\mathbb{T}_i$ of individuals chosen for mutation, mutate the row with probability ρ

- MEP: One genotype represents multiple solutions (phenotypes)

1:	ϕ_1	P_1	0	0	0	0
2:	ϕ_2	P_2	1	1	0	0
3:	ϕ_3	P_3	2	1	2	0
4:	ϕ_6	P_6	2	3	1	0
5:	ϕ_4	P_4	1	3	0	0
6:	ϕ_7	P_7	1	5	0	0
7:	ϕ_8	P_8	2	4	3	0
8:	ϕ_5	P_5	3	2	5	3
9:	ϕ_9	P_9	1	7	0	0

Approach

Multi-Expressive Enrichment Tables

- MEP: One genotype represents multiple solutions (phenotypes)
- Use MEP for enrichment tables

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4:	$\mathbb{o}_6$	P_6	2	3	1	0
5:	$\mathbb{o}_4$	P_4	1	3	0	0
6:	$\mathbb{o}_7$	P_7	1	5	0	0
7:	$\mathbb{o}_8$	P_8	2	4	3	0
8:	$\mathbb{o}_5$	P_5	3	2	5	3
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Multi-Expressive Enrichment Tables

- MEP: One genotype represents multiple solutions (phenotypes)
- Use MEP for enrichment tables
- Called multi-expressive enrichment table

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Approach

Population Initialization

- Add all dataset emitters

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Approach

Enrichment Table Compaction

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7:	$\mathbb{o}_8$	P_8	2	4	3	0
8:	$\mathbb{o}_5$	P_5	3	2	5	3
9:	$\mathbb{o}_9$	P_9	1	7	0	0

$\rightarrow$

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Approach

Enrichment Table Compaction II

1:	ω_1	P_1	0	0	0	0
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Semantic Genetic Operators

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- Intereseting properties of our problem domain:
  - Structure of the graph
  - Applicability of enrichment operators

- Idea: select two most promising phenotypes

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- With probability of 0.25: insert an enrichment operator merging both together

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Approach

Pre- & Postcondition Mutation

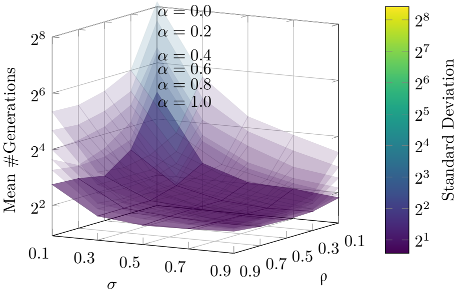
- Idea: method on enrichment operators states applicability
- Select row for mutation
- Broadcast pre-/postconditions to operators
- Operators return applicability
- Roulette wheel selection proportionate on applicability

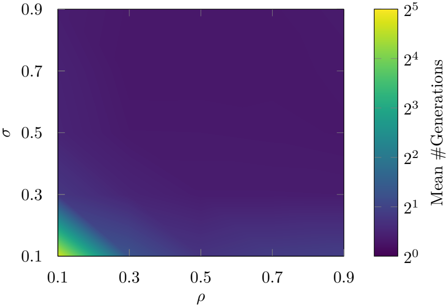
- **Fist set of experiments:** Hyperparameter Optimization
  - Grid search
  - Mutation probability $\sigma \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$
  - Mutation rate $\rho \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$
  - Offspring fraction $\alpha = \frac{\lambda}{\mu} \in \{0, 0.2, 0.4, 0.6, 0.8, 1.0\}$
- **Second set of experiments:** Performance on real world example

Evaluation

Hyperparameter Optimization

- Very simple toy learning problem
- 3 enrichment operators, order does not matter
- only baseline algorithm $(\mu = 30, r = 7, g = 5000)$
- 1000 repetitions
- best set of parameter $(\alpha/\sigma/\rho) = (1.0/0.9/0.9)$

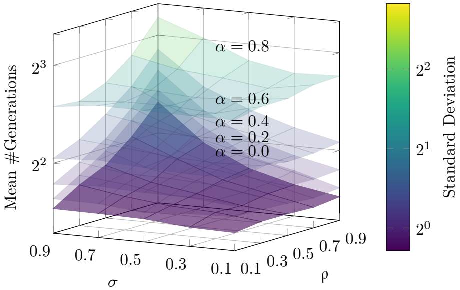


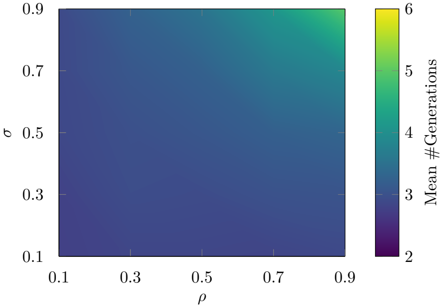


Evaluation

Hyperparameter Optimization

- Very simple toy learning problem
- 3 enrichment operators, order does not matter
- with enrichment table compaction enabled
- 1000 repetitions
- best set of parameter $(\alpha/\sigma/\rho) = (0.0/0.1/0.1)$

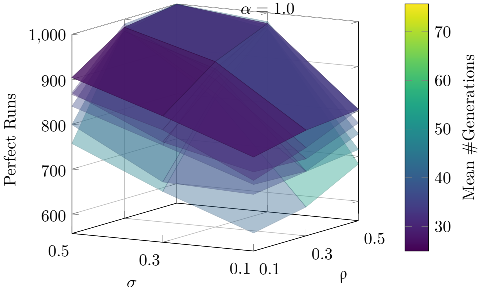


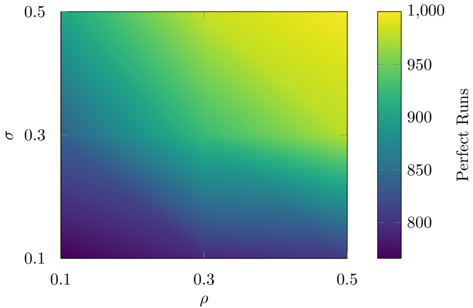


Evaluation

Hyperparameter Optimization

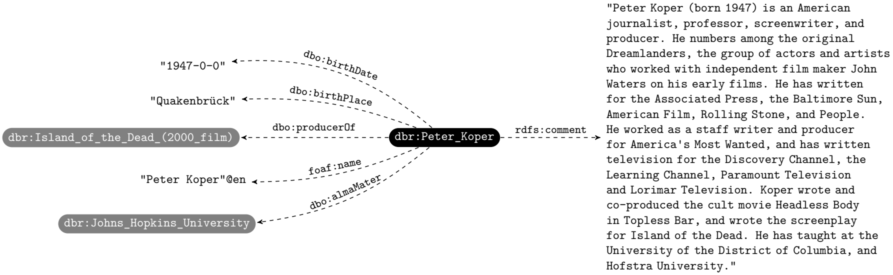
- Much harder problem
- 5 enrichment operators, order *does matter*
- with all optimizations enabled
- 1000 repetitions
- best set of parameter $(\alpha/\sigma/\rho) = (1.0/0.5/0.5)$



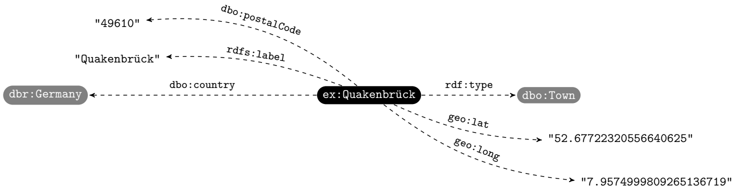


Evaluation

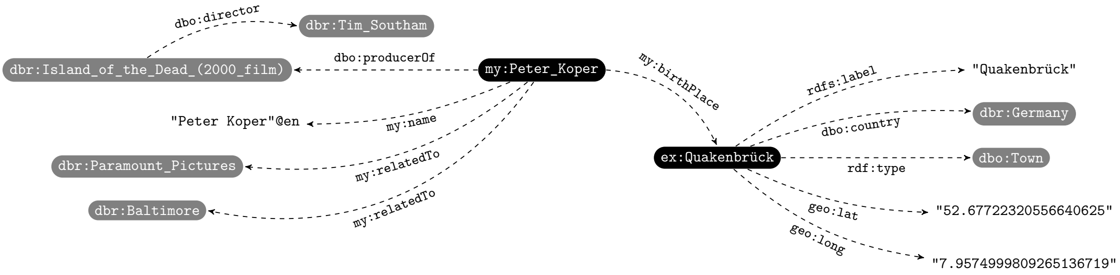
Performance on Real World Example



(1)



(2)


dbo:director
dbr:Tim_Southam
dbr:Island_of_the_Dead_(2000_film)
dbo:producerOf
my:Peter_Koper
my:birthPlace
"Peter Koper"@en
my:name
dbr:Paramount_Pictures
my:relatedTo
dbr:Baltimore
my:relatedTo
rdfs:label
"Quakenbrück"
dbr:Germany
dbo:country
ex:Quakenbrück
dbo:Town
rdf:type
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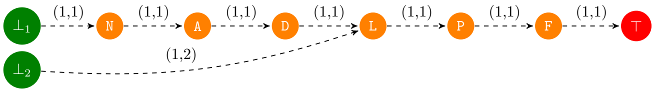
geo:long
"7.95749998092651367 19"

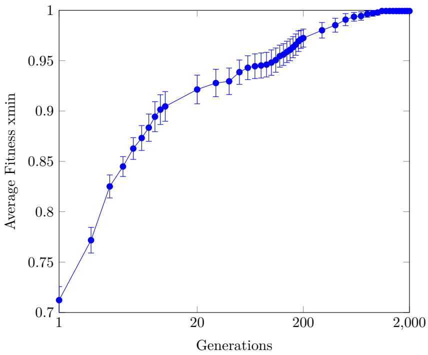
(3)


⊥1
(1,1)
N
(1,1)
A
(1,1)
D
(1,1)
L
(1,1)
P
(1,1)
F
(1,1)
⊤
⊥2
(1,2)

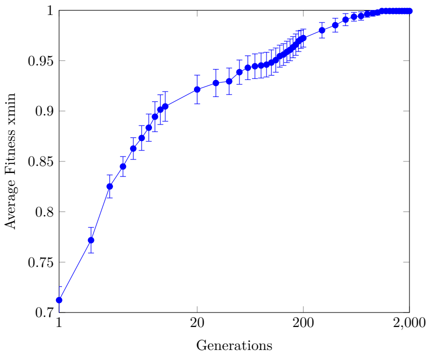
(4)

Evaluation

Performance on Real World Example



- 50 repetitions

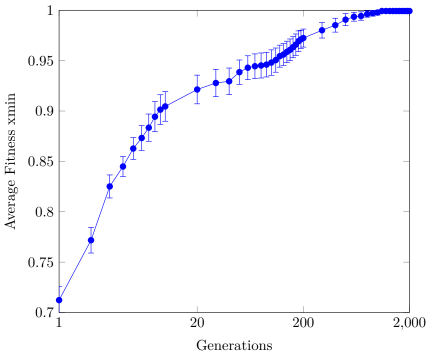


- maximum 2000 generations

- 50 repetitions

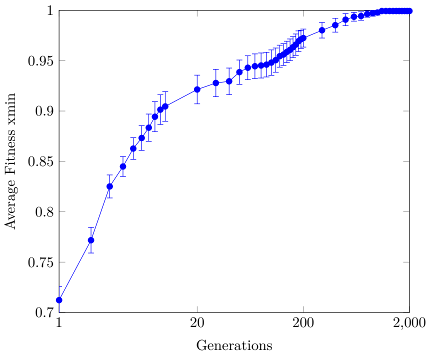
Evaluation

Performance on Real World Example

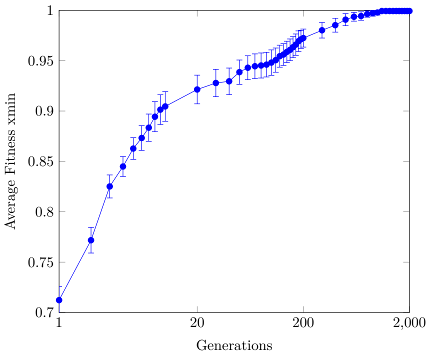


- maximum 2000 generations
- $\mu = 30, \alpha = 1, \sigma = 0.5, \rho = 0.5$

- 50 repetitions



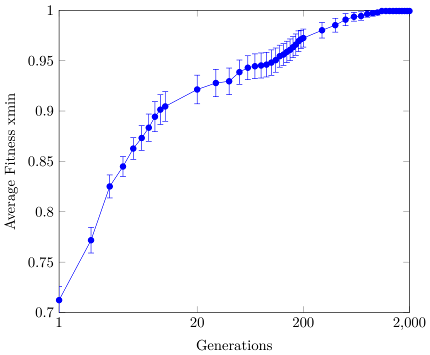
- maximum 2000 generations
- $\mu = 30, \alpha = 1, \sigma = 0.5, \rho = 0.5$
- measure best fitness in each generation
- 50 repetitions



- maximum 2000 generations
- $\mu = 30, \alpha = 1, \sigma = 0.5, \rho = 0.5$
- measure best fitness in each generation
- compute average fitness for each generation
- 50 repetitions

Evaluation

Performance on Real World Example

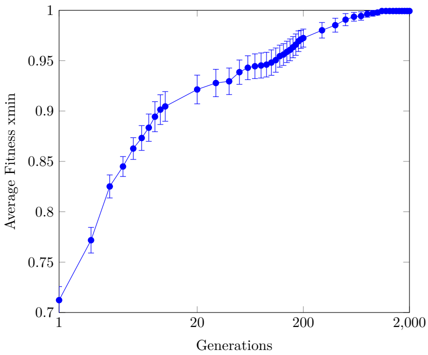


- maximum 2000 generations
- $\mu = 30, \alpha = 1, \sigma = 0.5, \rho = 0.5$
- measure best fitness in each generation
- compute average fitness for each generation
- compute 95%-confidence intervals using Students t-distribution

- 50 repetitions

Evaluation

Performance on Real World Example



- 50 repetitions

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- $\mu = 30, \alpha = 1, \sigma = 0.5, \rho = 0.5$
- measure best fitness in each generation
- compute average fitness for each generation
- compute 95%-confidence intervals using Students t-distribution
- Result: on average solution quality over 99% after 500 generations with 95%-confidence interval of $\pm 0.6\%$

Conclusion

- Implemented a tool for generalistic DAG-shaped enrichment workflows

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- Developed a classification of enrichment graphs
- Derived a GP- and MEP-based learning approach for inherently confluent enrichment graphs
- Supplied several optimizations
- Optimizations successfully improved solution quality & time to convergence
- Over 99% after 500 generations with 95%-confidence interval of $\pm 0.6\%$ in a real-world test case

Conclusion

Thank You for Your Attention