Composition Algorithm Adaptation in Service Oriented Systems

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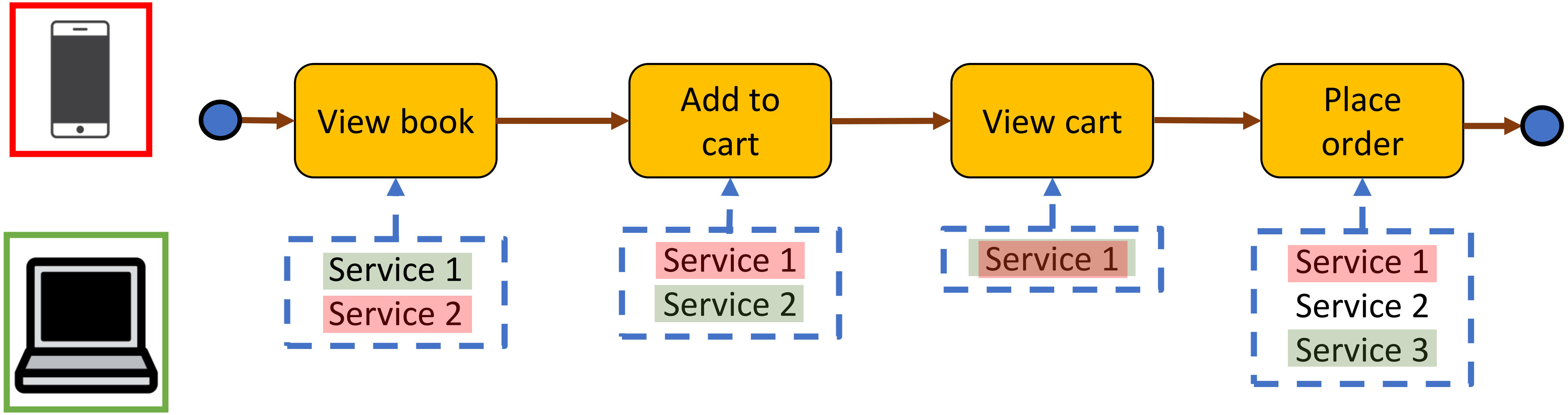
Motivation


View book
Add to cart
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Service 1
Service 2
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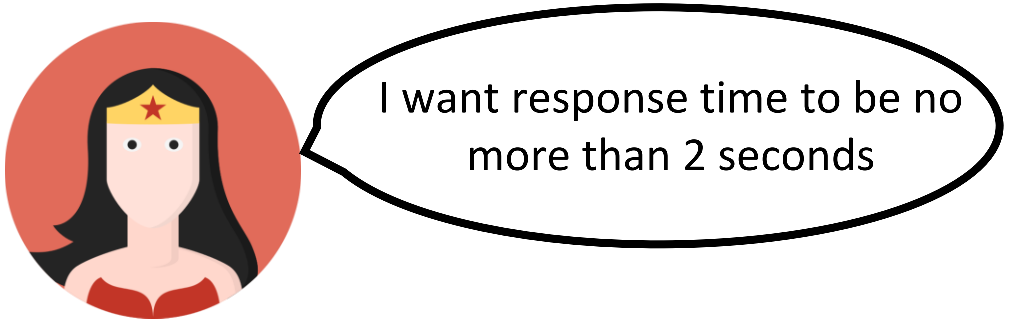
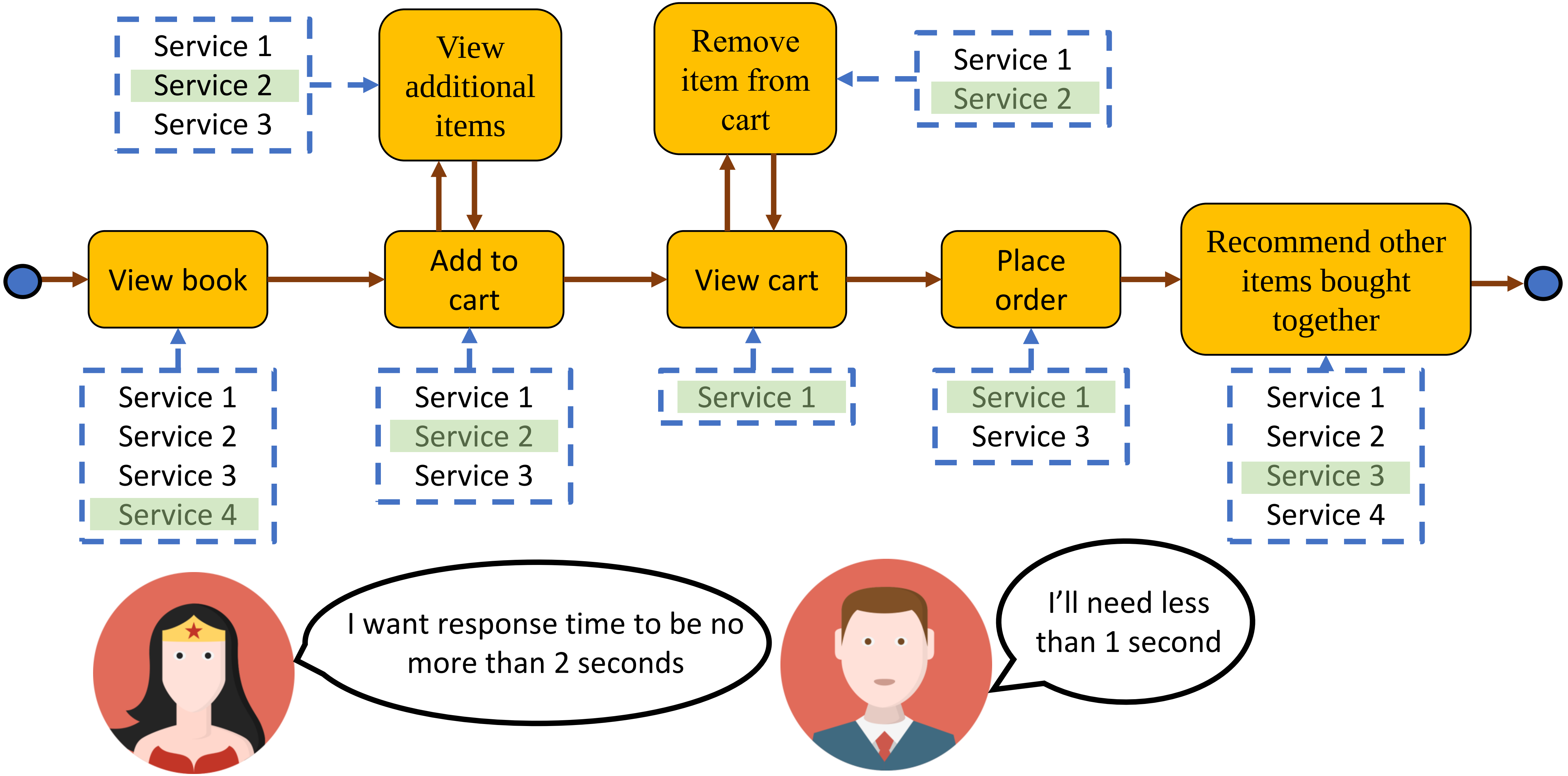
Service 3

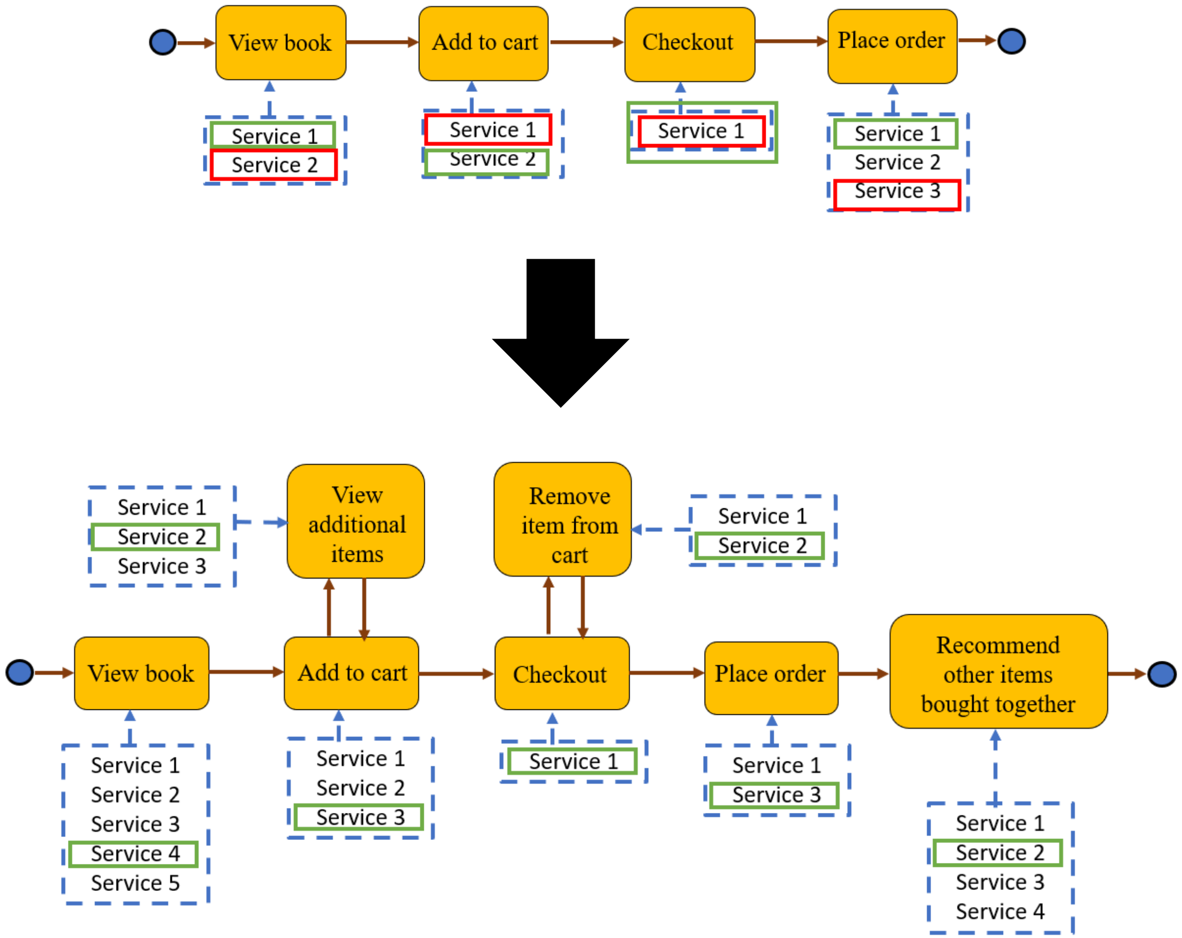

I want response time to be no more than 2 seconds

Service Composition: Dynamic Environment



Service Composition: Considerations

- Compositions need to meet nonfunctional user needs while constrained by compute resources
- Due to dynamic environment, composition needs to be adaptable
- *So, services are re-selected using a predetermined algorithm*



Current Approaches

- Most approaches perform adaptation at the services level or propose new composition algorithms (Wang et al. 2016, Ali et al. 2015, Schuller et al. 2014, Al-Helal et al. 2014, Ardagna et al. 2011)

- Current Approaches
  - Platforms
  - Algorithms

Current Approaches: Platforms

- MOSES (Cardellini et al., 2017)
  - Address adaptation at the services level using linear programming (LP) formulations
  - Support for dynamically adapting coordination patterns is also provided
- QoSMOS (Calinescu et al., 2009)
  - Selects candidate services at runtime or allocates resources to services for execution to meet Quality of Service (QoS) requirements
- Integrating reinforcement learning with multi-agent techniques (Wang et al. 2017)
  - Proposes adaptive service selection at runtime using a Markov Decision Process
  - Multi-agent techniques have communication overhead
  - Can easily become compute intensive

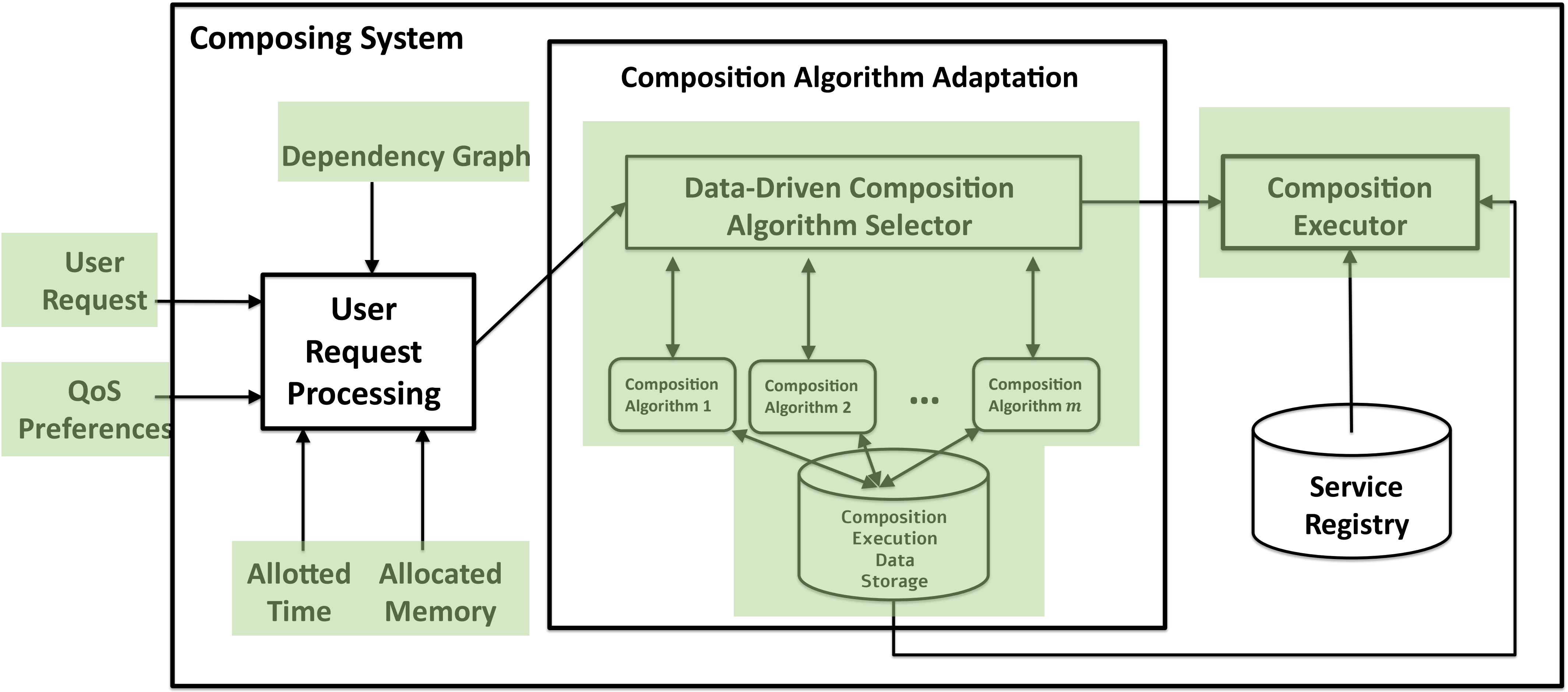
Current Approaches: Composition Algorithms

- Alrifai et al. 2009
  - Decomposes global constraints into local constraints to select services
- Trummer and Faltings, 2011
  - Propose dynamic algorithm selection for a set of batched user requests
  - Focus is on recommending algorithms to minimize cost
  - Recommendations are most recent executions

Research Question

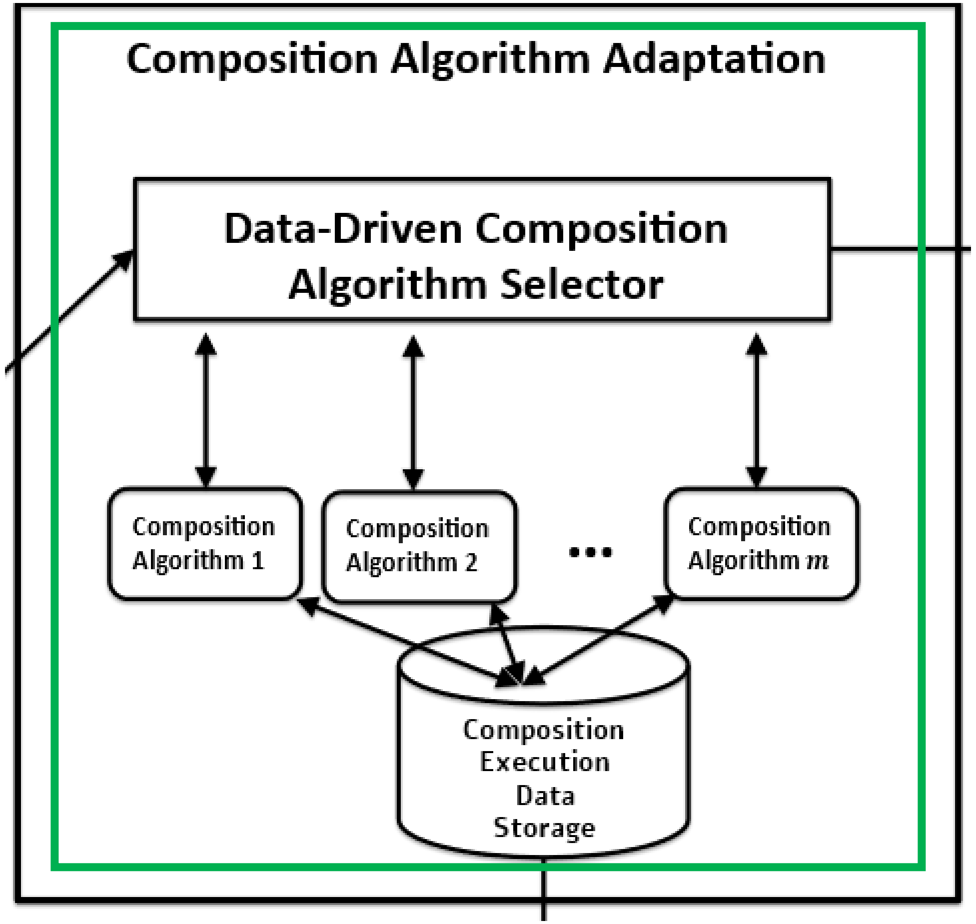
- Given a wide variety of available service composition methods, we focus on this question: how can we determine the right method for a given service composition task?
  - Goal 1: How can we determine the right composition method for a given service composition task?
  - Goal 2: How does selecting a composition algorithm on a per-instance basis perform compared to a pre-selected algorithm?

System Overview



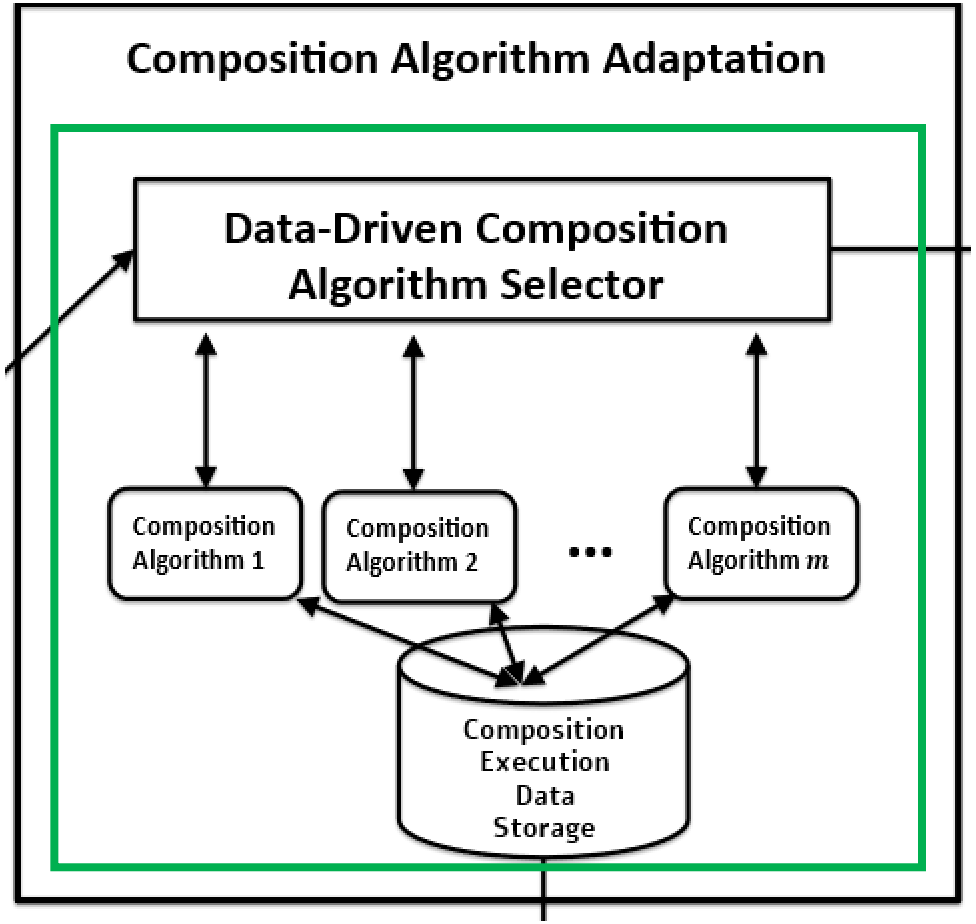
Composition Algorithm Selector

- Steps followed
  - Dataset creation
  - Classifier selection
  - Evaluation of classifier-based selector



Composition Algorithm Selector

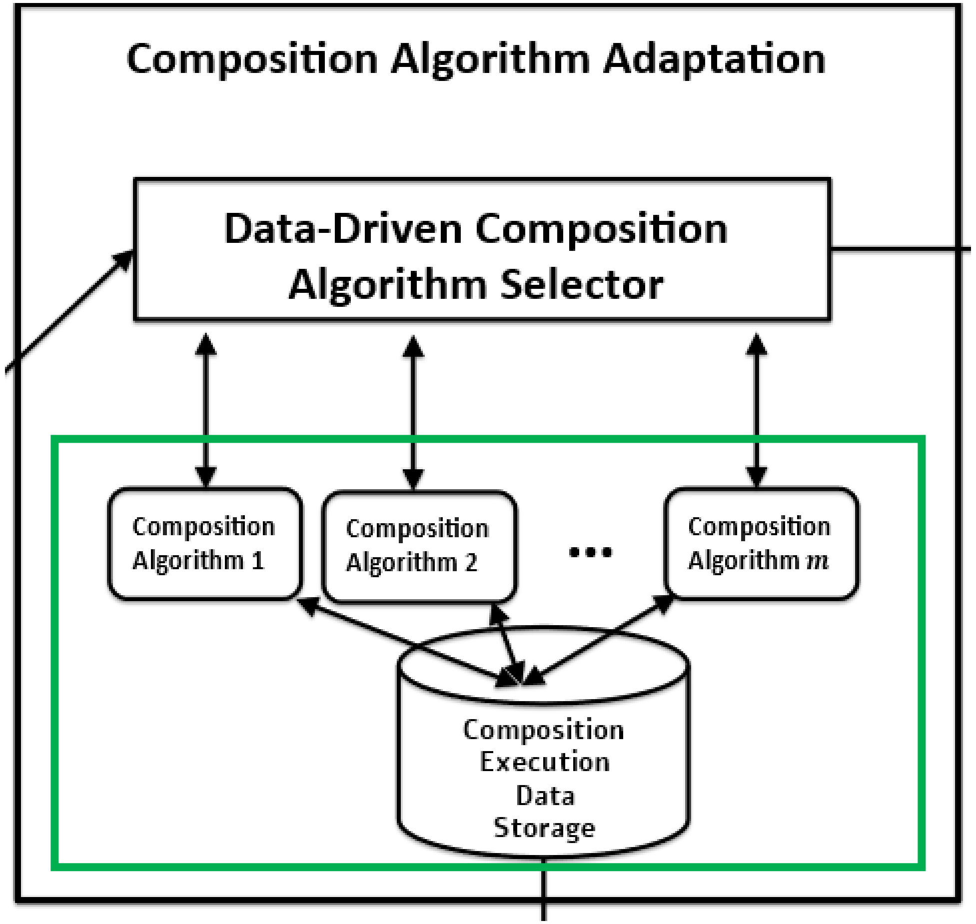
- <u>Goal 1:</u> How can we determine the right composition method for a given service composition task?
- We examine the use of classifiers as a selector
- Composition algorithms considered
  - Multi-Constraint Shortest Path (MCSP) (Yue et al., 2007),
  - Ant Colony System (ACS) (Zhang et al., 2010) and
  - Genetic Algorithm (GA) (Trummer and Faltings, 2011)



Composition Algorithm Selector

- Dependency graphs
  - Number of Abstract Service (#AS): 5, 10, 20, 30, 40
  - Number of Candidate Services (#CS): 5, 10, 15, 20, 30, 35, 40

- QWS[1] dataset randomly sampled for candidate services
- We use the Lp metric (Zhang et al., 2010) to compute multi-objective solution quality



[1]https://qwsdata.github.io/

Composition Algorithm Selector

- Example dataset entry

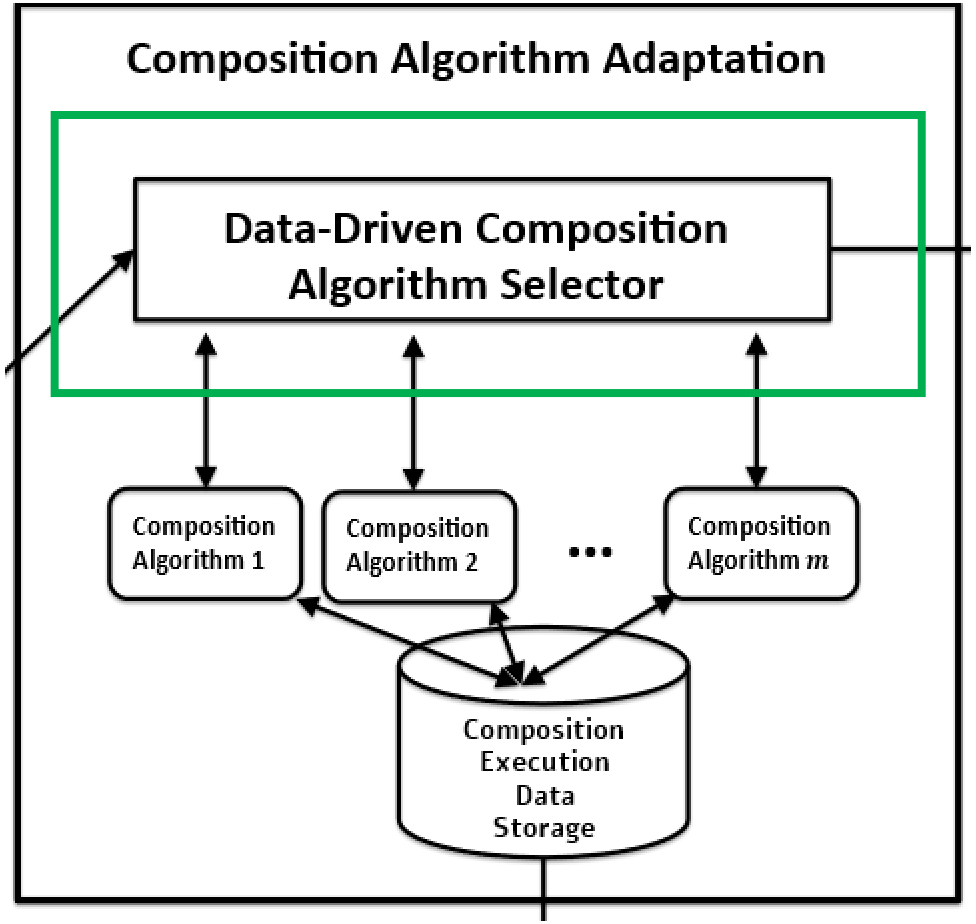
# AS	# CS	Weight 1	…	Weight 8	QoS 1	…	QoS 8	Time (s)	Memory (kB)	Label
20	25	0.125		0.2	0.4		0.8	15	125,000	GA

- Labeling scheme

# AS	# CS	Desired solution quality (Lp)	Delivered solution quality (Lp)	Allotted time	Utilized time	Allocated memory	Utilized memory	Label
20	25	0.7	0.90	15	25	90,000	120,000	MCSP
20	25	0.7	0.60	15	5	90,000	56,000	GA
20	25	0.7	0.71	15	16	90,000	95,000	ACS

Composition Algorithm Selector

- Classifiers considered
  1. Random Forest,
  2. Decision Tree,
  3. Logistic Regression,
  4. Quadratic Discriminant Analysis,
  5. Support Vector Machines
- Dataset shuffled, 70/30 train-test split
- 5 fold cross validation repeated 10 times



Preliminary Results: Classifier Selection

Classifier	Accuracy	F1-score
Random Forest	0.95	0.94
Decision Tree	0.94	0.93
QDA	0.92	0.92
Logistic Regression	0.88	0.88
SVM - rbf	0.51	0.39
SVM - sigmoid	0.52	0.35

- *QDA performance indicates nonlinear decision boundary, different inter-class variances. The best performance was found with regularization parameter was found to be 0.5*
- *Thus, the algorithm selector is Random Forest with 200 trees and a maximum depth of 6.*

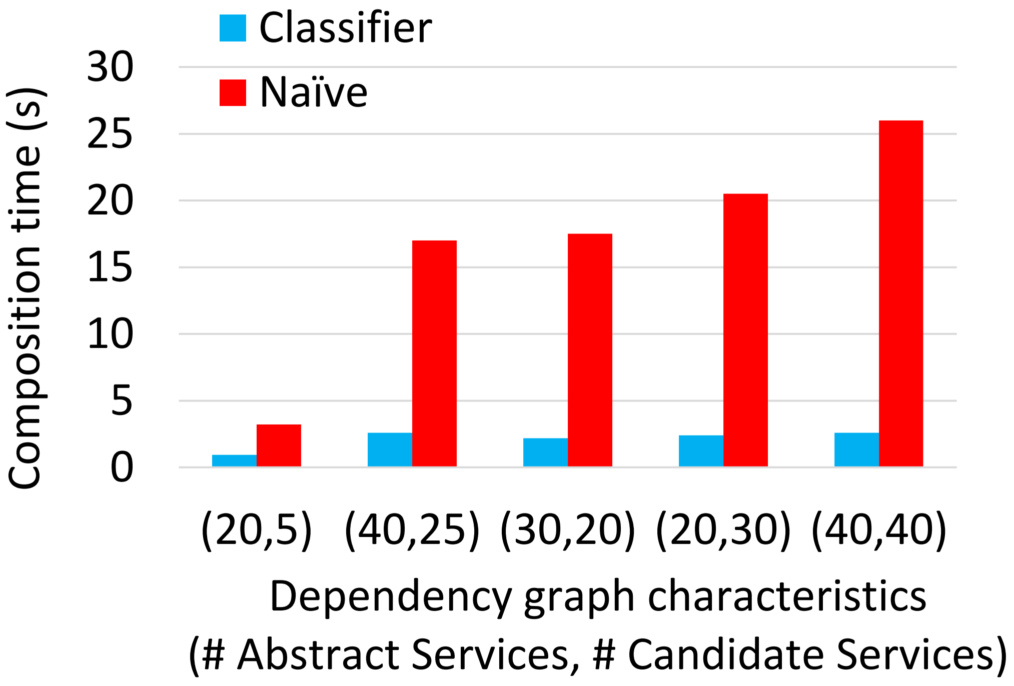
Conclusions on Goal # 1

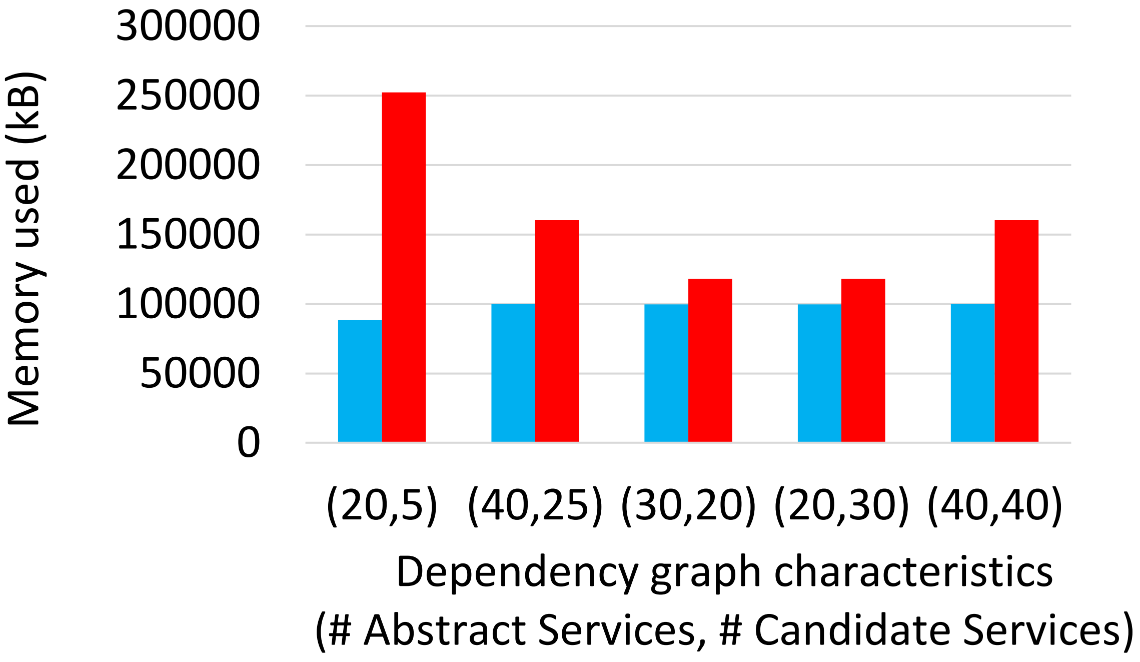
- Goal 1: How can we determine the right composition method for a given service composition task?
- A set of classifiers evaluated
  - Considering different decision boundaries between variables
  - Presence of non-linear decision boundaries indicated
  - Performance observed for one set of solution utilities
- Findings
  - Random forest outperforms the rest

Classifier-based Selector Performance

- Goal 2: How does selecting a composition algorithm on a per-instance basis perform compared to a pre-selected algorithm?
- We compare classifier selection to a naive approach, which selects based purely on solution utility
- Measured time and memory resources used by both selections

Preliminary Results: Usage

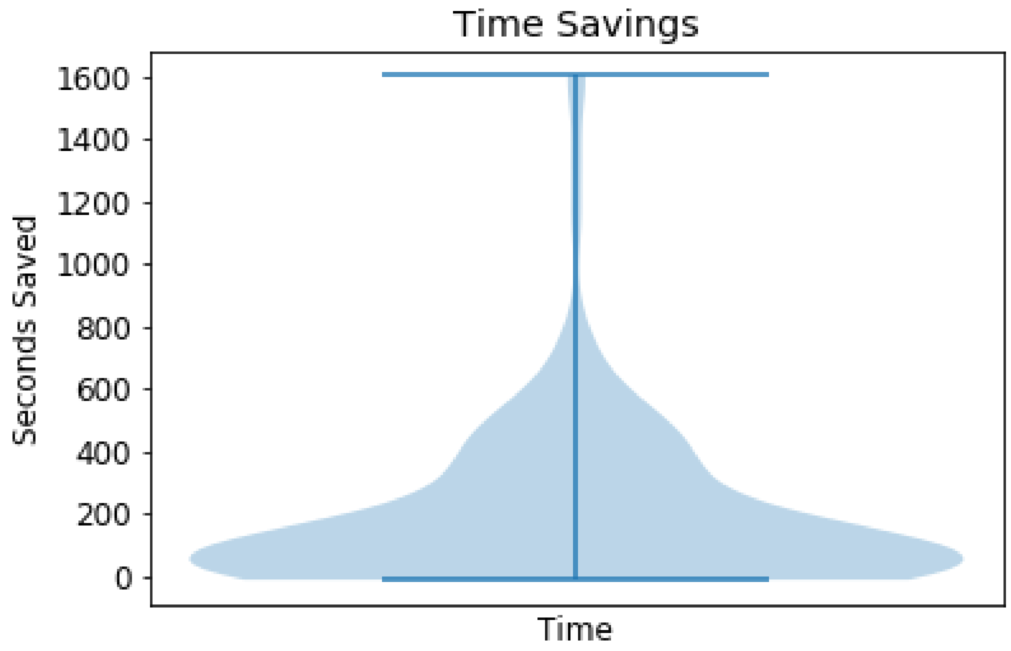


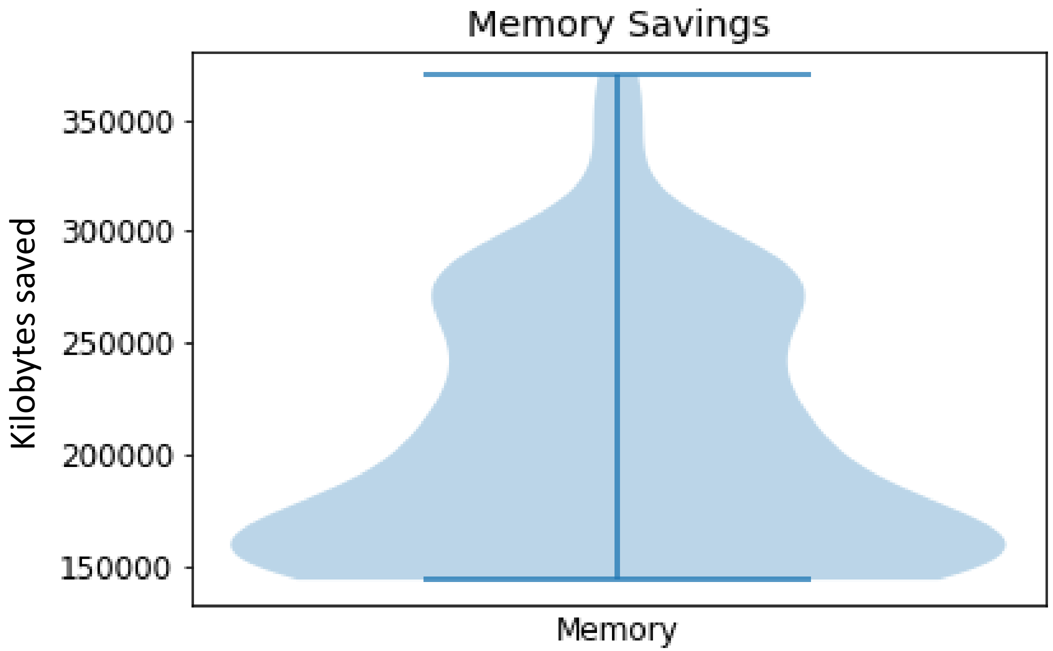


- *On average, classifier-based selection took :*
  - *33% less time*
  - *24.8% less memory*

Dataset Creation | Classifier Selection | Evaluation of Approach

Preliminary Results: On Average





- *Observation: Both time and memory savings observed for the test set. At a minimum about 150000 kB were saved, while time savings peaked approximately around 100 seconds*

Conclusions on Goal 2

- Goal 2: How does selecting a composition algorithm on a per-instance basis perform compared to a pre-selected algorithm?
- Performance compared to a naïve approach
  - Classifier-based selection saves time and memory required for composition
- Findings
  - On average, classifier selected algorithms took
    - 33% less time
    - 24.8% less memory
  - Overheads
    - Selection overhead: ~1% of processing time

Future Work

- Preliminary results demonstrate considerable compute resource savings for various solution utility requirements.
- We will expand our experiments to include
  - Diverse solution qualities
  - Other types of learning algorithms that do not require labels
  - Addition of diverse composition algorithms
- In addition to this, we will deploy our approach as an online feedback loop to be used at runtime.

Summary

- We proposed selection of composition algorithms per composition task
- Preliminary results demonstrate considerable compute resource savings
- Future work includes expansion of experiments include
    - Diverse solution qualities
    - Other types of learning algorithms that do not require labels
    - Deployment as an online feedback loop

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