

An Empirical Study

Meta and Hyper Heuristic Search for
Multi-Objective Release Planning

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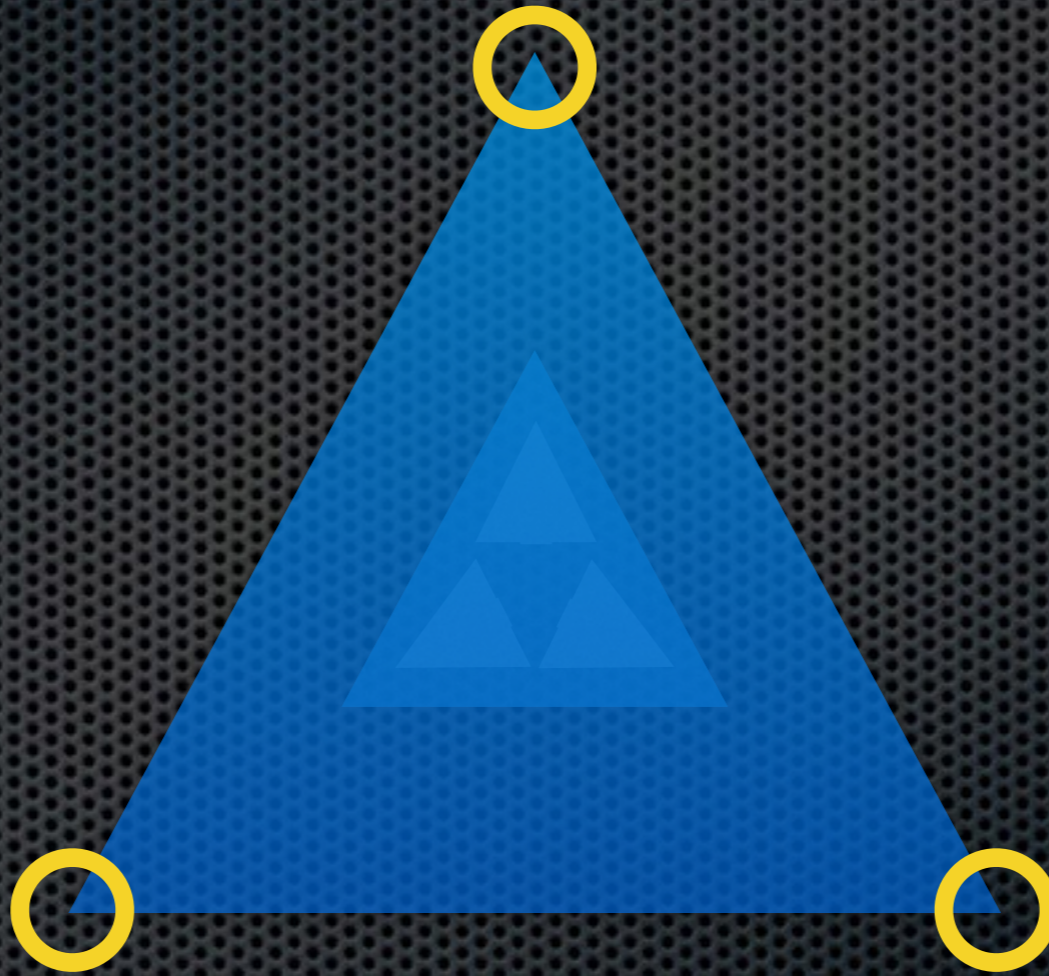
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Agenda

- ✦ Contributions
- ✦ Background
- ✦ Data sets
- ✦ Fitness functions
- ✦ Algorithms
- ✦ RQs
- ✦ Results & analysis

A Thorough Empirical Study

Fitness Functions



Data Sets

Algorithms

A Thorough Empirical Study

Fitness Functions



Data Sets

Algorithms

A Thorough Empirical Study

Fitness Functions

**10 Real World
Data Sets**

Data Sets

Algorithms



A Thorough Empirical Study

**Scenario
Based
Objectives**
Fitness Functions

**10 Real World
Data Sets**

Algorithms

Data Sets



A Thorough Empirical Study

Fitness Functions

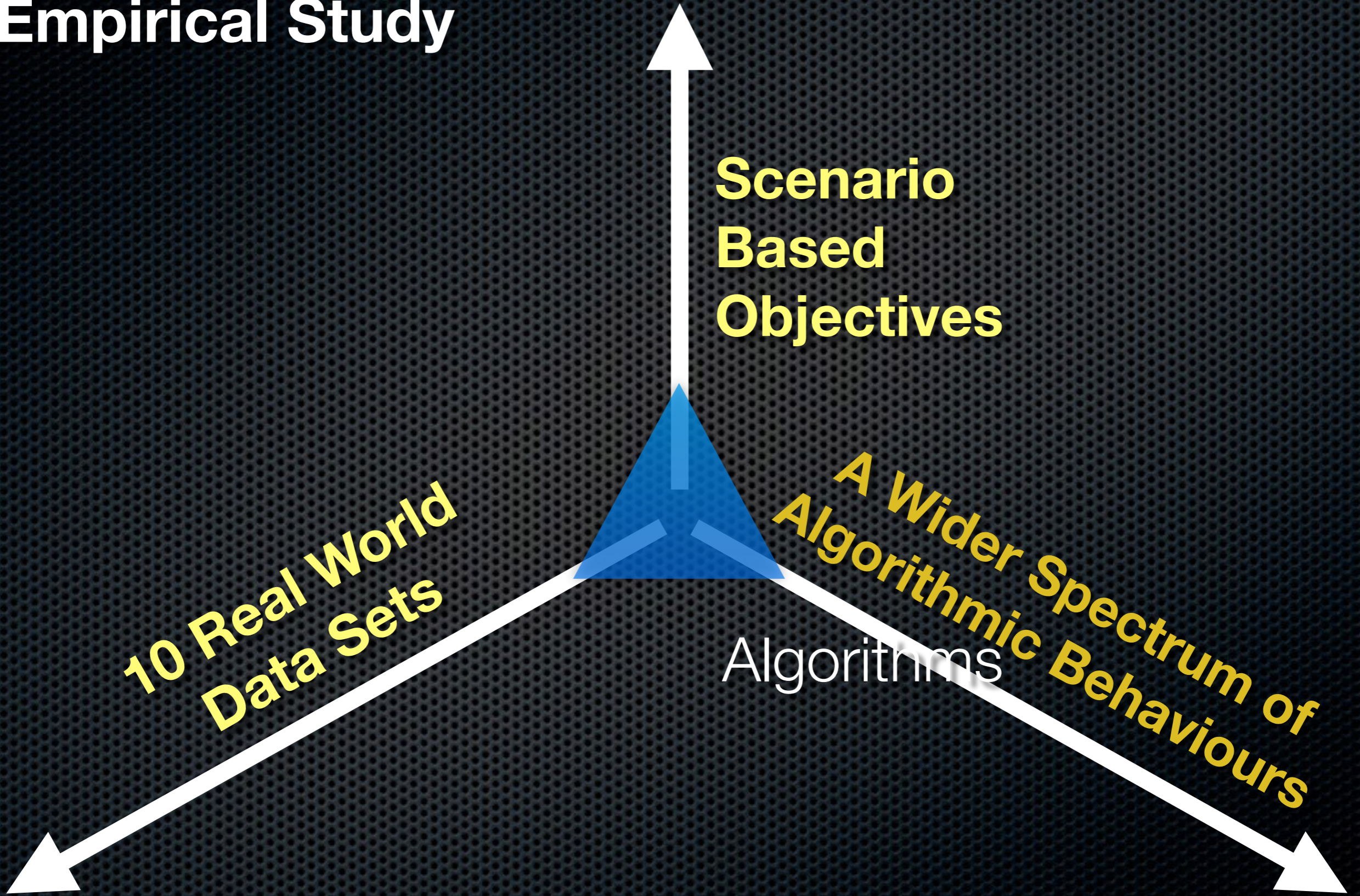
**Scenario
Based
Objectives**

**10 Real World
Data Sets**

**A Wider Spectrum of
Algorithmic Behaviours**

Algorithms

Data Sets



Release Planning



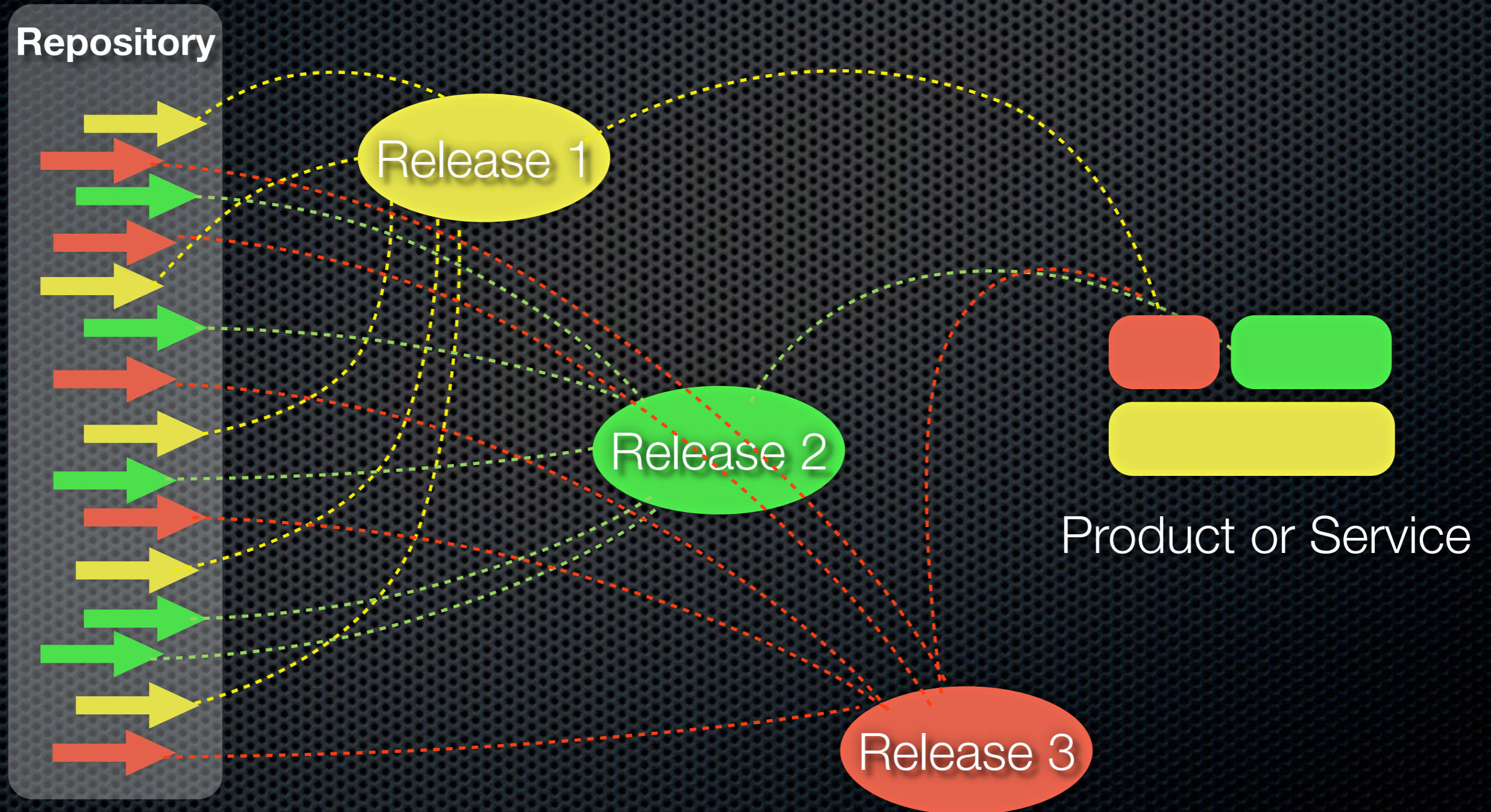
requirements and change requests

Release Planning



requirements and change requests

Release Planning



Strategic Release Planning (SRP)

- SRP is concerned with how to select and assign requirements to multiple subsequent releases.

Operational Release Planning (ORP)

- ORP deals with how to assign developers to the tasks to be performed.

Models



Stakeholders

Stakeholders
Number (M)

Stakeholders
Weight (W)

Models



Requirements

Cost (C)

Value (V)

Time to market (T)

Risk (R)

Frequency of use (F)

Models



Requirements

Dependence (D)

And

Or

Precedence

Value-related

Cost-related

Models

Release 1

Release 2

Release 3

Releases

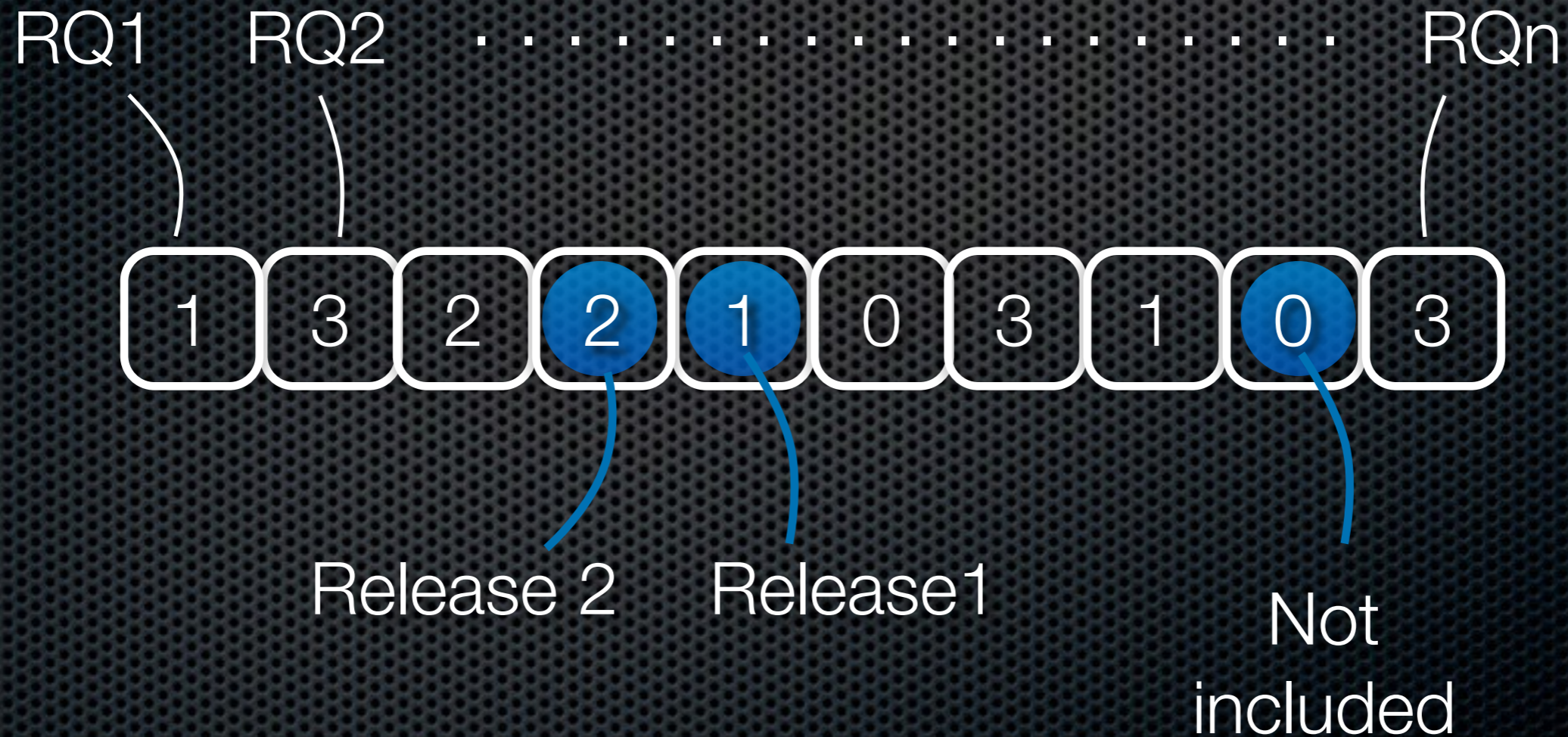
Release
Number (K)

Release
Importance (I)



Data Representation

A set of requirements



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10 Real World Data Sets



Data Sets	# Requirements	# Stakeholders	Objectives	
			Maximise	Minimise
Baan	100	17	Revenue	Cost
StoneGate	100	91	Sales Value	Impact
Motorola	35	4	Revenue	Cost
RalicP	143	55	Revenue	Cost
RalicR	143	79	Revenue	Cost
Ericsson	124	14	Importance for today & the future	Cost
MS Word	50	4	Revenue	Risk
Eclipse	3502	536	Importance	Cost
Mozilla	4060	768	Importance	Cost
Gnome	2690	445	Importance	Cost

Scenario-based Fitness Functions

FREQUENCY,
IMPORTANCE, ...

$$\text{Maximize } f(\vec{x}) = \sum_{i=1}^N \text{VALUE}_{i,k} \cdot I_k$$

$$\text{Minimize } f(\vec{x}) = \sum_{i=1}^N \text{COST}_{i,k}$$

IMPACT,
RISK, ...

A Wider Spectrum of Algorithmic Behaviours

Local In-Between Global

Hill Climb Simulated Annealing NSGA-II

**A Wider Spectrum of
Algorithmic Behaviours**



Local

In-Between

Global

Hill Climbing

Simulated Annealing

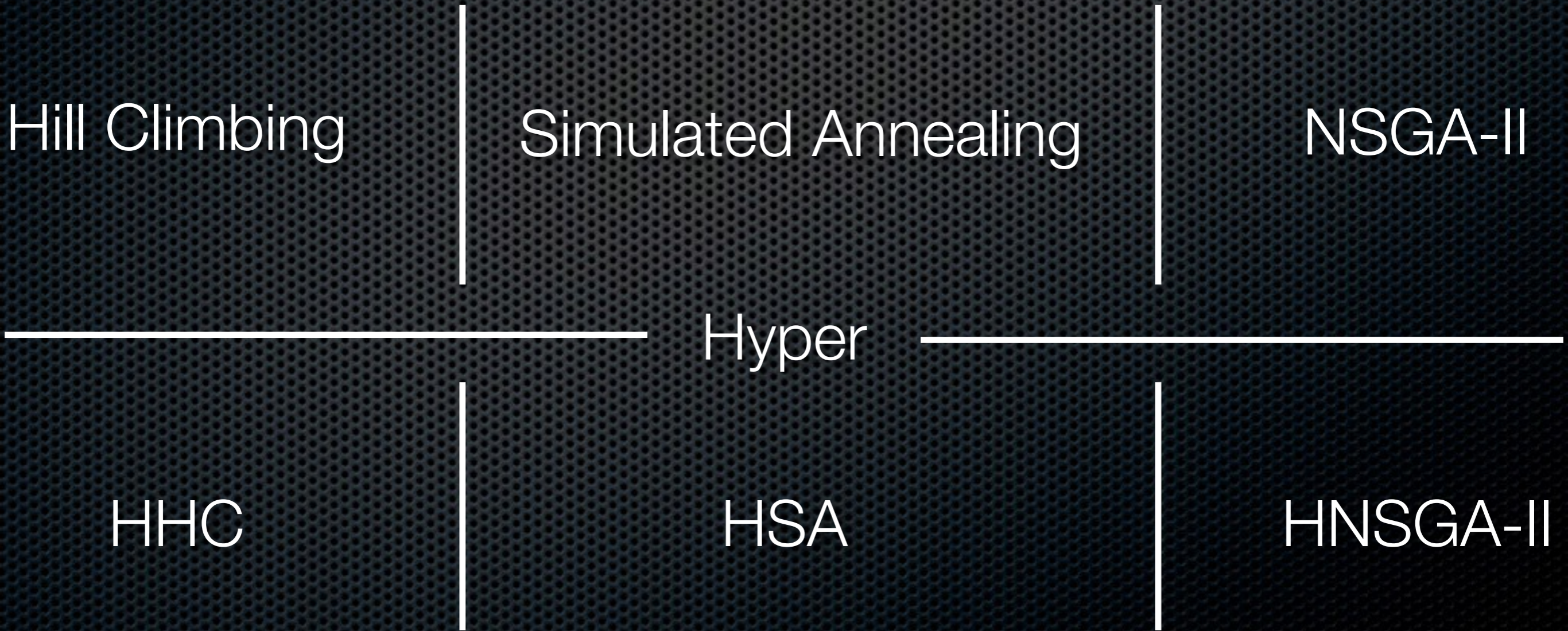
NSGA-II

Hyper

HHC

HSA

HNSGA-II



**A Wider Spectrum of
Algorithmic Behaviours**



Meta-heuristics

Hyper-heuristics

Hill Climbing

HHC

Simulated Annealing

HSA

NSGA-II

HNSGA-II

Random

10 Hyper-Heuristic Operators

Ruin & Recreate

1 Random

2 Swap

3 Delete_Add

4 Delete_Add_Best

5 Delete_Worst_Add

6 Delete_Worst_Add_Best

7 Delay_Ahead

8 Delay_Ahead_Best

9 Delay_Worst_Ahead

10 Delay_Worst_Ahead_Best

Operator: Delete_Add_Best

delete a requirement from the release with
uniform probability



Operator: Delete_Add_Best

add the best requirement (based on one of fitness values) to one release



find the best requirement



Adaptive Operator Selection

- ✦ Credit assignment
 - ✦ Extreme value credit assignment
 - ✦ Fitness improvement: hypervolume difference
 - ✦ Reference value: the fitness of the parents
- ✦ Operator selection
 - ✦ Probability matching

Performance Metrics

- ✦ Quality
 - ✦ Convergence
 - ✦ Hypervolume
 - ✦ Contribution
 - ✦ Unique Contribution
- ✦ Diversity **is only interesting if the algorithm's quality is strong**
- ✦ Speed

All the metrics were normalised between 0.0 and 1.0 and converted to 'Maximising metrics'.

Research Questions

RQ 1 - Quality: Which algorithm performs best?

RQ 2 - Diversity: What is the diversity of the solutions produced by each algorithm?

RQ 3 - Speed: How fast can the algorithm produce the solutions?

RQ 4 - Scalability: What is the scalability of each algorithm with regard to solution quality, diversity and speed?

Results & Analysis

RQ 1 - Quality

RQ 1 - Quality

Data Sets		Meta-heuristics			Hyper-heuristics		
		HC	SA	NSGA-II	HHC	HSA	HNSGA-II
7 smaller datasets	2 Fits						
	3 Fits						
3 larger datasets							



For the meta-heuristic algorithms, NSGA-II performs best overall for quality on smaller datasets



SA performs noticeably better on the three larger datasets



The three hyper-heuristic algorithms outperform their meta-heuristic counterparts;
HNSGA-II is beaten by its meta-heuristic counterpart only on the Ericsson dataset.

Results & Analysis

RQ 2 - Diversity

RQ 2 - Diversity

Data Sets		Random	Meta-heuristics			Hyper-heuristics		
			HC	SA	NSGA-II	HHC	HSA	HNSGA-II
7 smaller datasets	2 Fits	Light Green	Dark Grey	Dark Grey	Dark Grey	Dark Grey	Dark Grey	Light Green
	3 Fits	Light Green	Dark Grey	Dark Grey	Dark Green	Dark Grey	Dark Grey	Light Green
3 larger datasets		Light Green	Dark Grey	Dark Grey	Dark Grey	Dark Grey	Dark Grey	Dark Green

- Light Green: Random search perform very well, but the solutions are largely suboptimal
- Light Green: Of the Hyper-heuristic algorithms, HNSGA-II exhibits the best diversity
- Dark Green: NSGA-II significantly outperforms HNSGA-II for Ericsson dataset
- Dark Green: HNSGA-II significantly outperforms NSGA-II on Mozilla and Gnome

Results & Analysis

RQ 3 - Speed

RQ 3 - Speed

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			HC	SA	NSGA-II	HHC	HSA	HNSGA-II
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	3 Fits							
3 larger datasets								

The speed of random search is worse than all other algorithms for the larger datasets

HNSGA-II is fastest overall

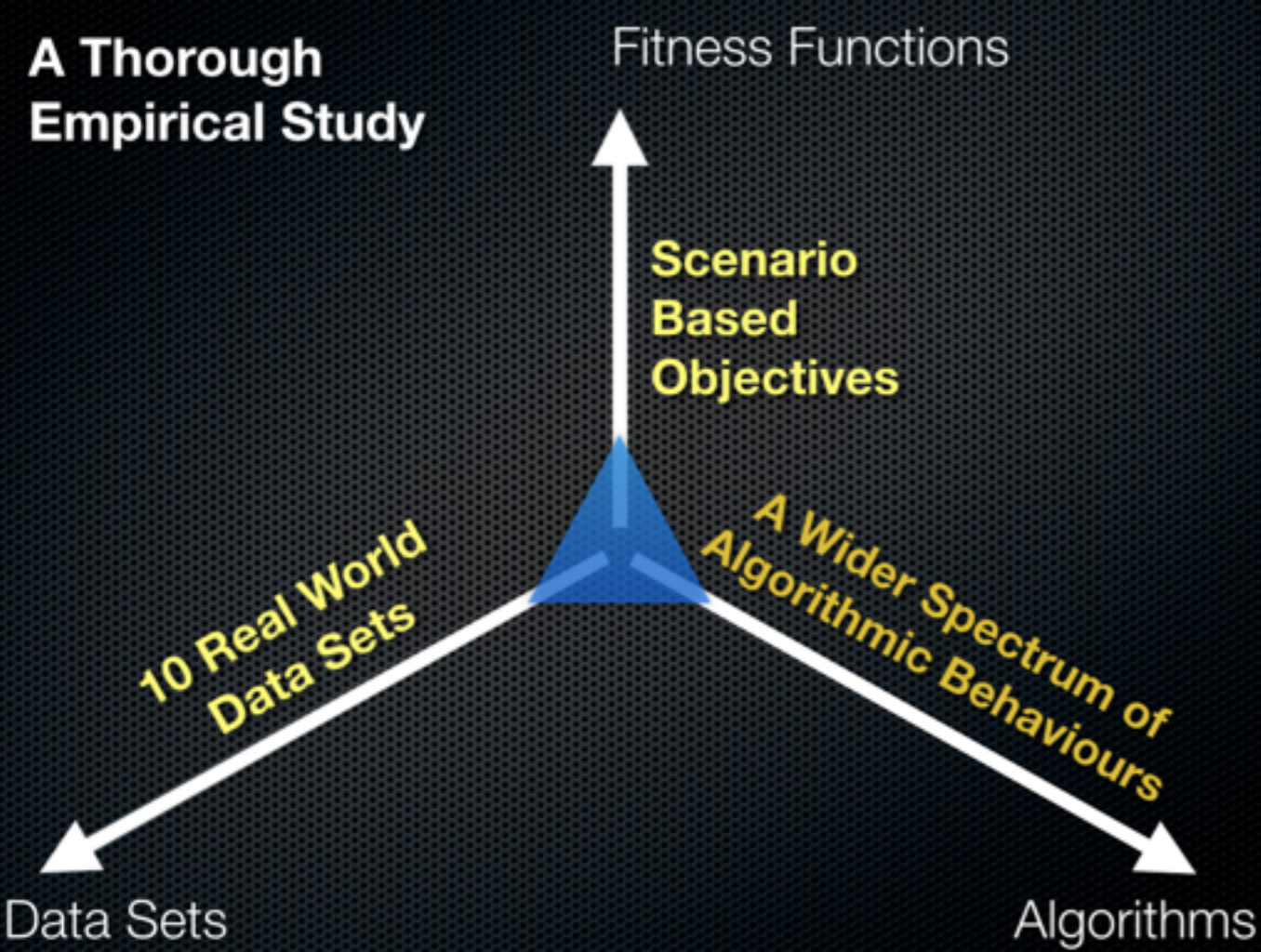
Results & Analysis

RQ 4 - Scalability

RQ 4 - Scalability

- ✦ The quality of solutions NSGA-II produced **decrease** as the problem size increase
 - ✦ NSGA-II's contribution to the reference front **decrease**, as the number of requirements increase
 - ✦ A **negative** correlation between the number of requirements and convergence of NSGA-II
- ✦ For the other algorithms, there is **no negative** correlation between problem size and solution quality
- ✦ The algorithms **increase** their diversity as the scale of the problem increase

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