

Janus:
Fine-grained and efficient
provenance querying for Taverna

Paolo Missier

Information Management Group

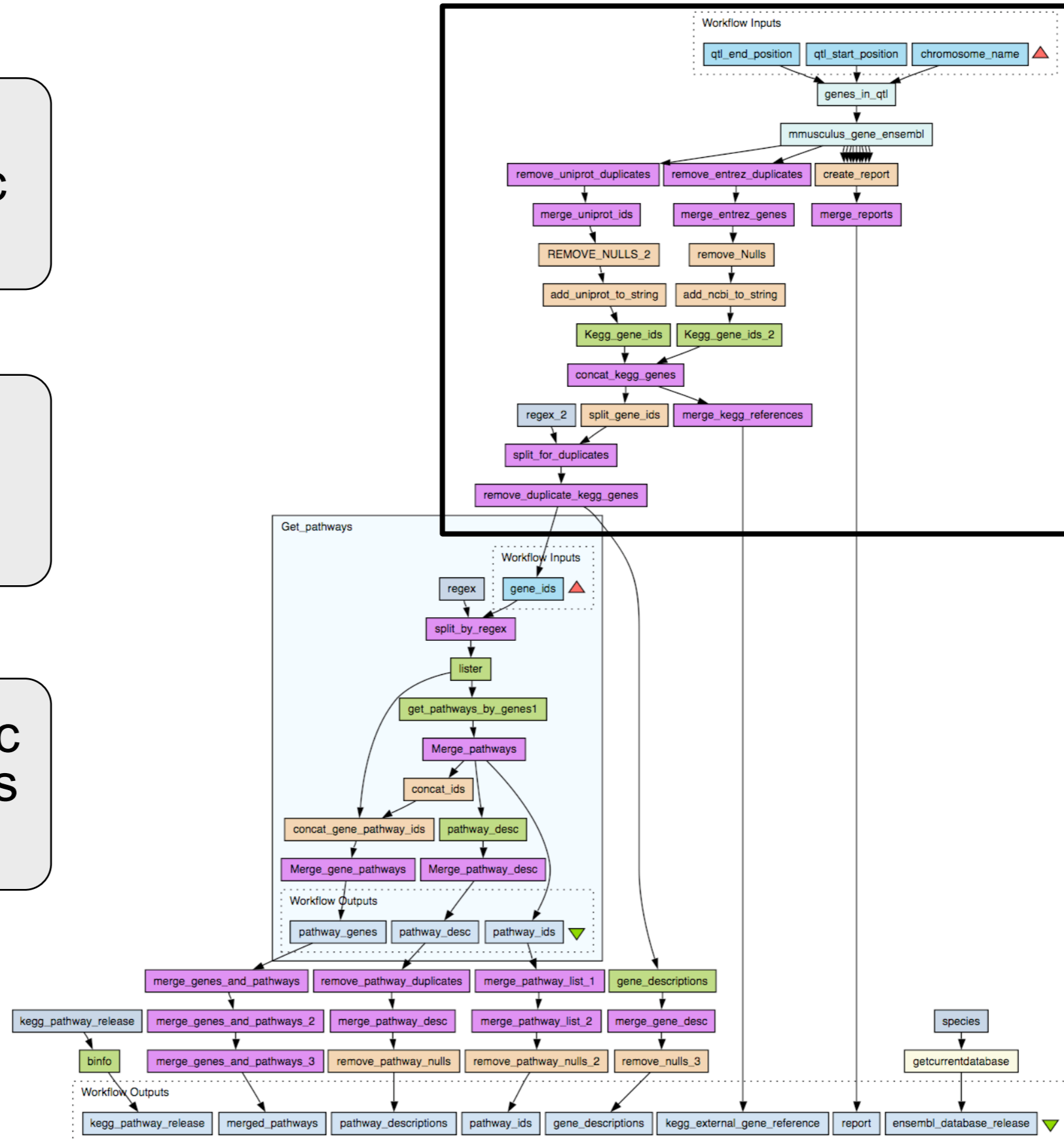
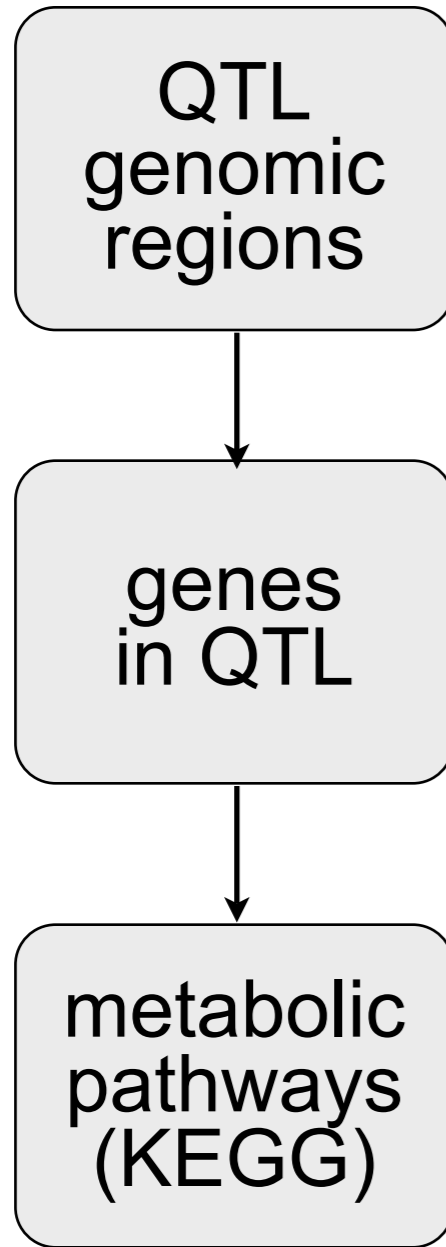
School of Computer Science, University of Manchester, UK

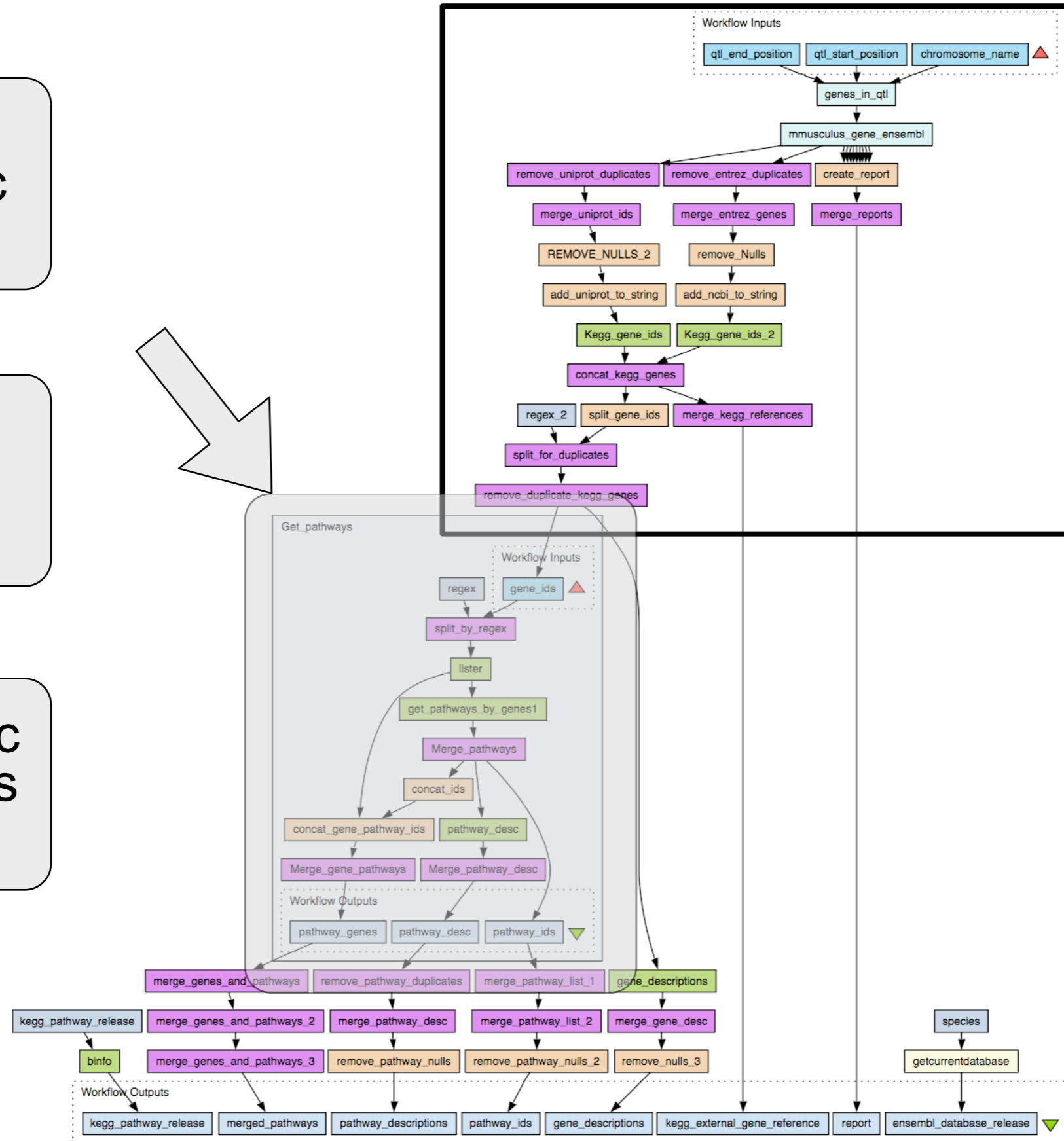
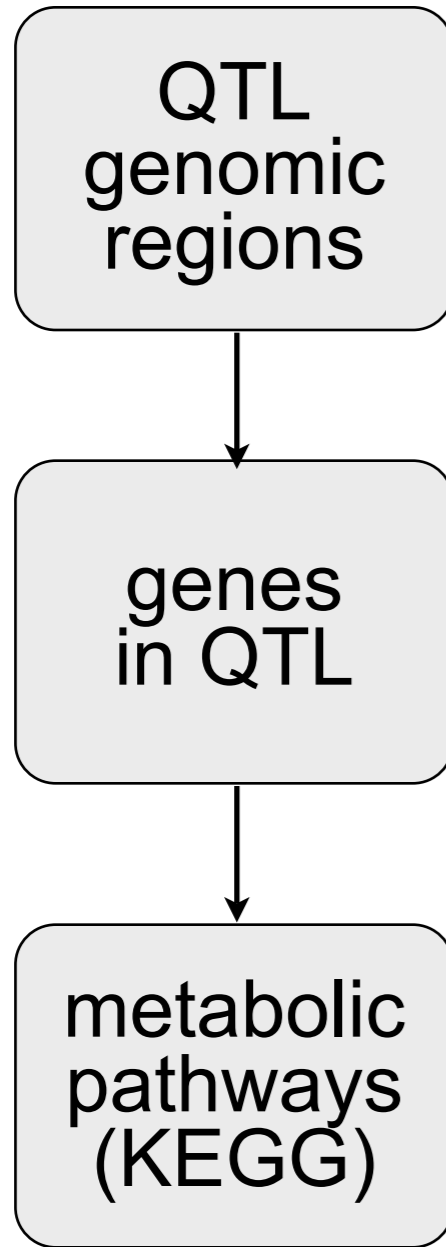
in collaboration with:

Norman Paton, Khalid Belhajjame

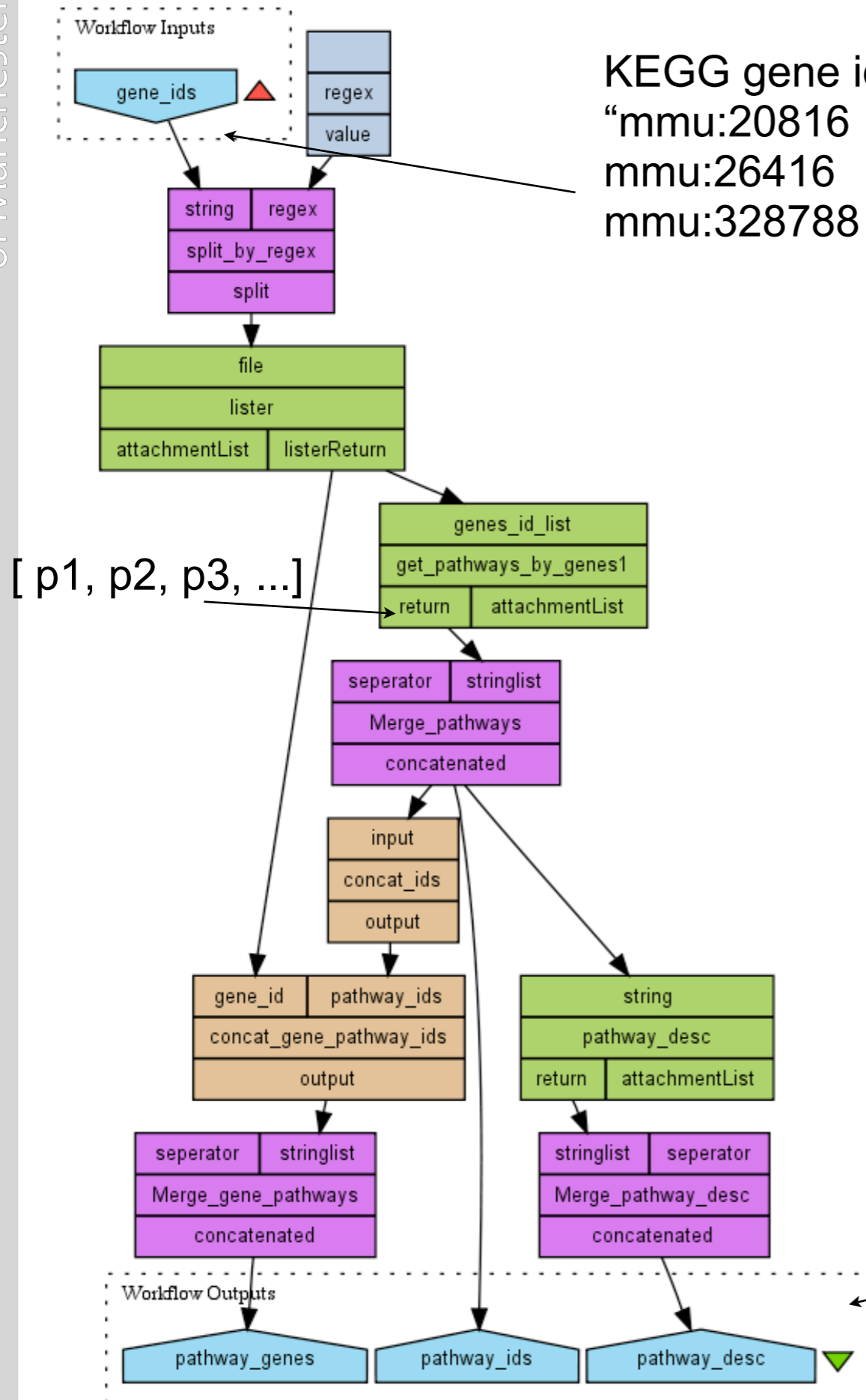
IMG Seminar, June 2009

- Motivation: Taverna for rapid information integration
- Fine-grained process provenance and its role in Taverna
- Context and scope: forms and uses for process provenance
- Technical challenges in querying provenance traces
- A solution, and experimental results



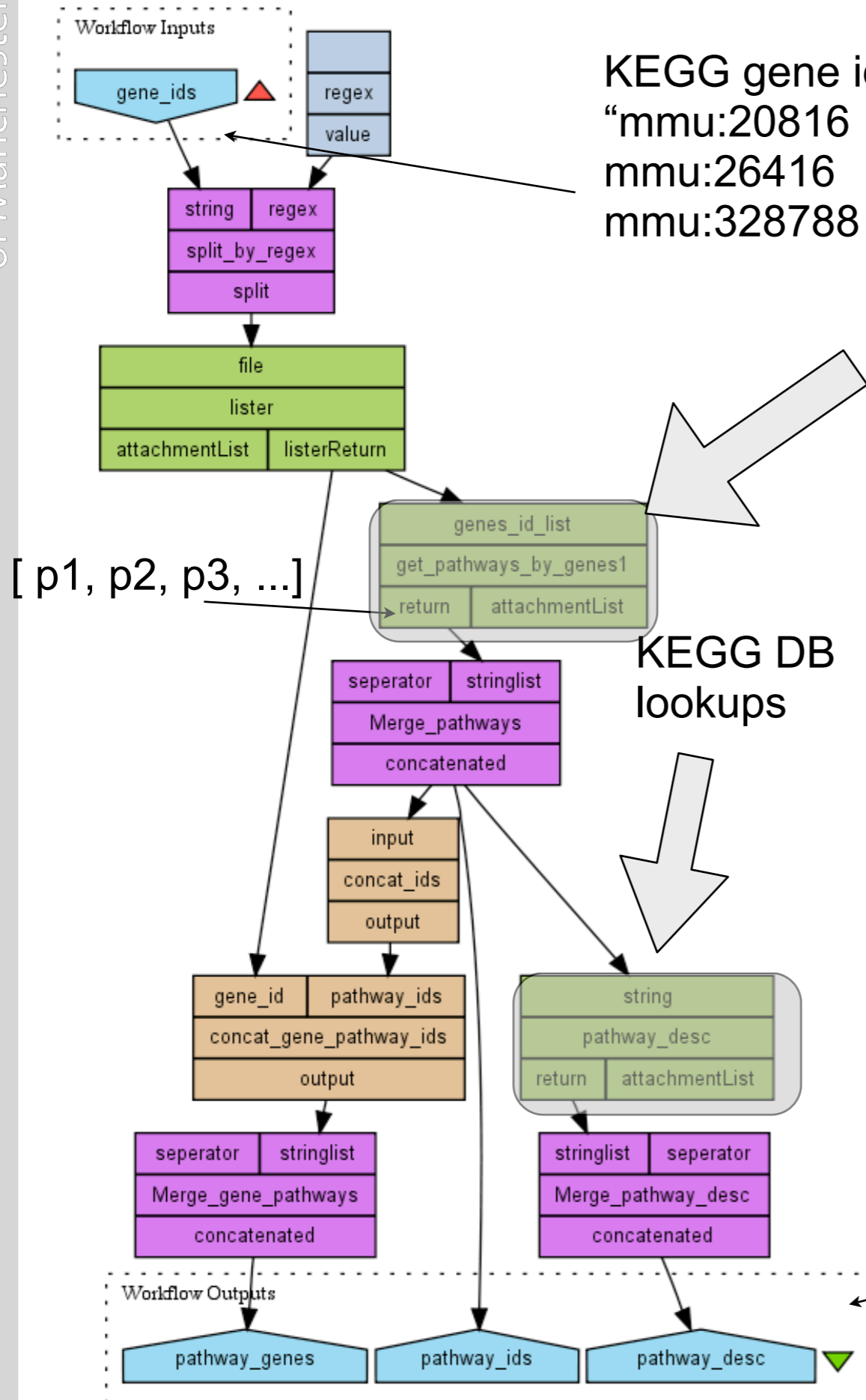


KEGG gene ids:
 "mmu:20816 (g1)
 mmu:26416 (g2)
 mmu:328788 (g3)"



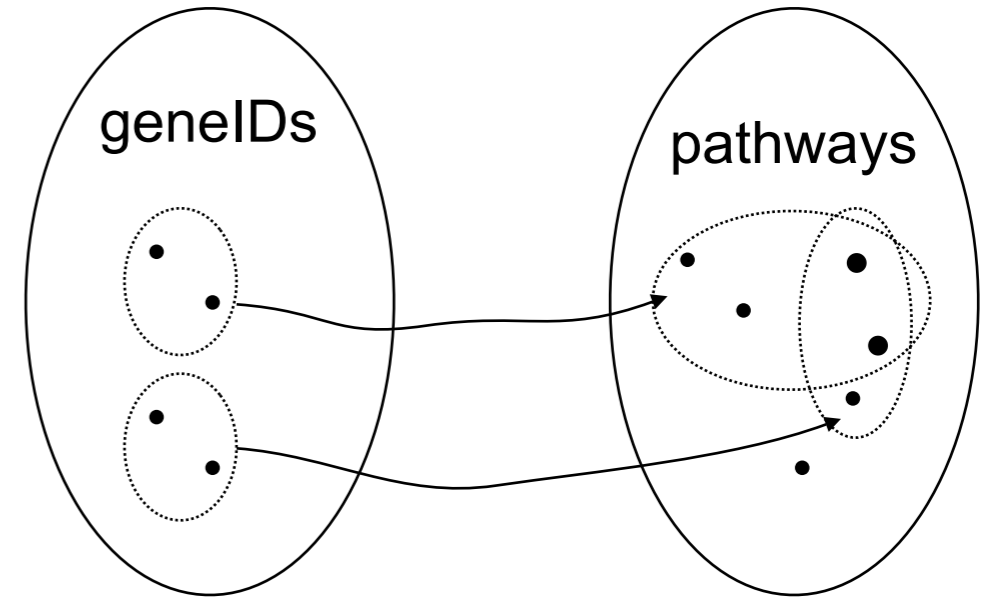
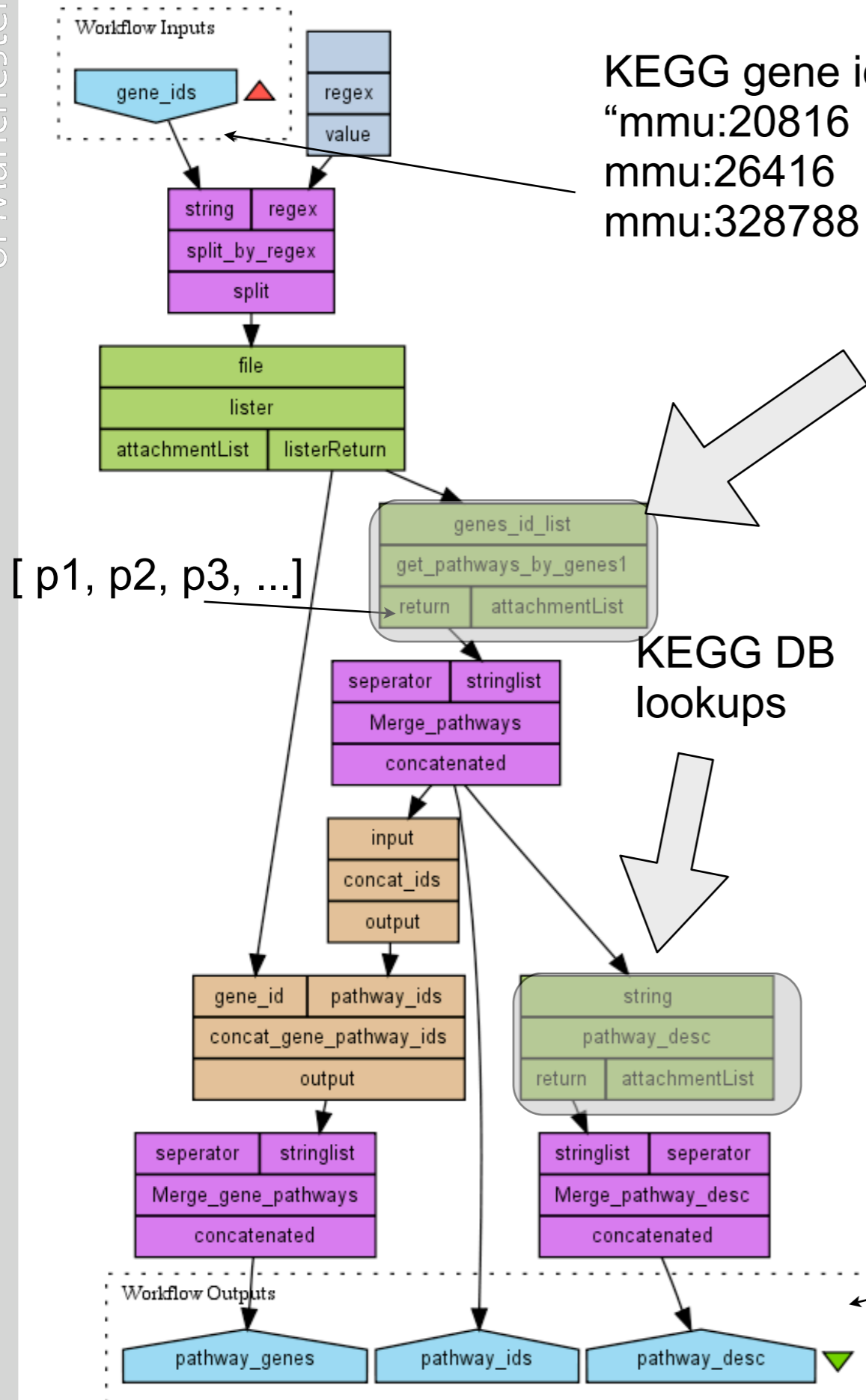
[p1, p2, p3, ...]

"p1 MAPK signaling pathway
 p2 VEGF signaling pathway
 ..."

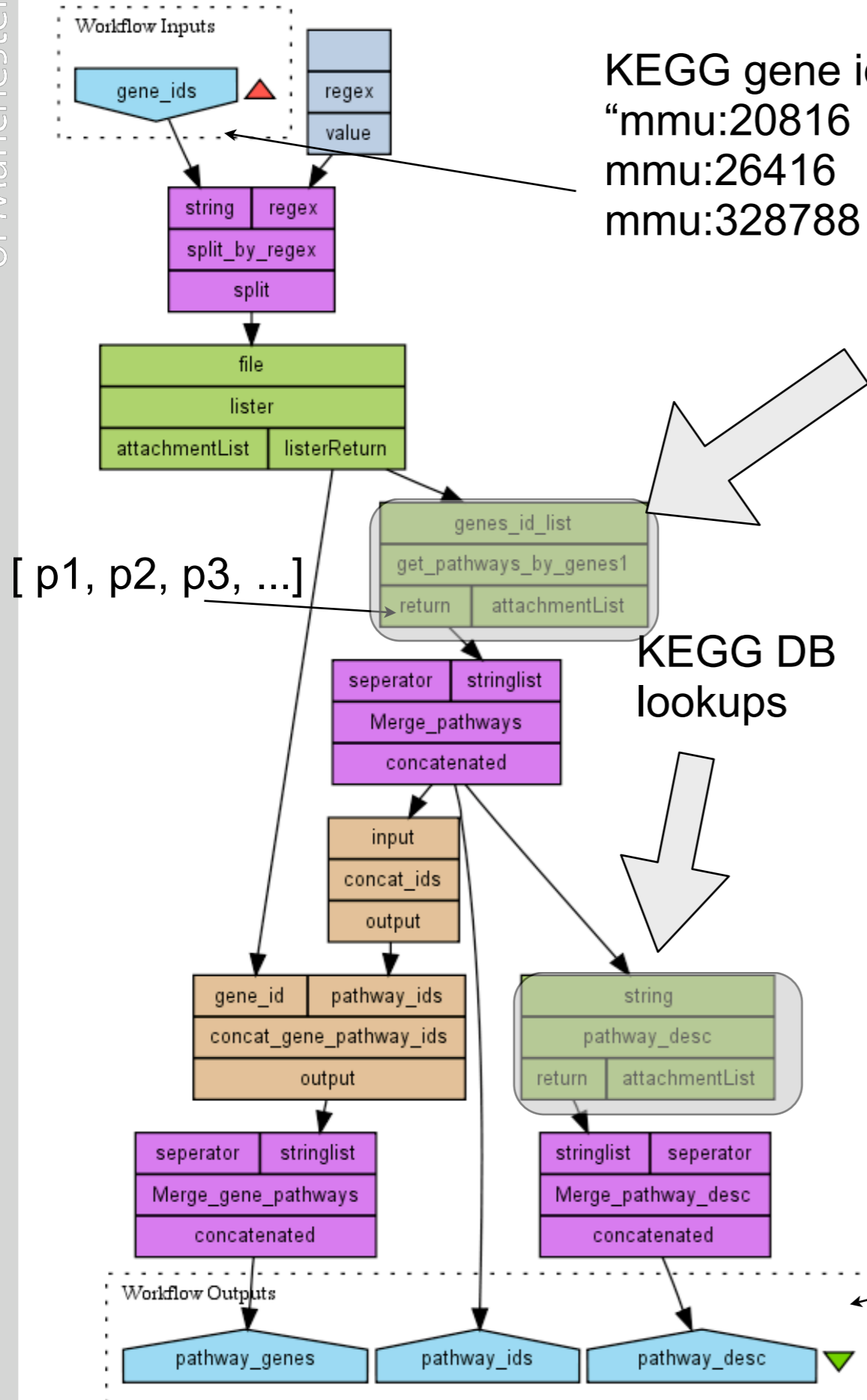


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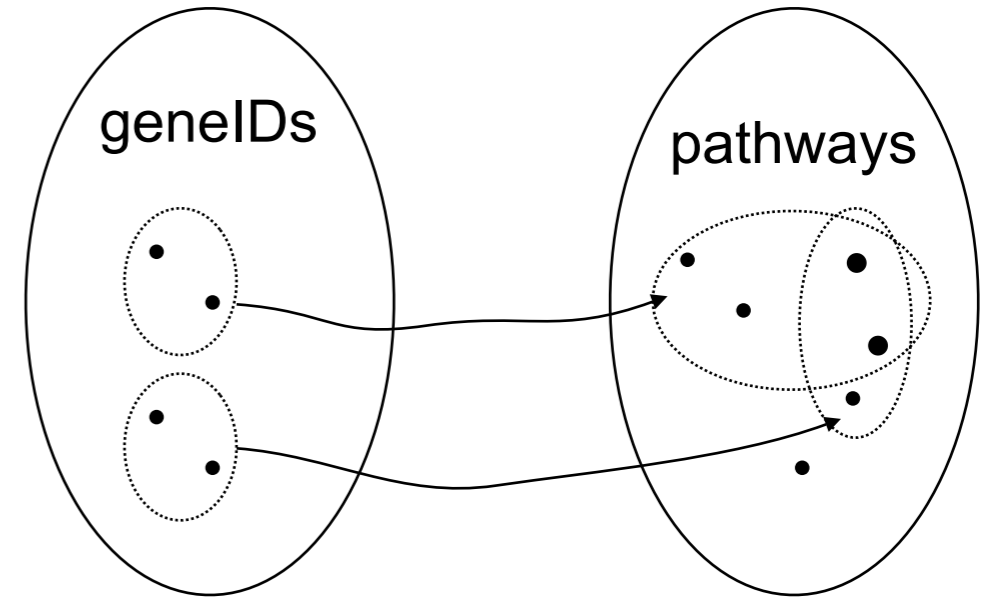
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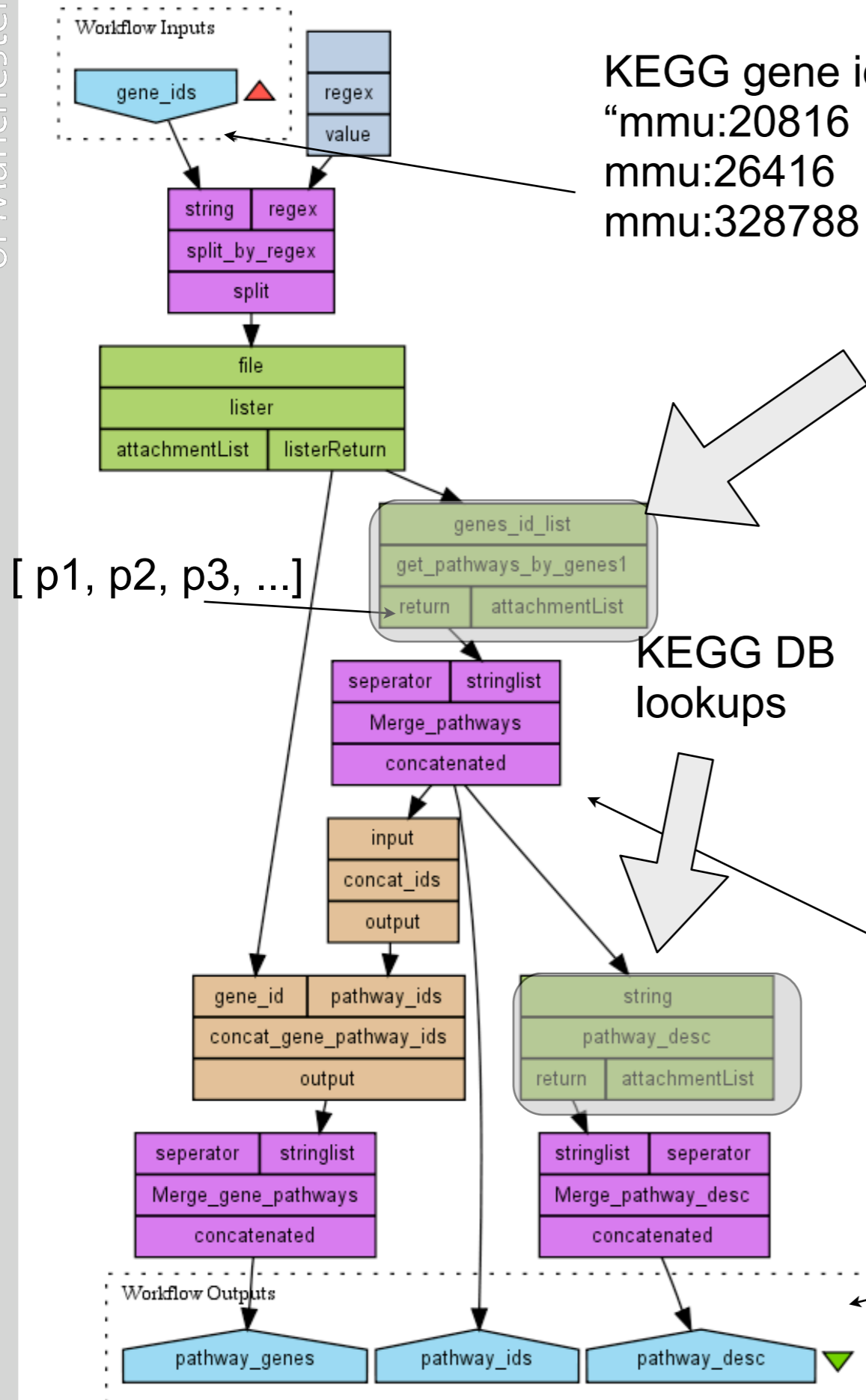
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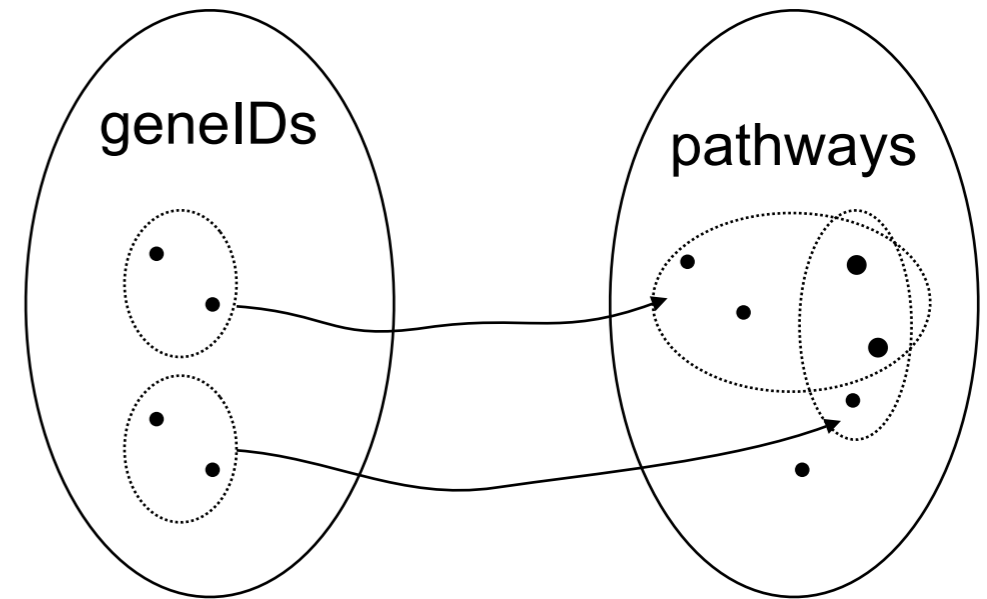
goal:

- list all pathways that are mapped from both sets of genes
- substantial list manipulation involved in achieving this

“p1 MAPK signaling pathway
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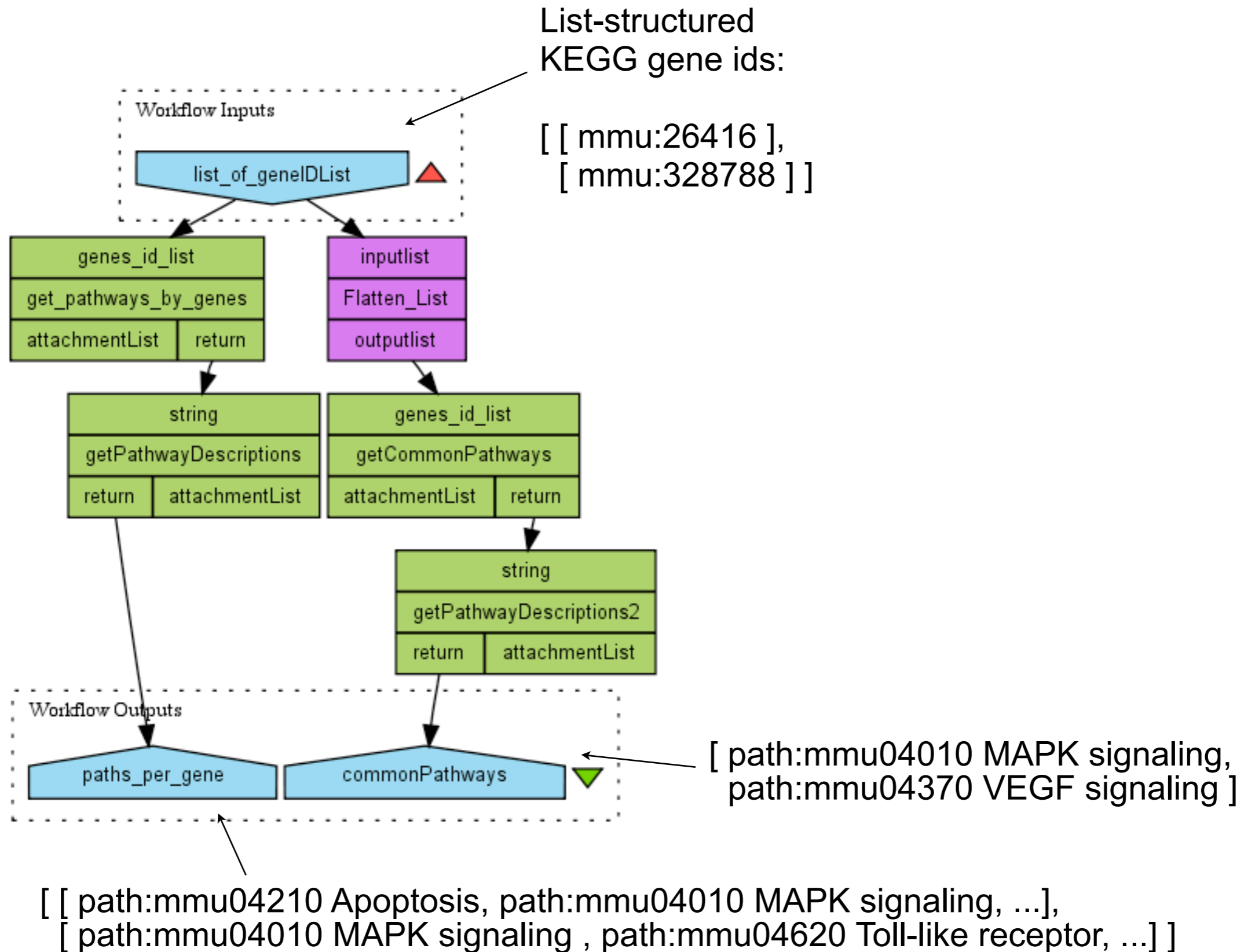
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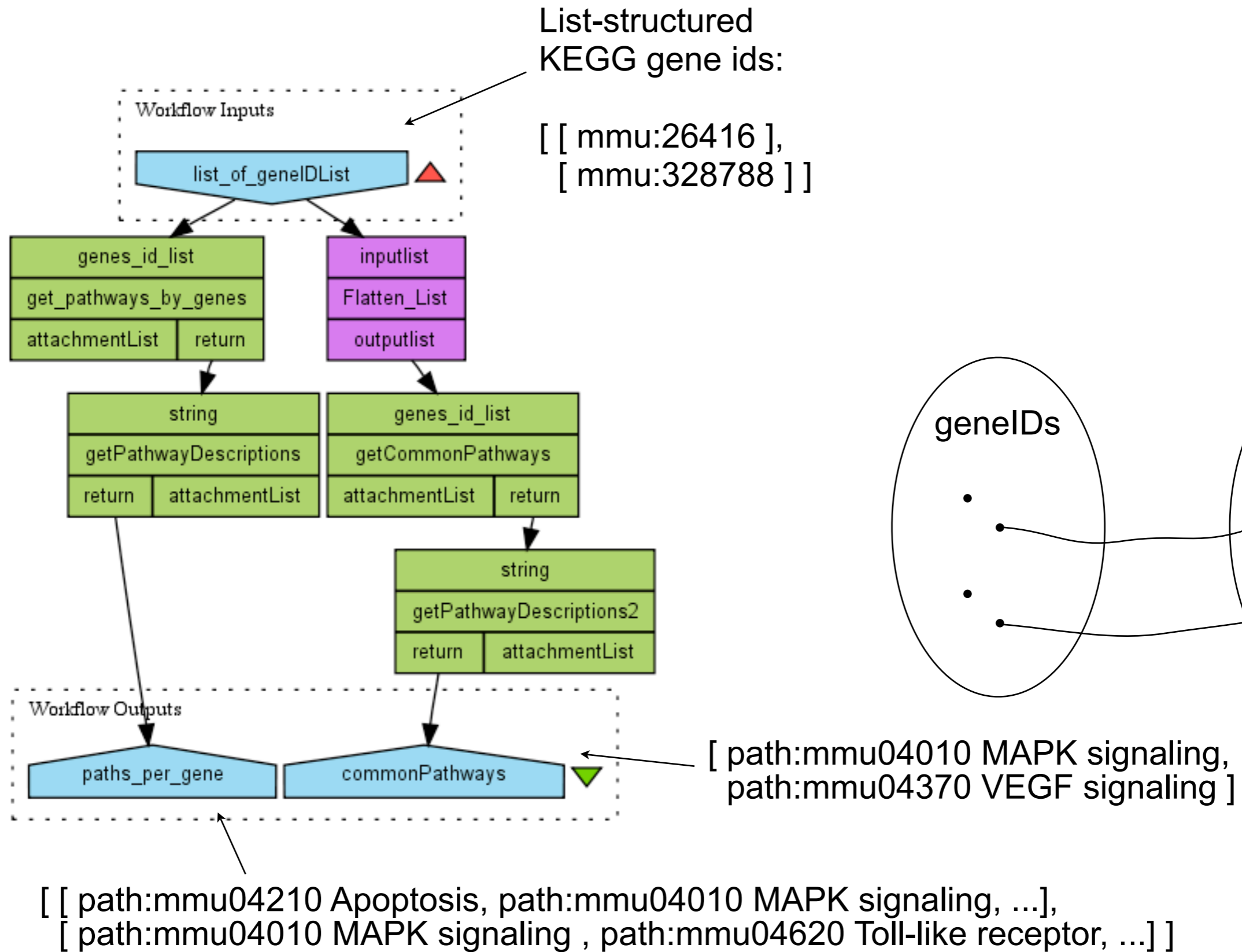


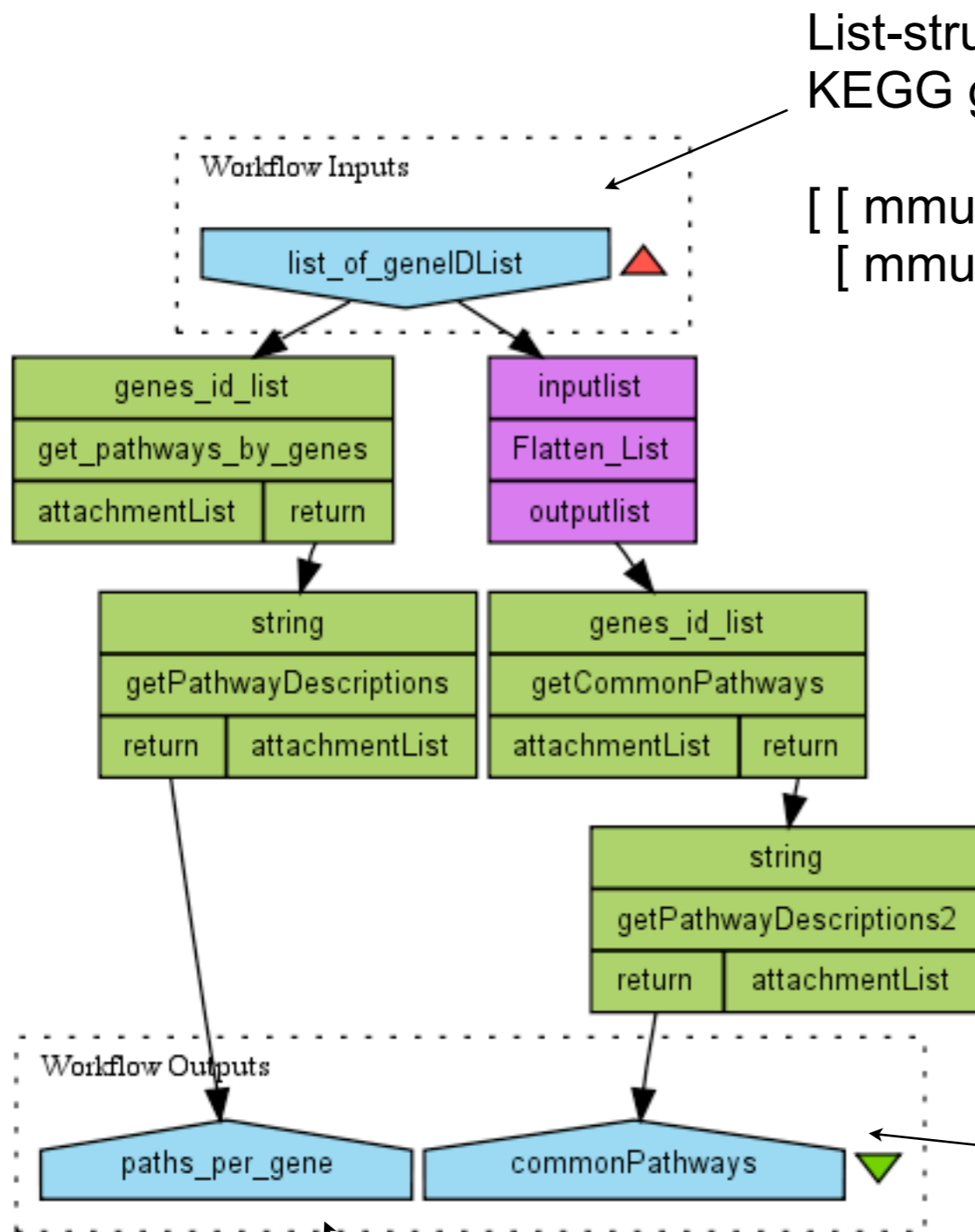
- goal:
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[[g1, g2, g3],
 ["g1 p1 p2 ...", "g2 p1 p2 ..." , "g3 p1 p2 ..."]
 [g1, g2, g3]]

"p1 MAPK signaling pathway
 p2 VEGF signaling pathway
 ..."

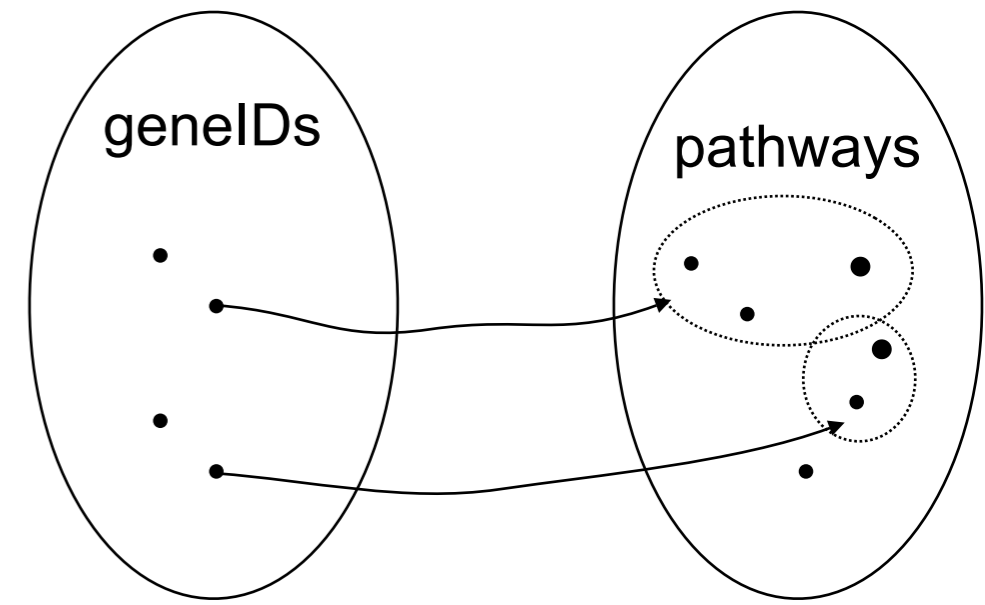
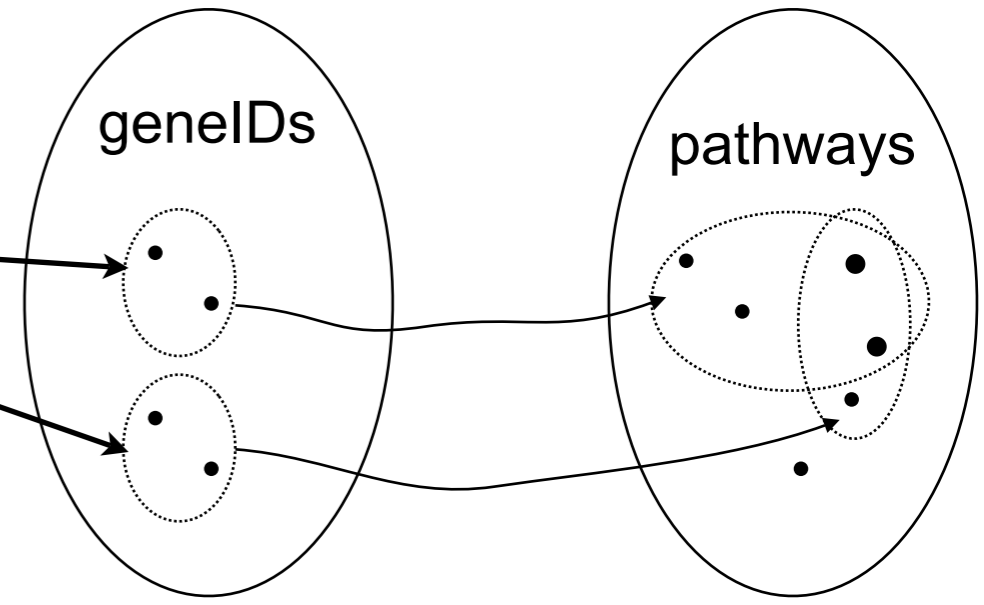






List-structured KEGG gene ids:

[[mmu:26416],
[mmu:328788]]



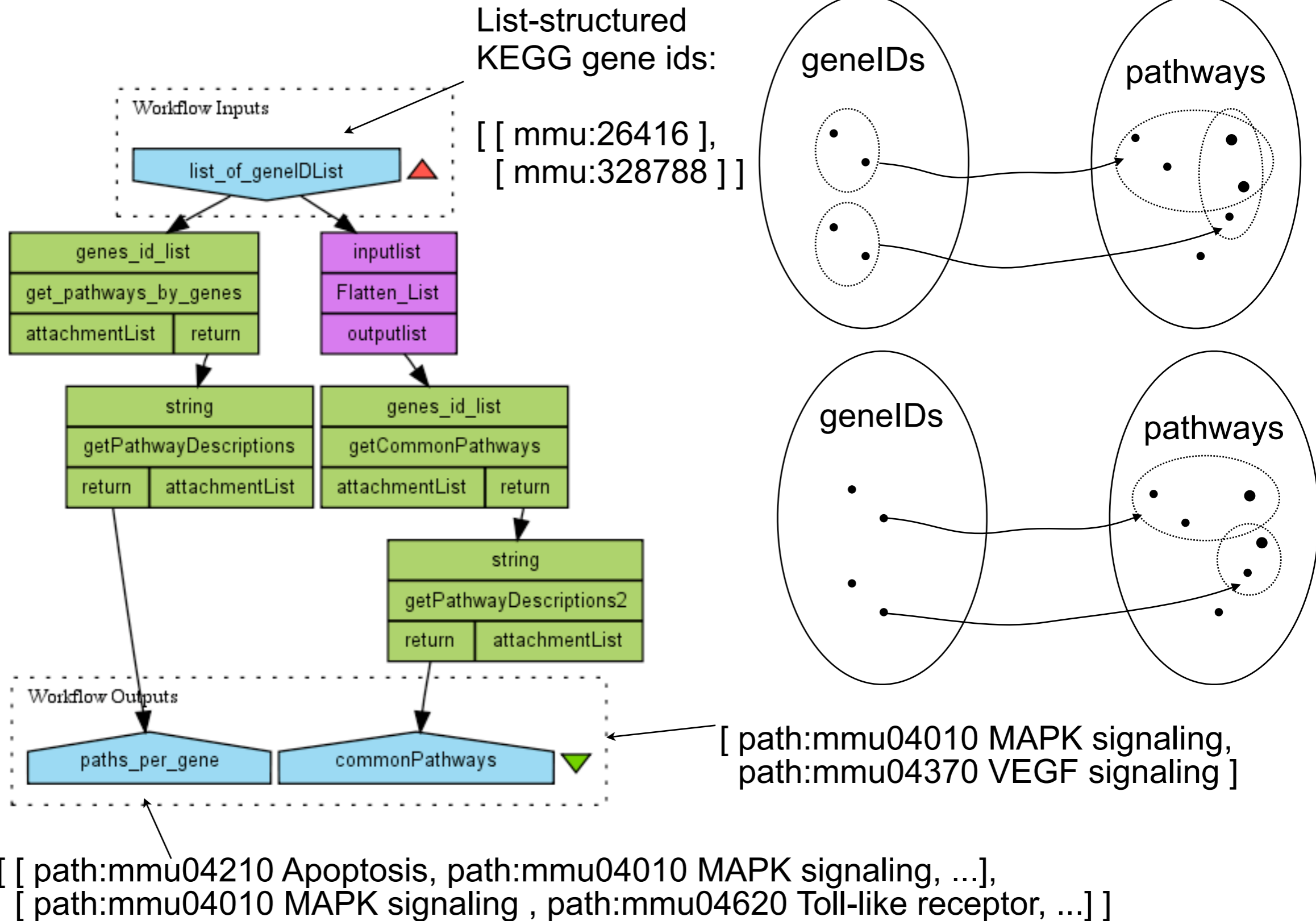
[path:mmu04010 MAPK signaling,
path:mmu04370 VEGF signaling]

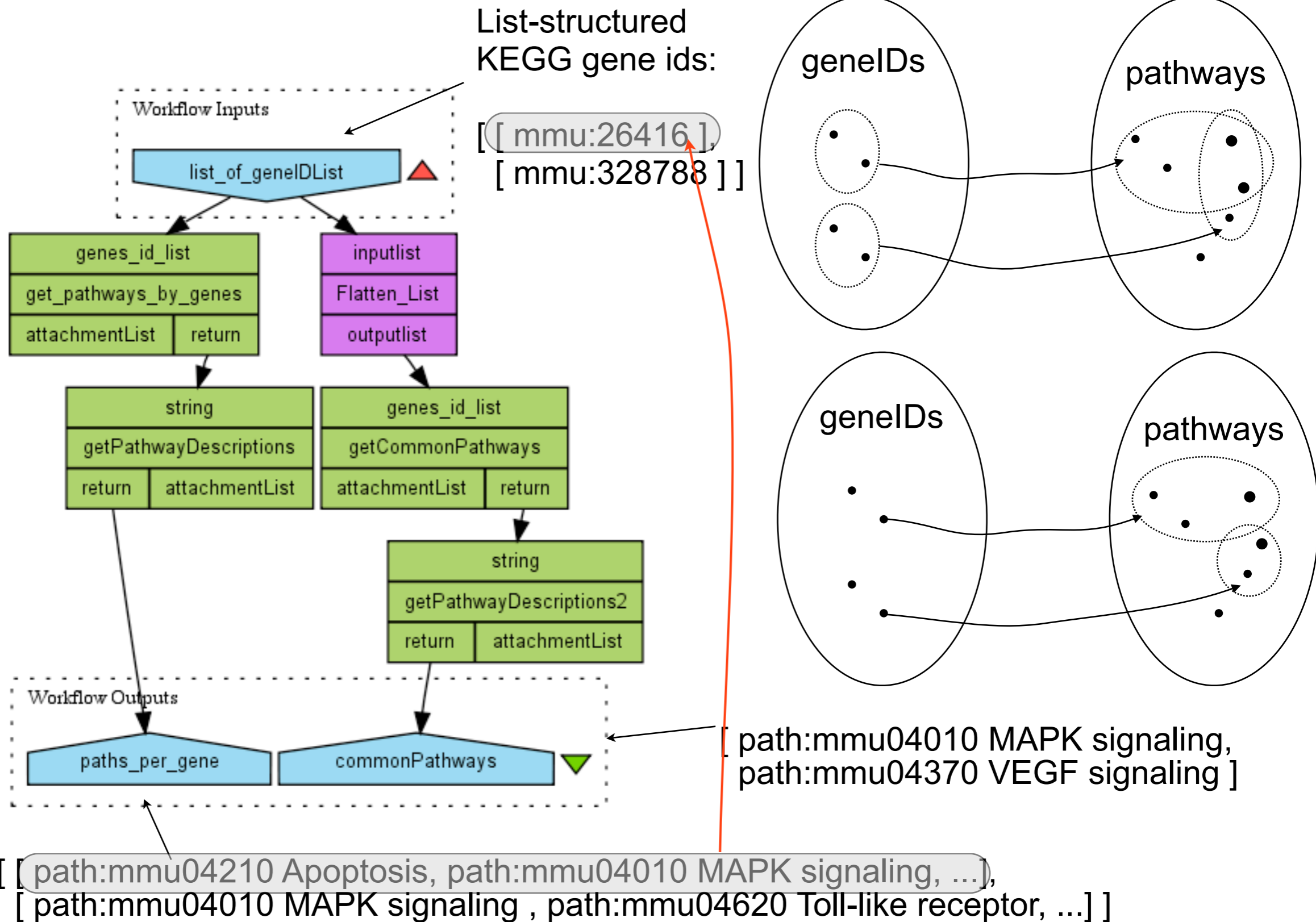
[[path:mmu04210 Apoptosis, path:mmu04010 MAPK signaling, ...],
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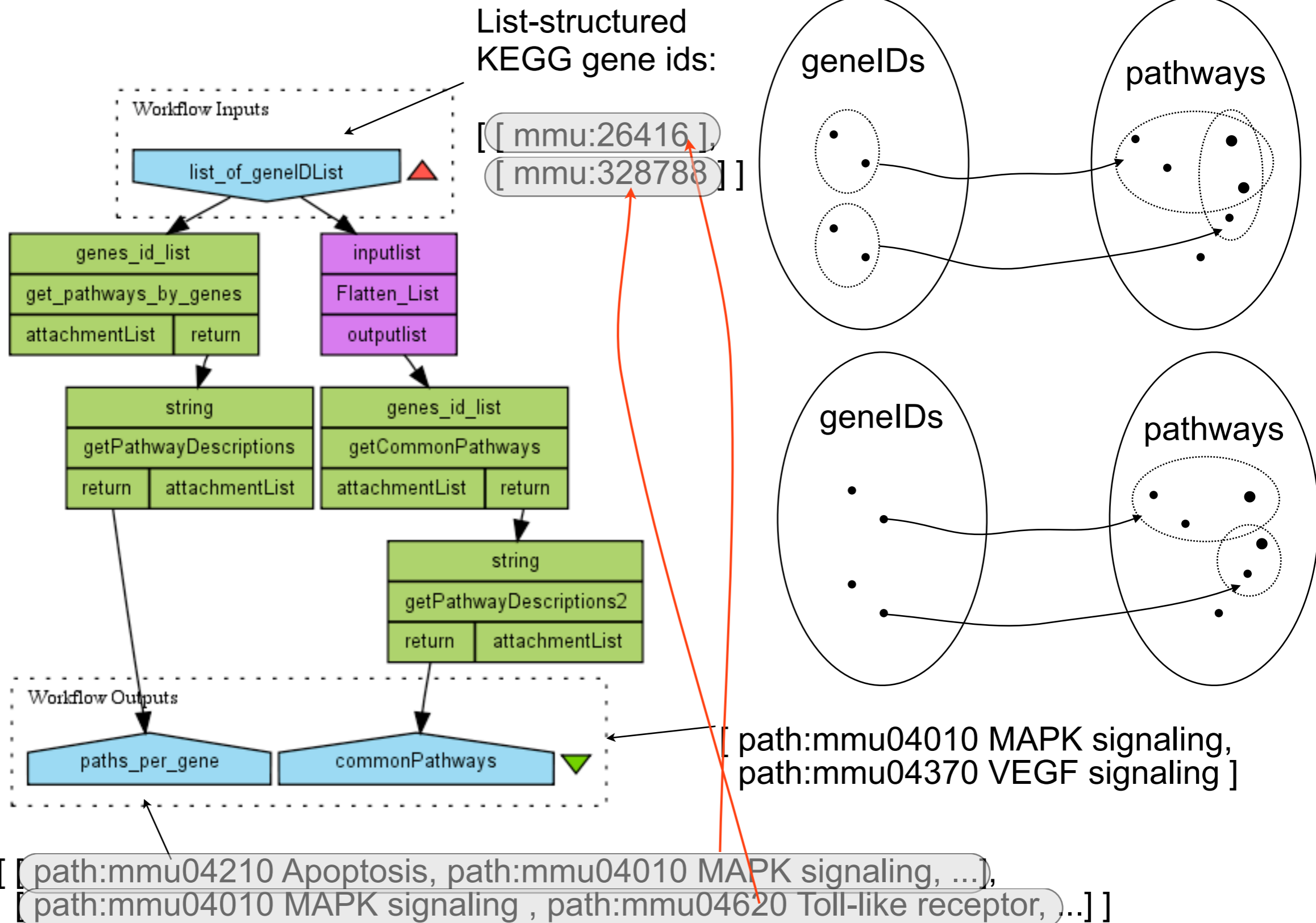
- **Pros:**
 - simpler to design and understand (hopefully)
 - (no shims!)
 - accepts multiple gene sets
 - returns list of pathways separately for each gene set
 - in addition to those shared by the union of all sets
- **Cons:**
 - no genes in output list:

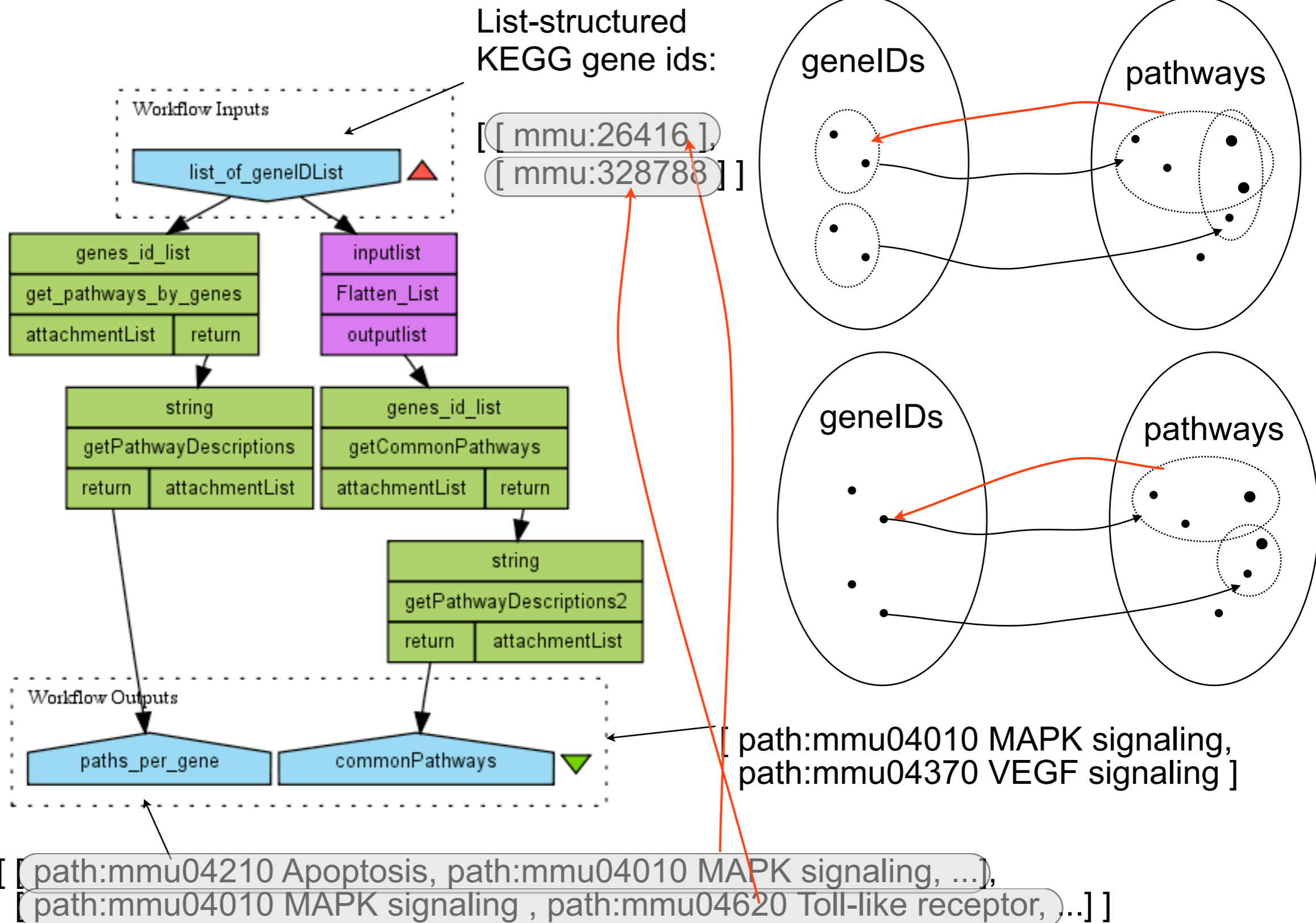

```
[ [ path:mmu04210 Apoptosis, path:mmu04010 MAPK signaling, ...],
  [ path:mmu04010 MAPK signaling , path:mmu04620 Toll-like receptor, ...] ]
```
 - so the relationship between the gene set and the pathway set is lost...

...Or is it?









- Taverna type system: strings + nested lists
 - “cat”, [“cat”, “dog”], [[“cat”, “dog”], [“large”, “small”]]
- Taverna dataflow model: data-driven execution
 - services activate when input is ready
- Workflow provenance: a detailed trace of workflow execution
 - which services were executed
 - when
 - inputs used, outputs produced

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Taverna dataflow model + provenance traces
can be a powerful combination

- Causal relations:
 - which pathway sets come from which gene sets?
 - which processes contributed to producing this image?
 - which process(es) caused this data to be incorrect?
 - which data caused this process to fail?

- Process and data analytics:
 - show me the variations in output in relation to an input parameter sweep (multiple process runs)
 - how often has my favourite service been executed?
 - on what inputs?
 - who produced this data?
 - how often does this pathway turn up when the input genes range over a certain set S ?

Focus is on the data: the **observable outcomes from a process**

	raw provenance metadata	provenance metadata + interpretation framework
design	<ul style="list-style-type: none"> • process structure (workflow graph) • history of process composition - reuse • process versions 	<ul style="list-style-type: none"> • service annotations: • ex. <code>get_pathways_by_genes</code> • who created /edited: attribution • why: purpose, intent
execution	<p>process events:</p> <ul style="list-style-type: none"> - service invocation - data production / consumption - causal dependency graphs <p>ex.:</p> <ul style="list-style-type: none"> - <code>list_of_geneIDList = [a, b, c]</code> - <code>paths_per_gene = [[d,e,f], [g,h,j]]</code> - ... in run #32 	<ul style="list-style-type: none"> - data annotations, results interpretation in terms of conceptual data model: set of pathways → gene sets

	raw provenance metadata	provenance metadata + interpretation framework
design	<ul style="list-style-type: none"> • exploiting semantic properties of the process structure to improve provenance exploitation • exploring process space across versions and structural similarities • graph matching 	<ul style="list-style-type: none"> • semantic-based search of process space
execution	<ul style="list-style-type: none"> - enabling partial re-runs of resource-intensive workflows - storing very large provenance traces that accumulate over time - efficient query over large traces - presentation of query answers 	<ul style="list-style-type: none"> - semantic-based query answering over annotated traces

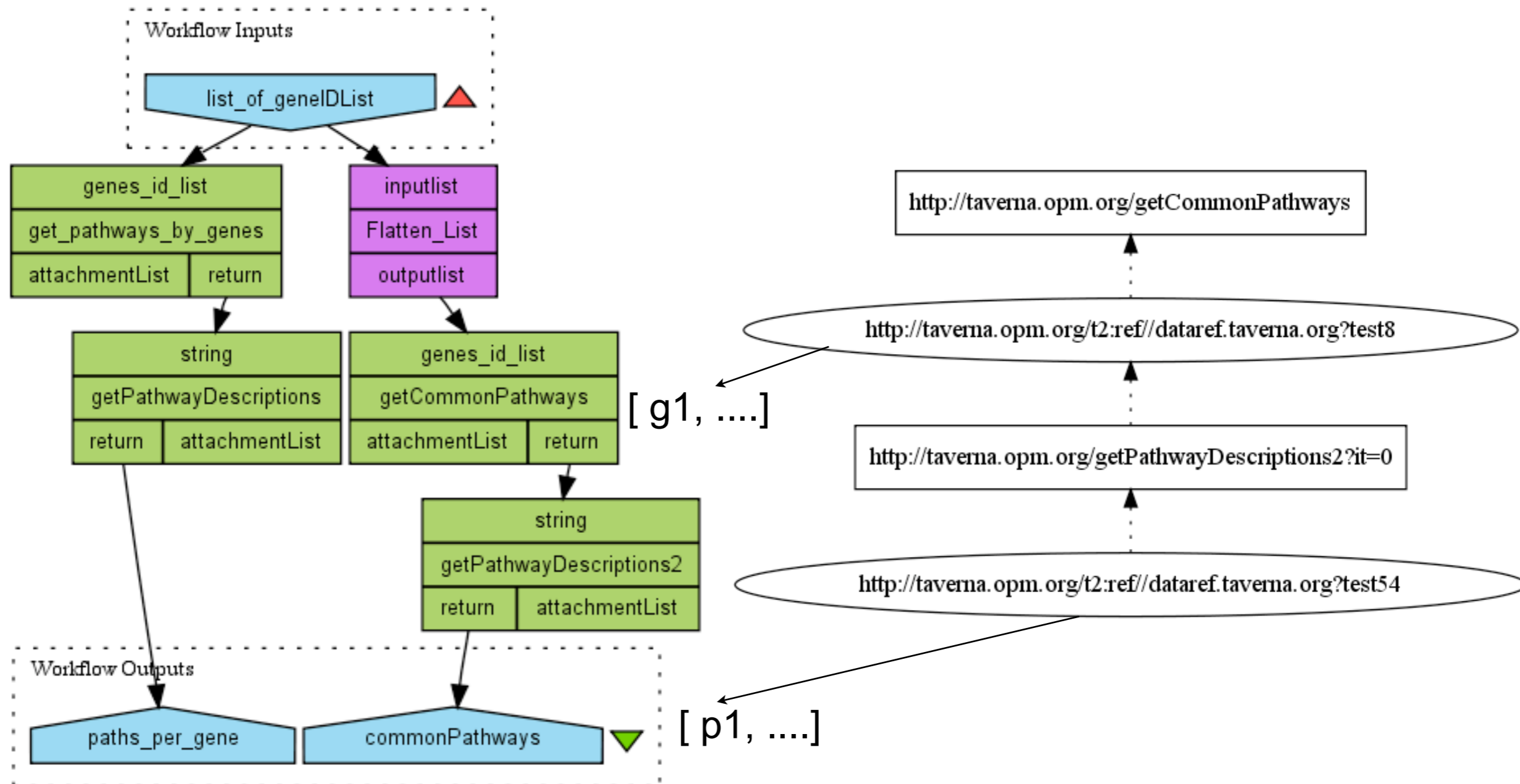
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The rest of
this talk!

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The rest of this talk!

- **Lineage queries** involve traversing a *provenance graph* from bottom to top



- In most approaches, the originating process are not used for querying
- consequence: query requires provenance graph traversal
 - large traces → computationally complex
 - view materialization used in practice to get around the computational complexity

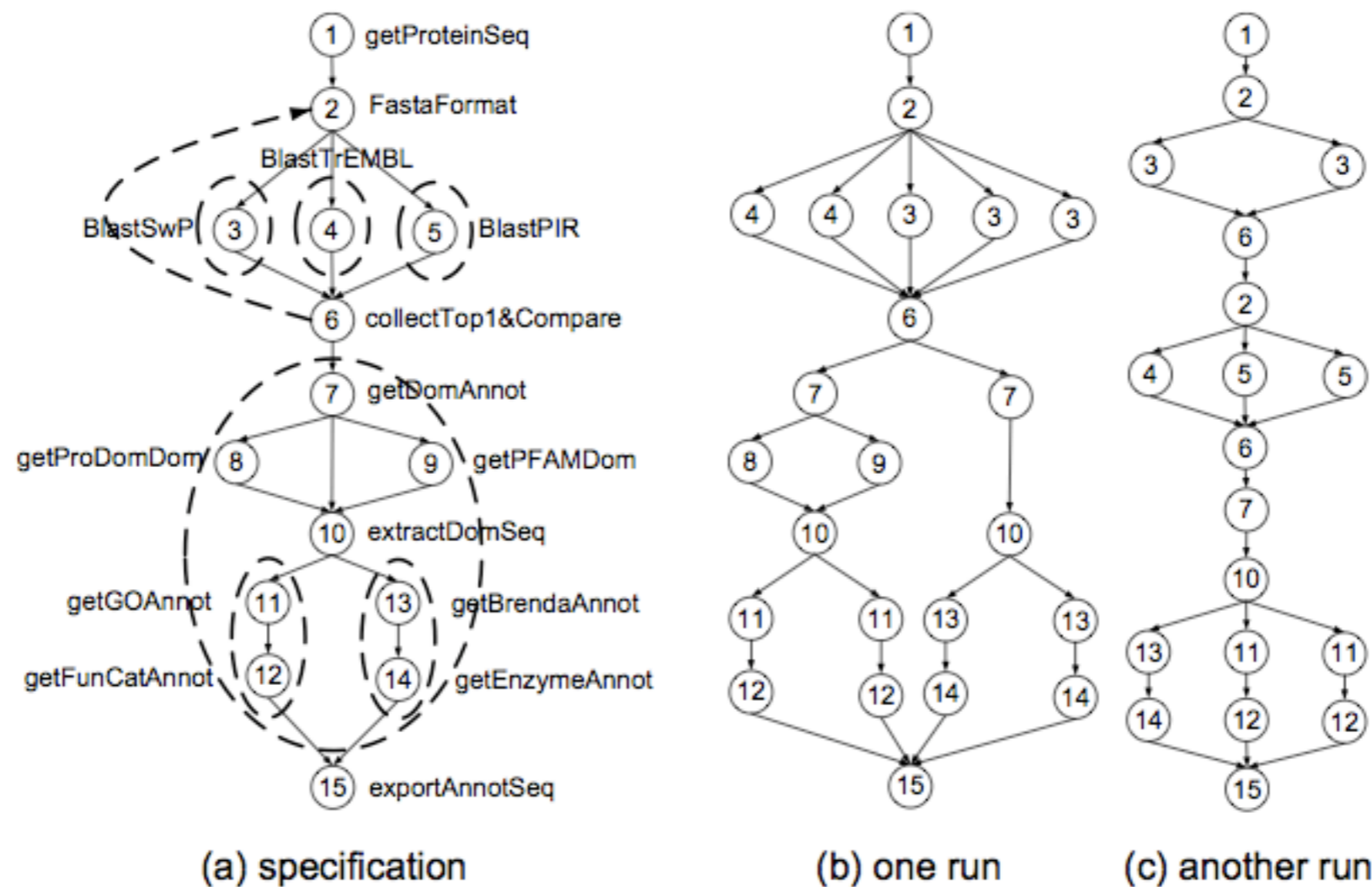
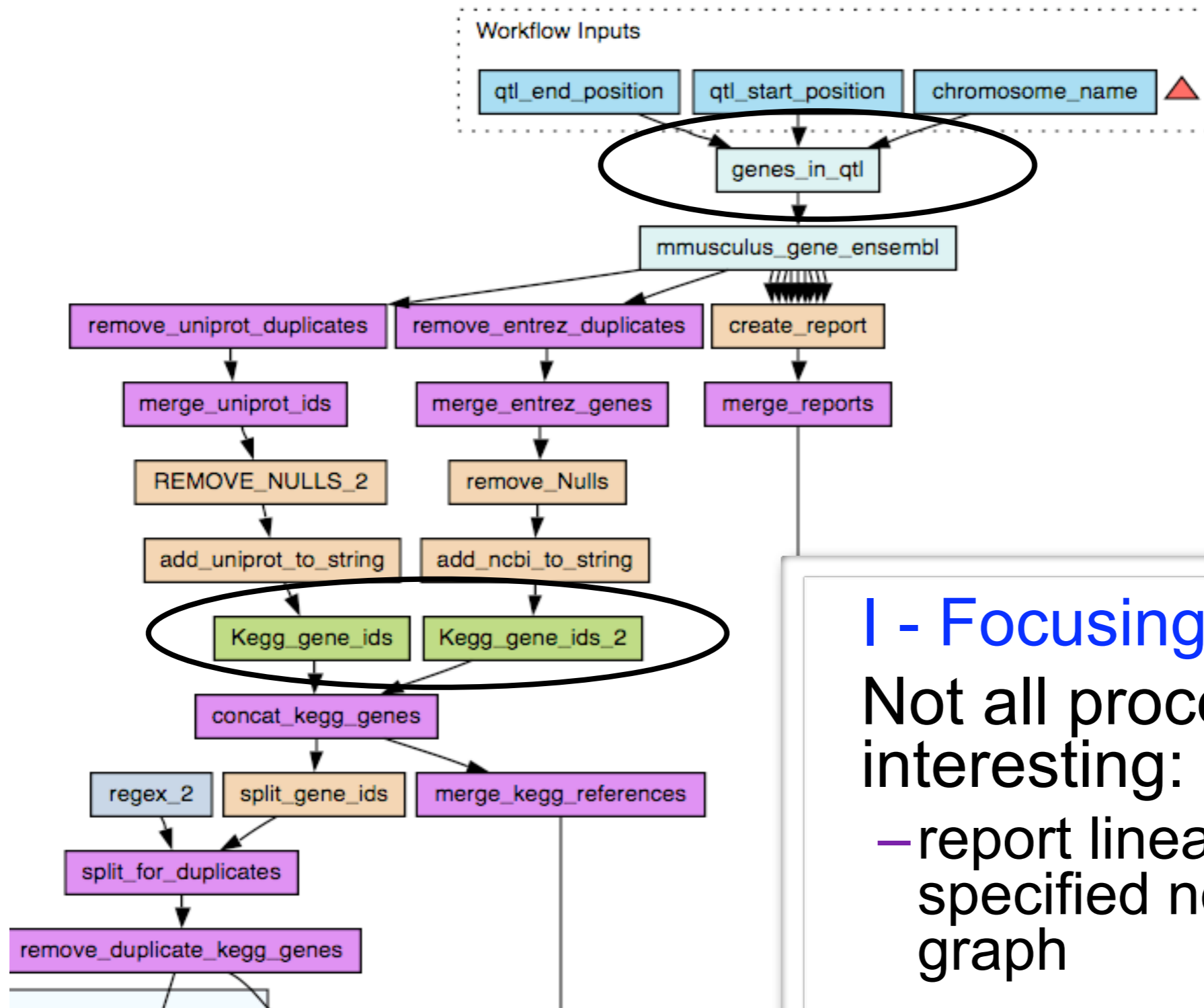


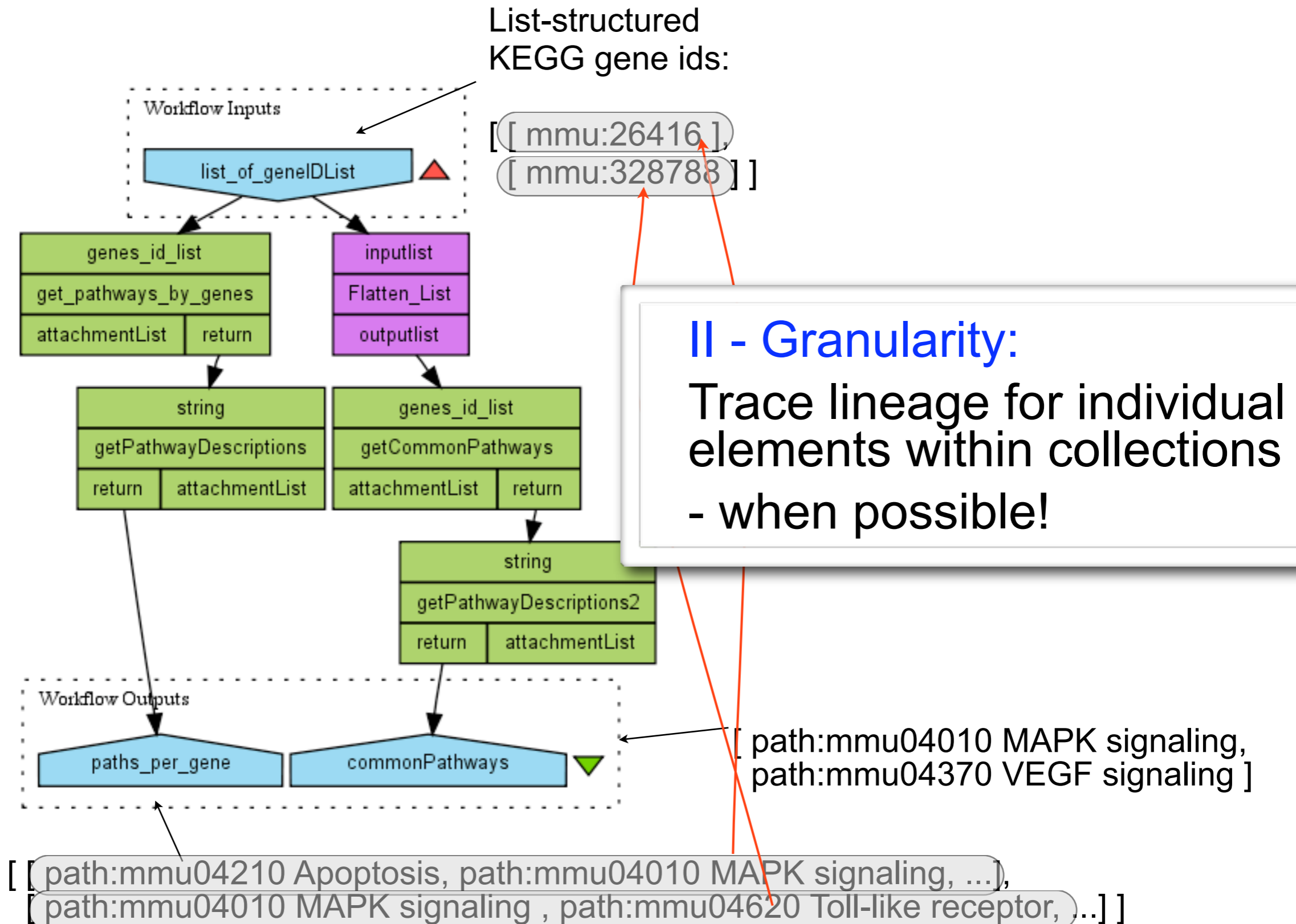
Fig. 1. Protein annotation workflow specification and runs



I - Focusing:

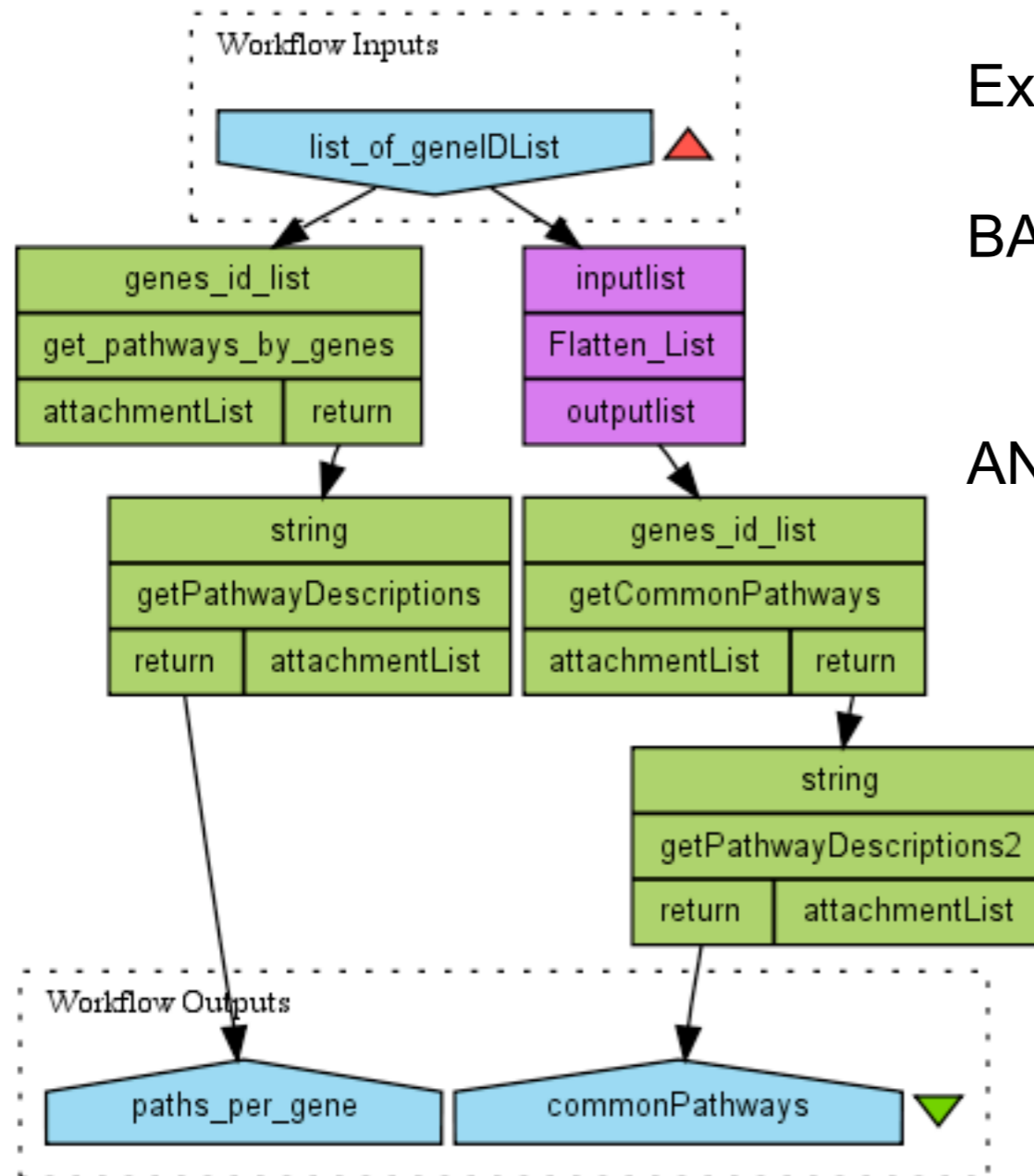
Not all processors are interesting:

- report lineage only at specified nodes in the graph



II - Granularity:
Trace lineage for individual elements within collections - when possible!

- III - Answer queries efficiently without special auxiliary data structures
- (and, please provide declarative query specification)



Example:

BACKTRACE

(paths_per_gene[3,4], paths_per_gene[1,2])

AT get_pathway_by_genes

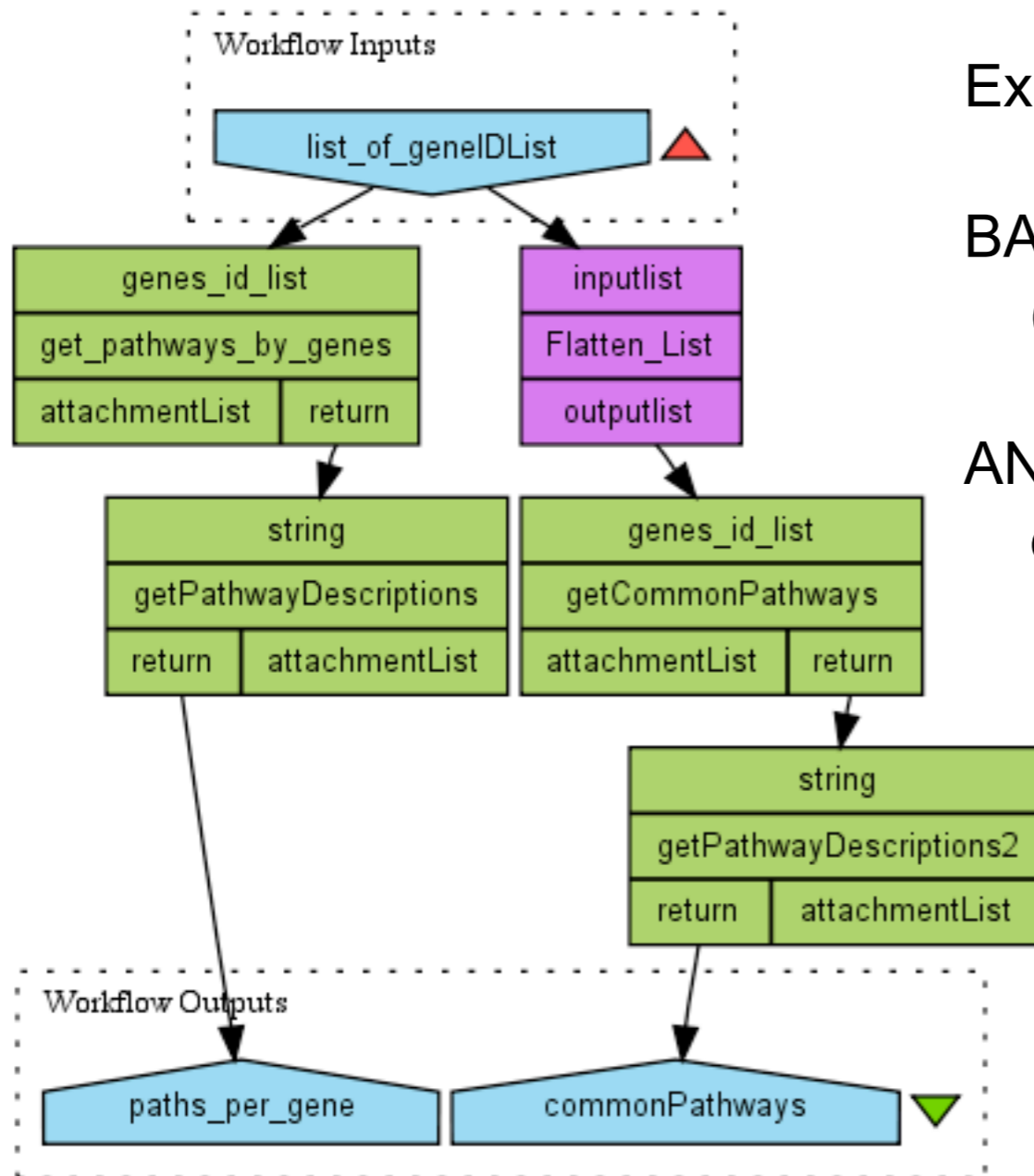
AND

commonPathways[1]

AT TOP

[[path:mmu04210 Apoptosis, path:mmu04010 MAPK signaling, ...],
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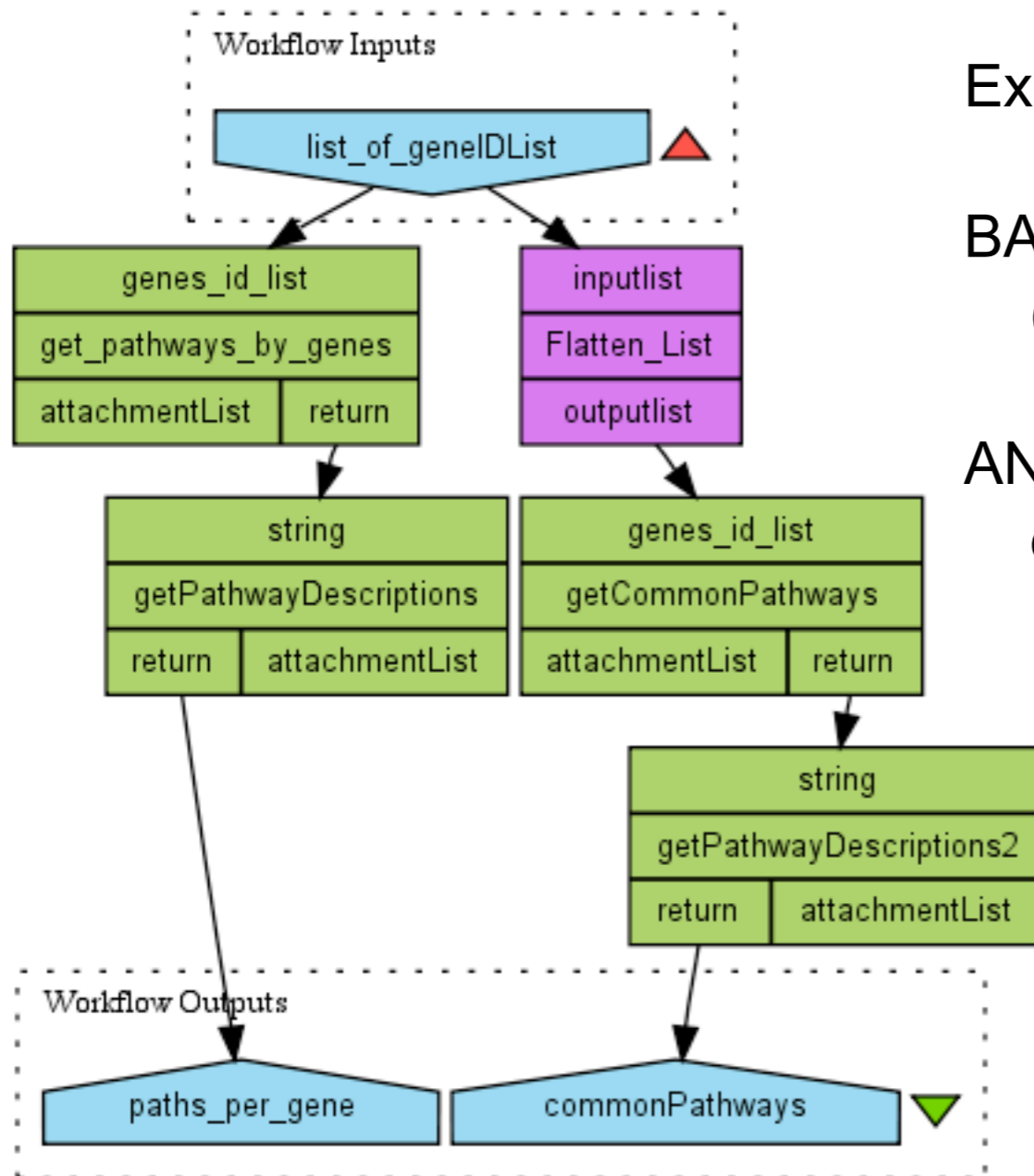
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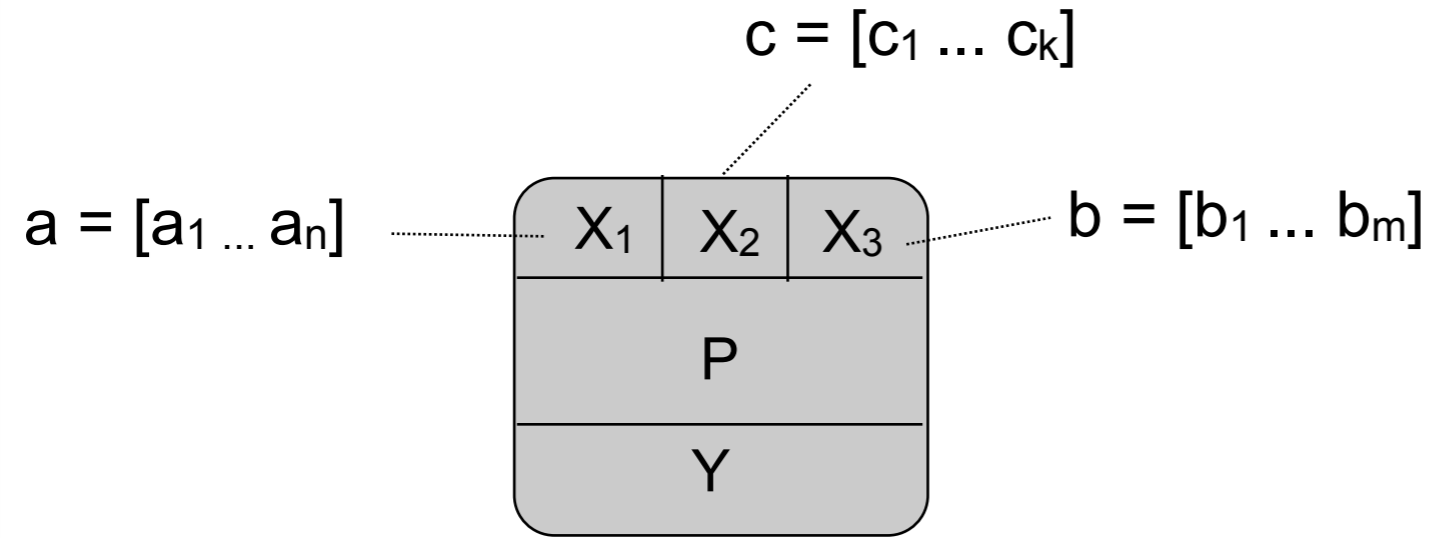
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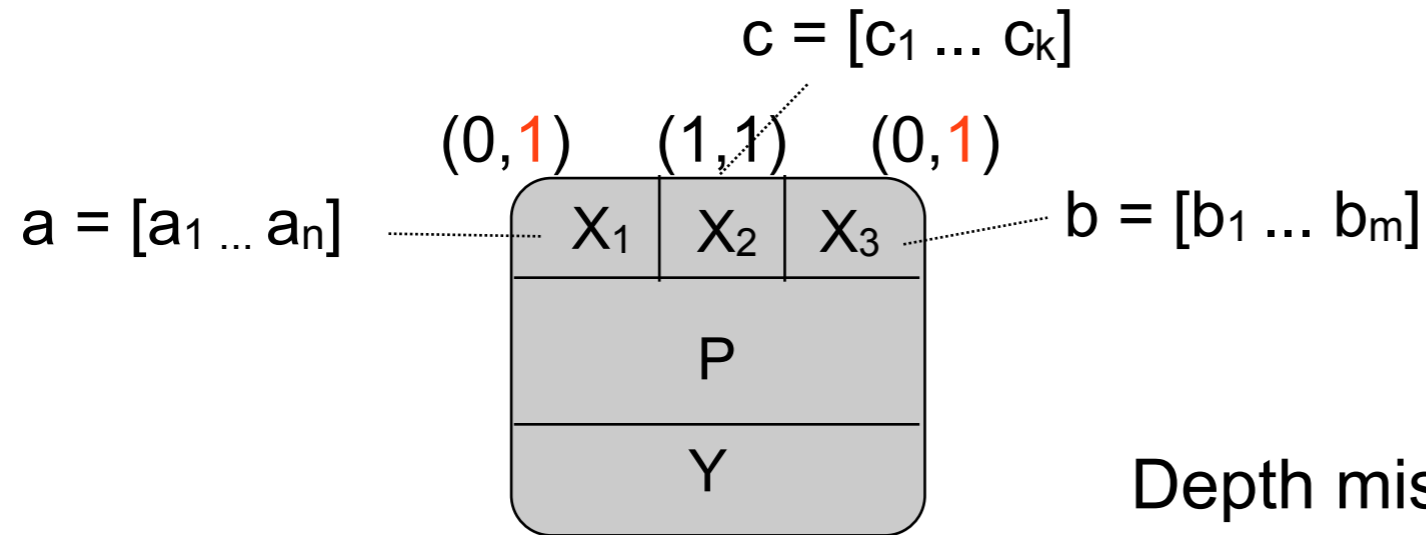
AT TOP

targets

selected processors

[[path:mmu04210 Apoptosis, path:mmu04010 MAPK signaling, ...],
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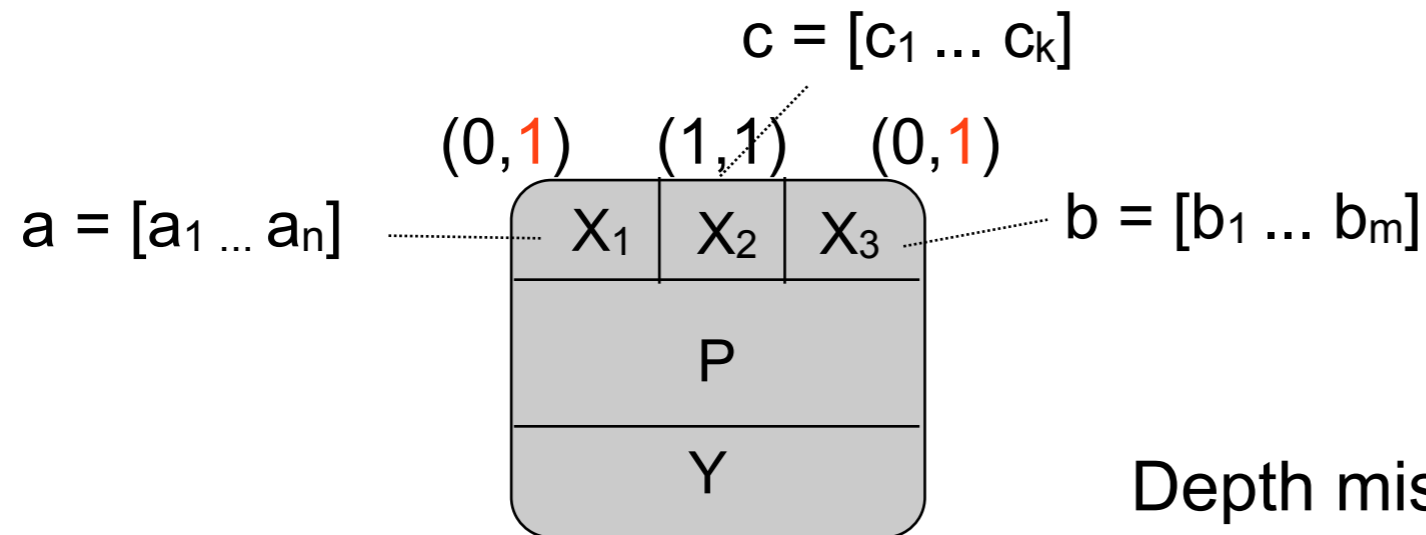


Depth mismatch between declared / offered type:

$$\text{depth}(P:X1) = 0 \text{ but } \text{depth}(a) = 1$$

$$\text{depth}(P:X2) = \text{depth}(c) = 1$$

$$\text{depth}(P:X3) = 1 \text{ but } \text{depth}(c) = 1$$



Depth mismatch between declared / offered type:

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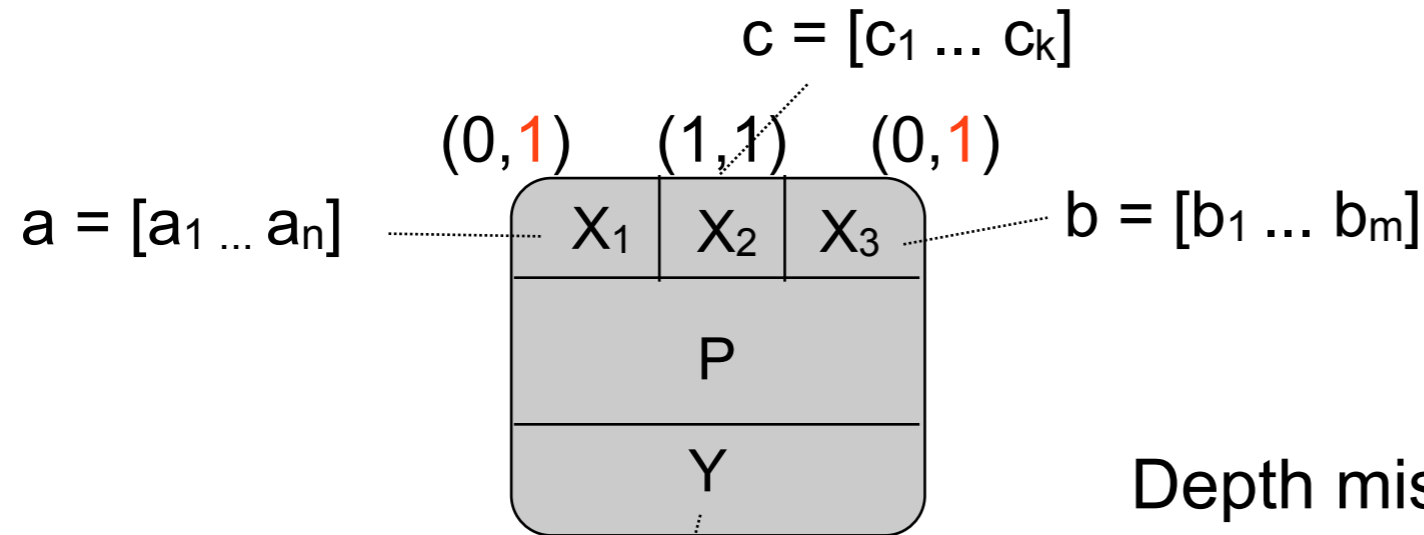
$$\text{depth}(P:X3) = 1 \text{ but } \text{depth}(b) = 0$$

How y is computed at P:

$$\text{let } l = a \otimes b = [[\langle a_i, b_j \rangle \mid b_j \in b] \mid a_i \in a] \quad // \text{ cross product}$$

$$l' = [[\langle a_i, c, b_j \rangle \mid b_j \in b] \mid a_i \in a] \quad // \text{ same product but with } c \text{ interleaved}$$

$$y = (\text{map } (\text{map } P) l') = [(\text{map } P [\langle a_1, c, b_1 \rangle \dots \langle a_1, c, b_m \rangle]), \dots, (\text{map } P [\langle a_n, c, b_1 \rangle \dots \langle a_n, c, b_m \rangle])] = [[y_{11} \dots y_{1n}], \dots [y_{n1} \dots y_{nm}]]$$



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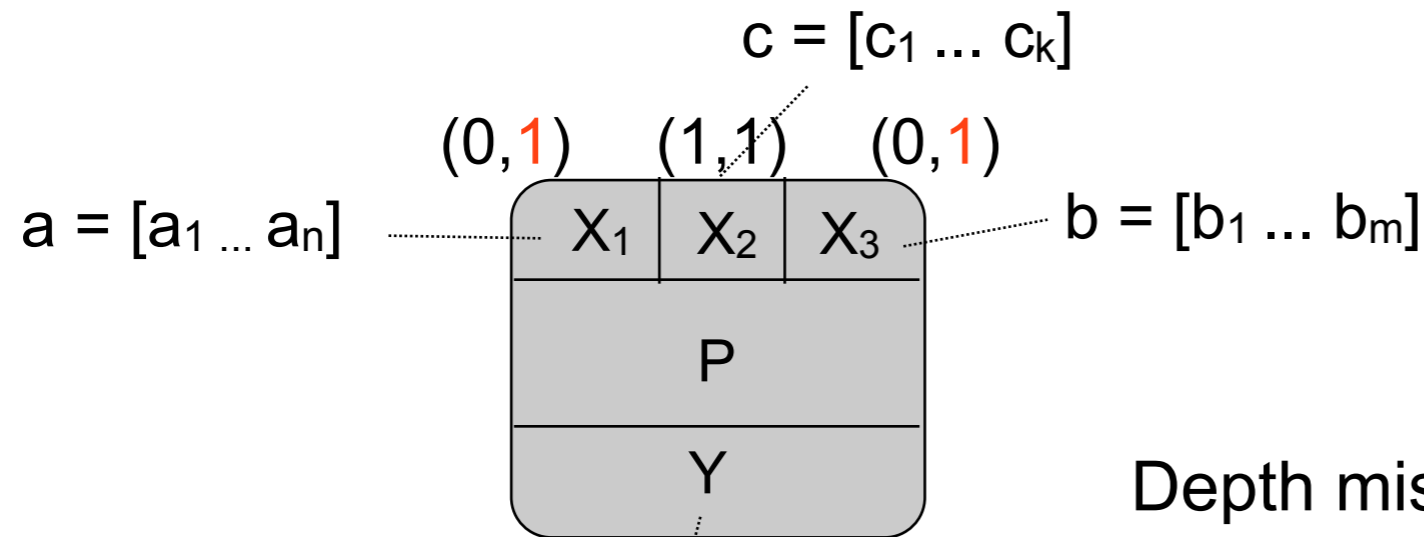
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Depth mismatch between declared / offered type:

$$y = [[y_{11} \dots y_{1n}], \dots [y_{m1} \dots y_{mn}]]$$

bottom line:
 y_{ij} depends only on values a_i, c, b_j

$$\text{depth}(P:X3) = 1 \text{ but } \text{depth}(c) = 1$$

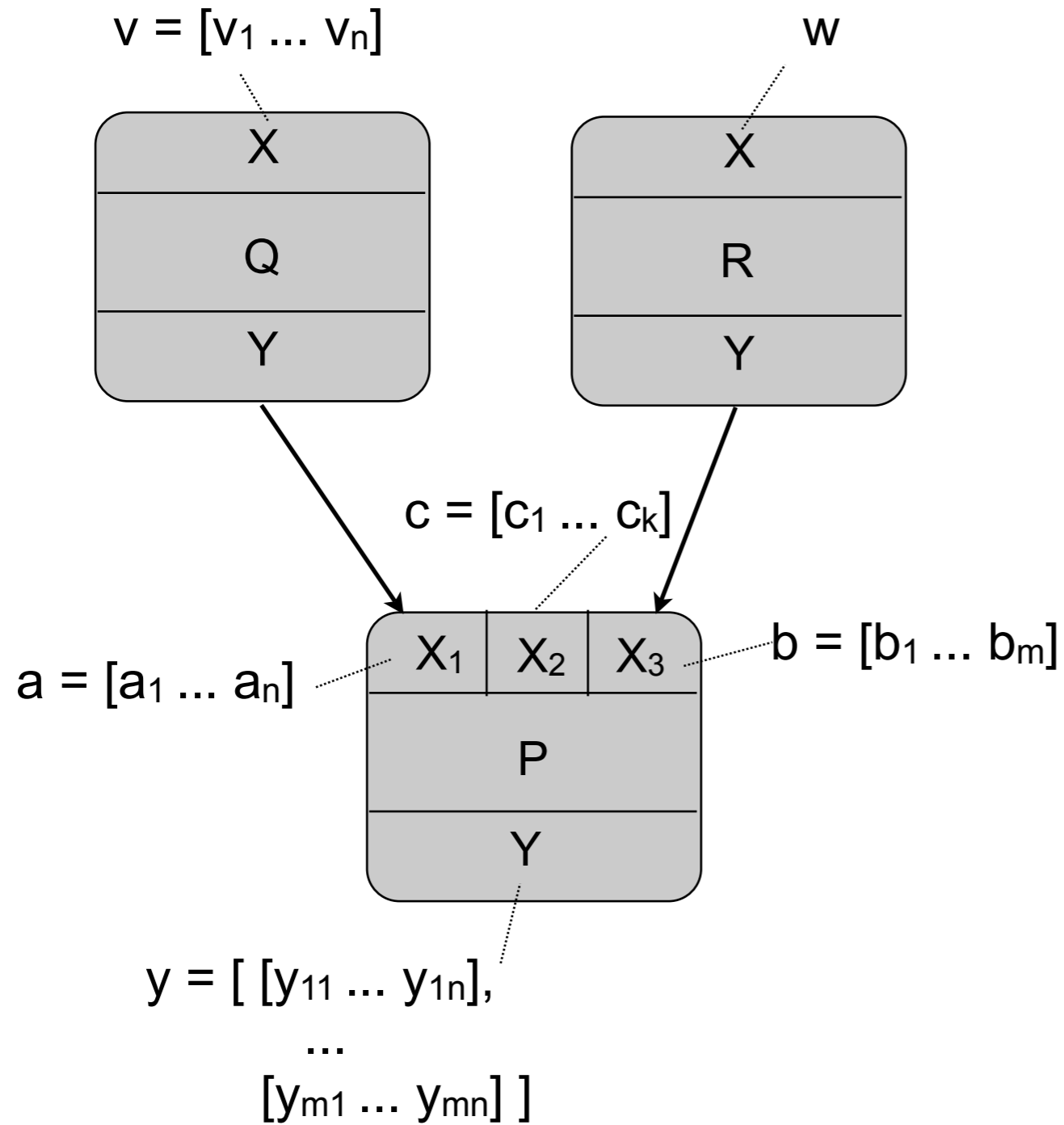
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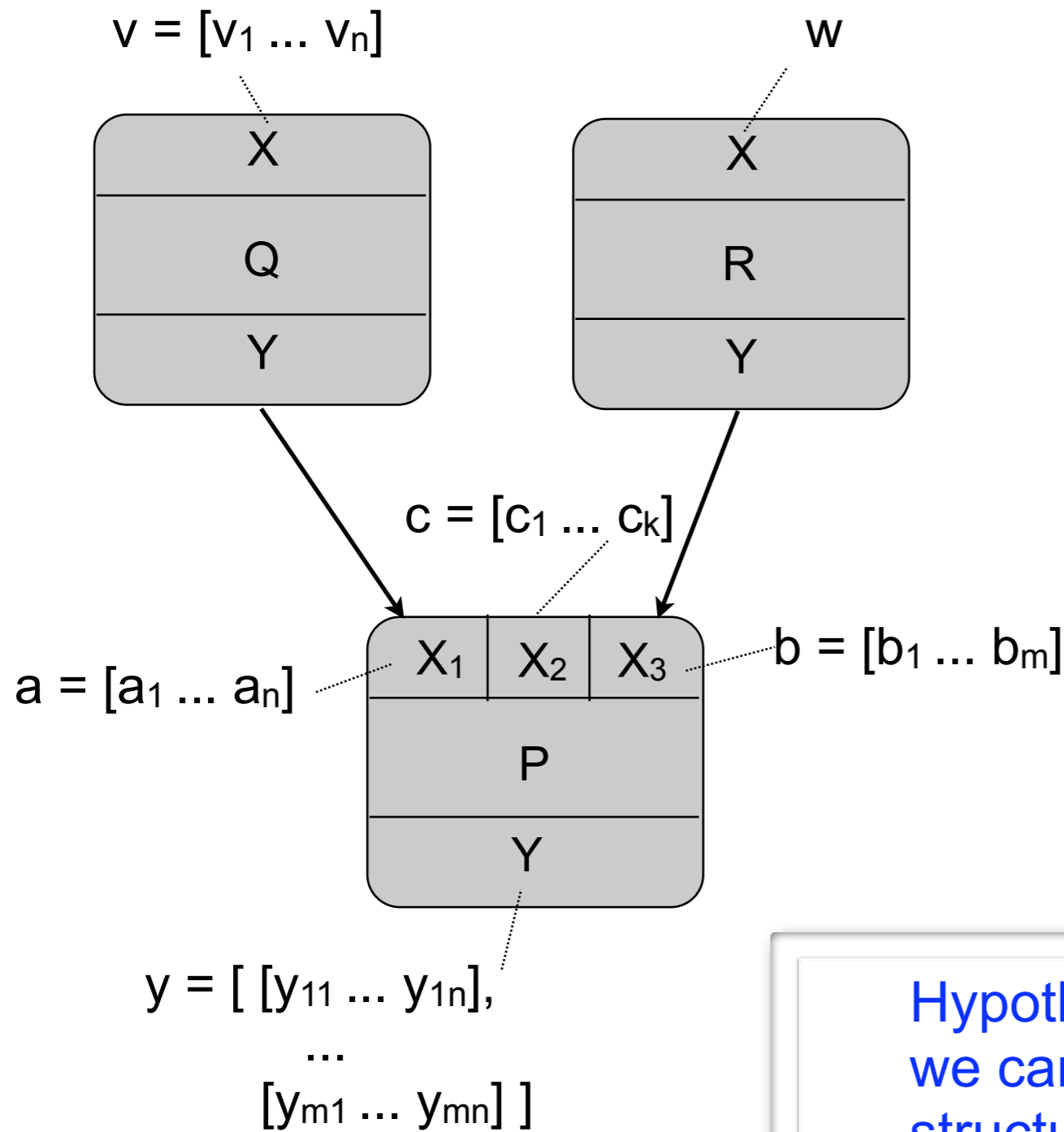
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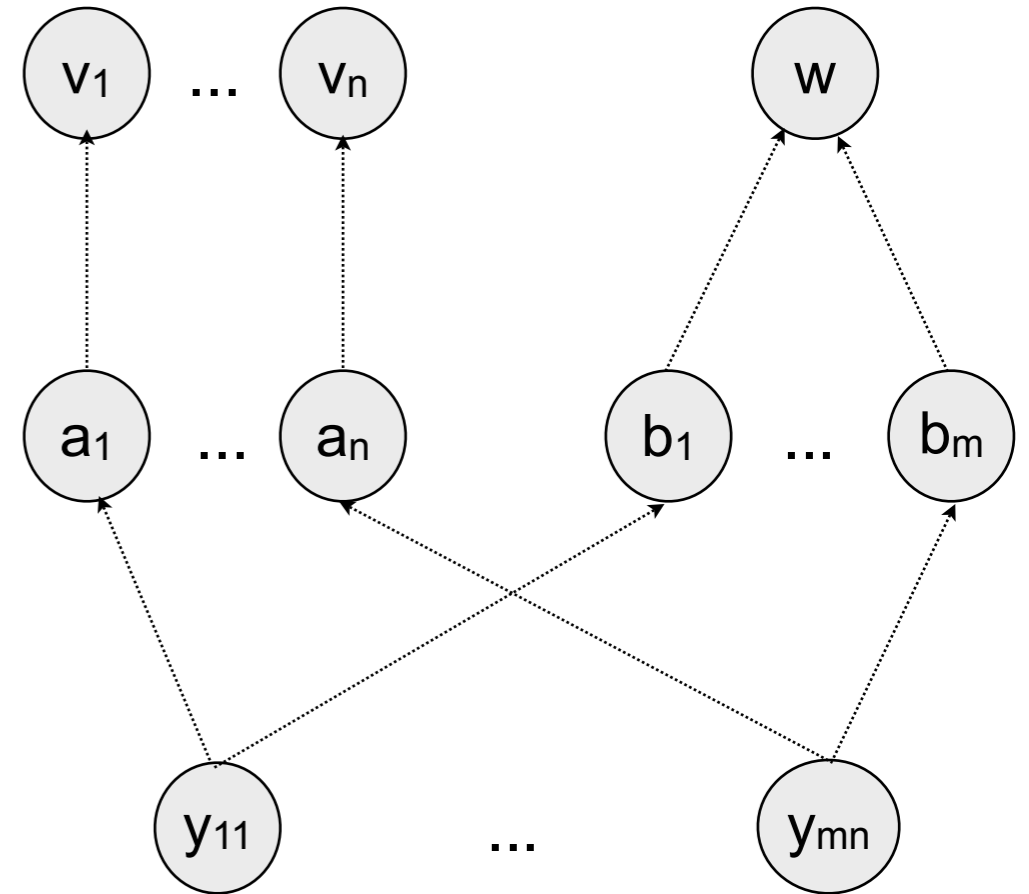
Workflow structure graph



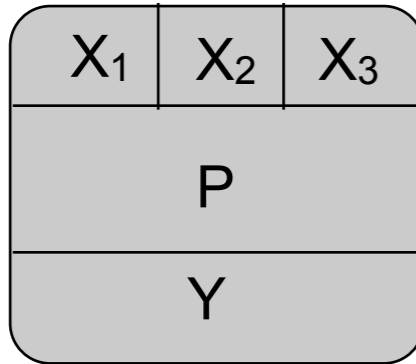
Workflow structure graph



Provenance graph



Hypothesis:
 we can exploit the static workflow graph structure to avoid explicitly traversing the entire trace to answer a query



1) In general the actual depth at the output is:

$$\text{depth}(y) = \text{depth}(Y) + \sum \delta(X_i = x_i)$$

where $\delta(X_i = x_i) = \text{depth}(x_i) - \text{depth}(X_i)$

Therefore:

$\delta(X=x)$ can be computed statically on the workflow graph structure,

- given the declared $\text{depth}(X)$
- using a simple propagation algorithm

$$Y[i..j] \rightarrow X1[i], X2[], X3[j]$$

$$[i_1 . i_2 . \dots . i_k] = \text{_____}$$

$(0,1)$ $(1,1)$ $(0,1)$

X_1	X_2	X_3
P		
Y		

 $(0,2)$ $Y[i..j] \rightarrow X1[i], X2[], X3[j]$

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$$[i_1 . i_2 . \dots . i_k] = \frac{\delta(X_1 = x_1)}{\dots}$$

$(0,1)$ $(1,1)$ $(0,1)$

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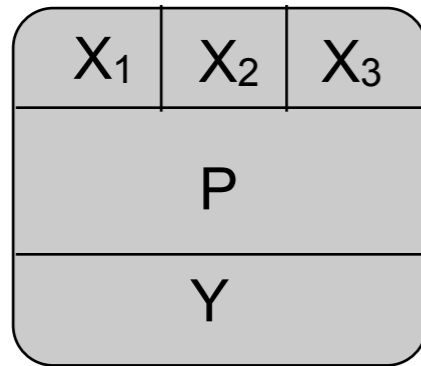
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$$[i_1 . i_2 . \dots . i_k] = \frac{\delta(X_2 = x_2)}{X_1}$$

(0,1) (1,1) (0,1)



(0,2)

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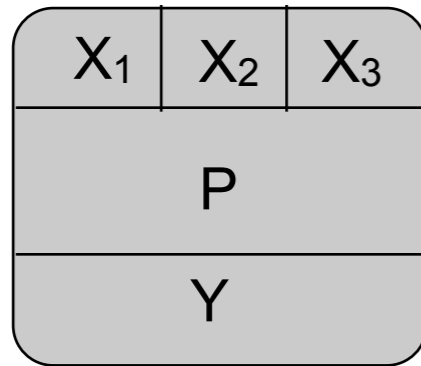
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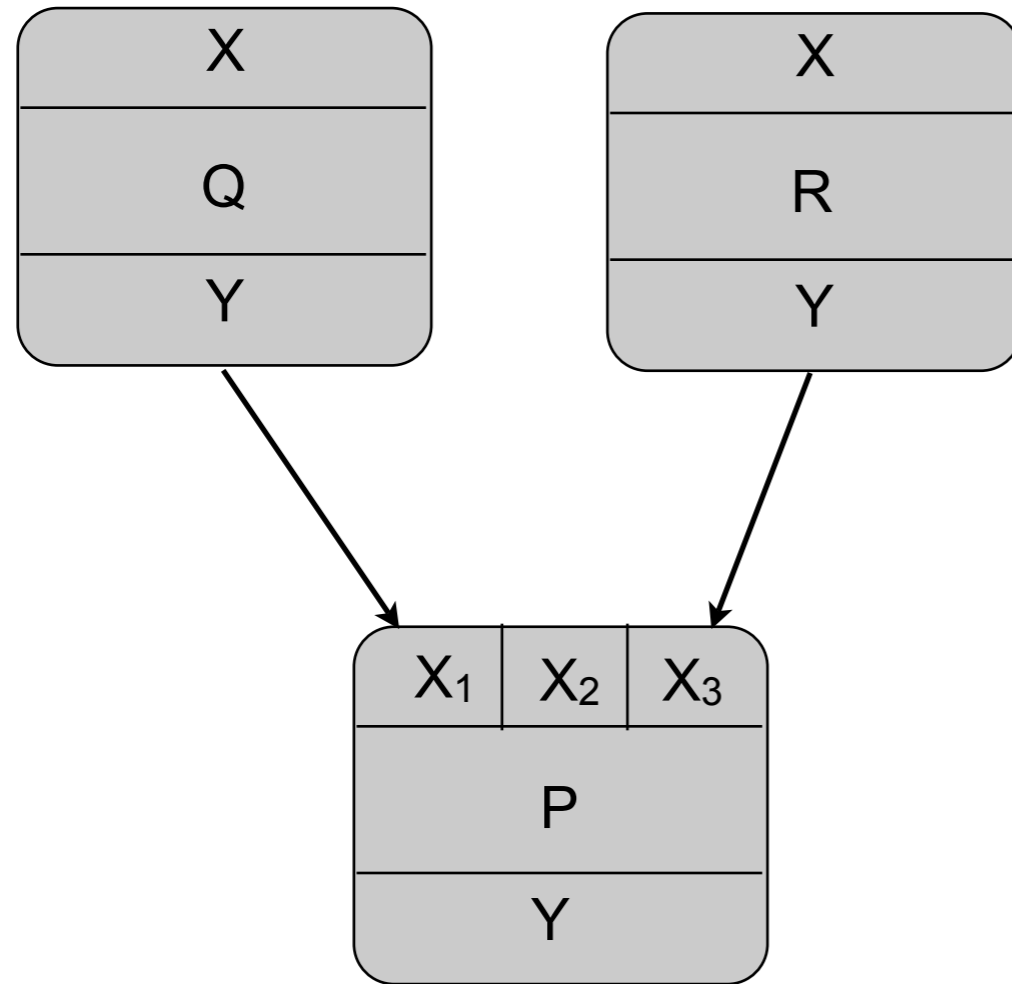
where $\delta(X_i = x_i) = \text{depth}(x_i) - \text{depth}(X_i)$

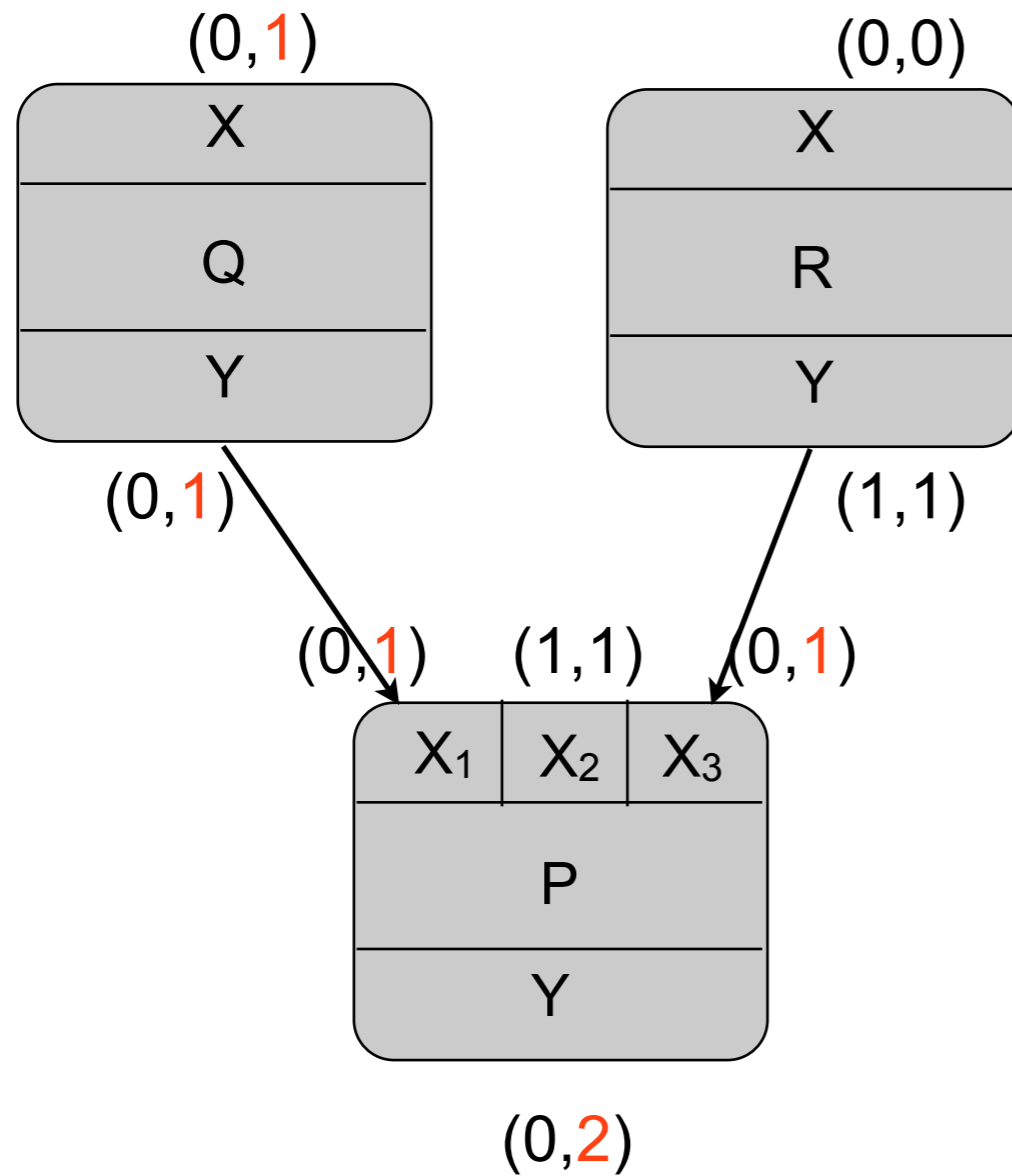
Therefore:

$\delta(X=x)$ can be computed statically on the workflow graph structure,

- given the declared $\text{depth}(X)$
- using a simple propagation algorithm

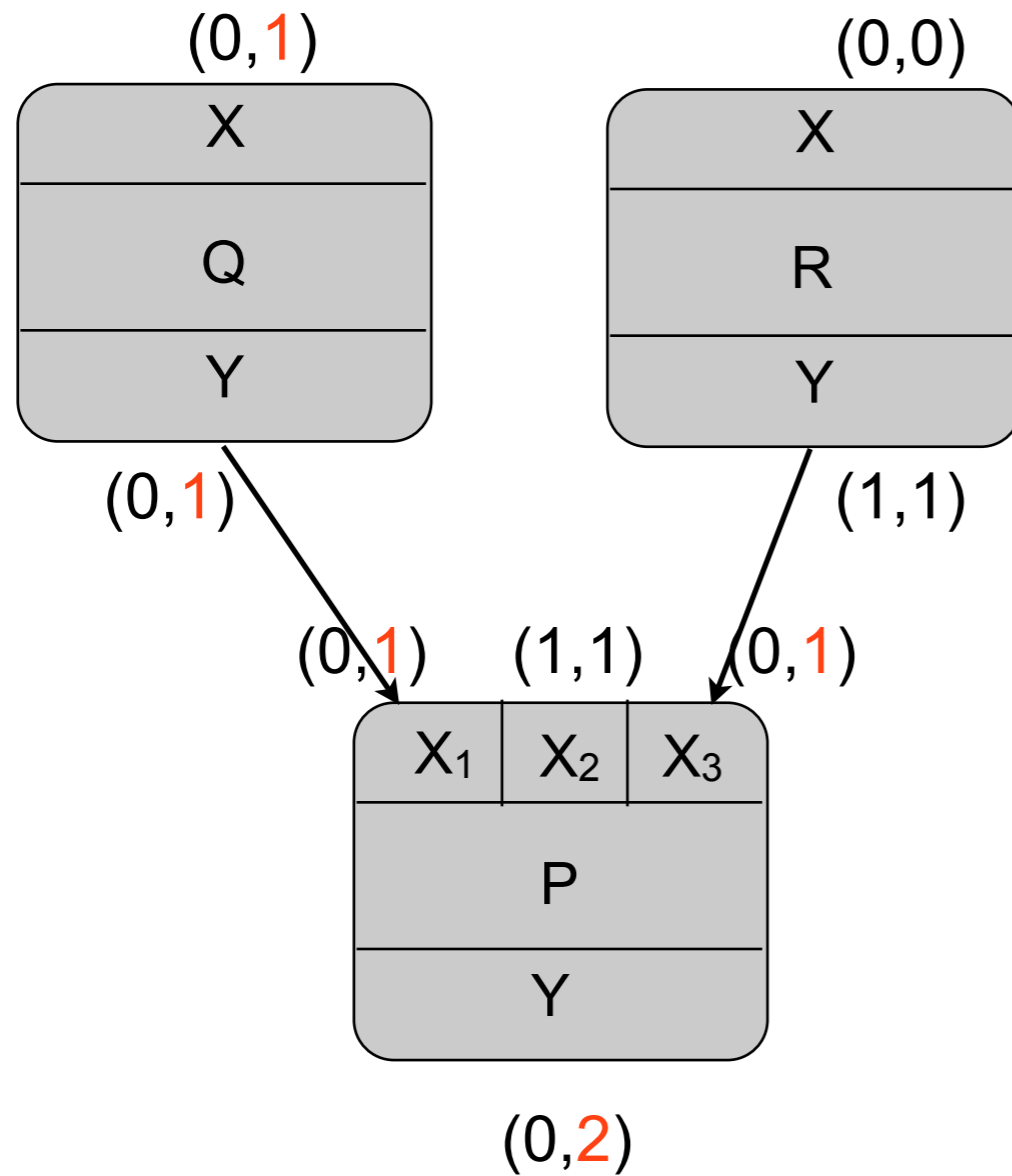
$$[i_1 . i_2 . \dots . i_k] = \frac{\quad}{X_1} \quad \frac{\quad}{X_2} \quad \frac{\delta(X_k = x_k)}{\quad}$$





$$Y = [[\dots], \dots [\dots]]$$

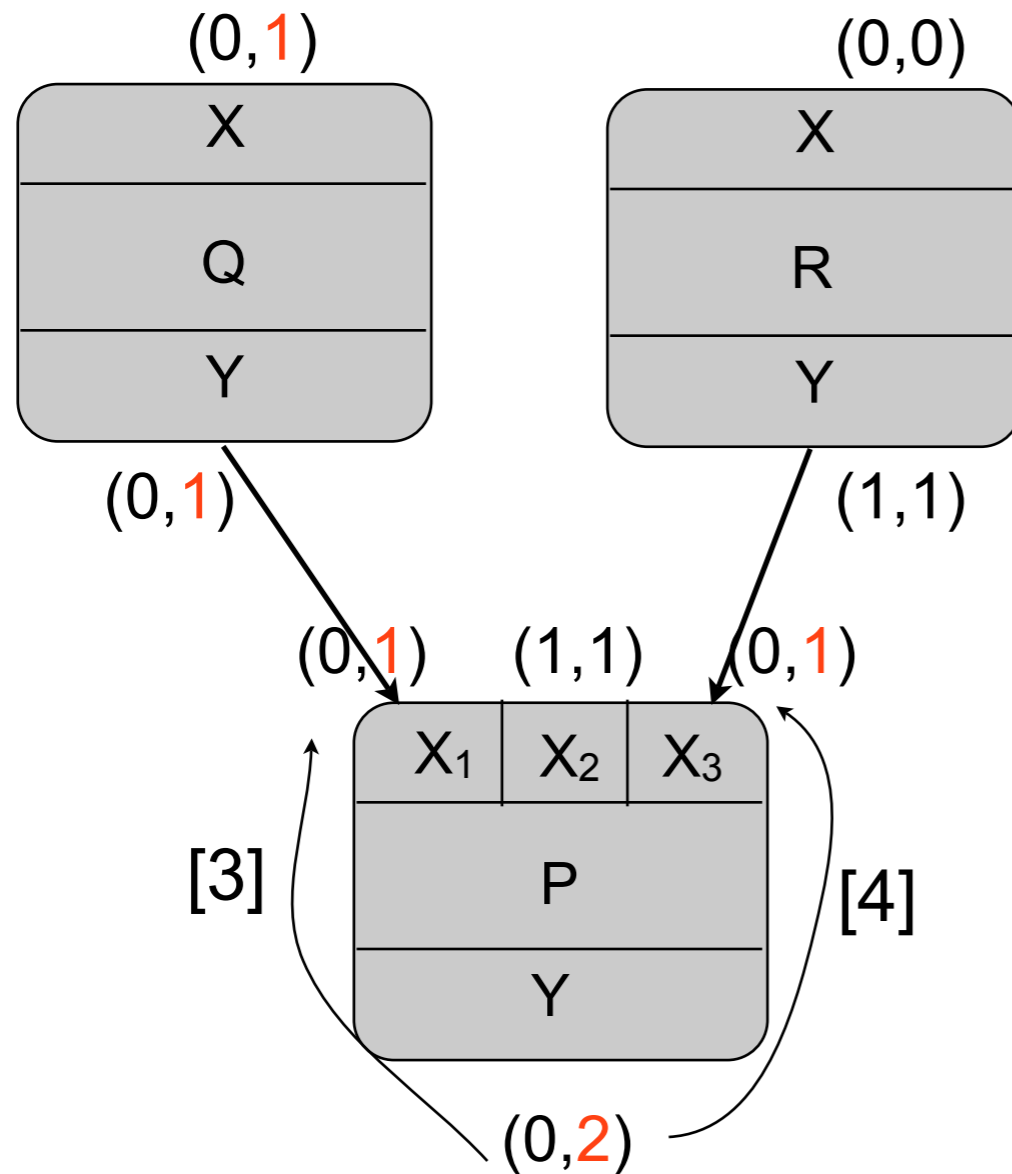
Extension to the entire workflow graph



lineage(P:Y[3,4]) \rightarrow lineage(P:X1[3]),
 lineage(P:X2[]),
 lineage(P:X2[4])

$Y = [[\dots], \dots [\dots]]$

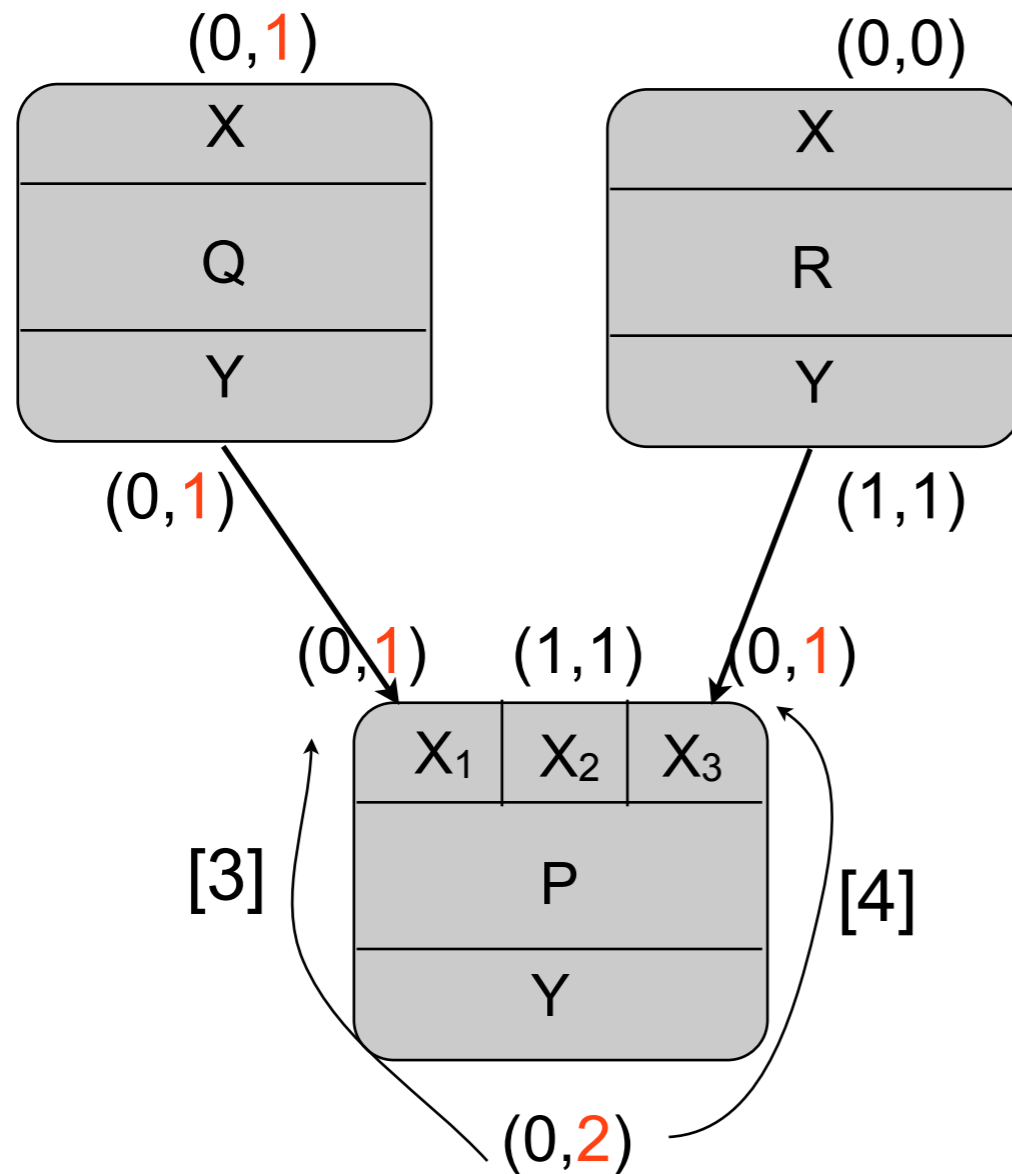
Extension to the entire workflow graph



lineage(P:Y[3,4]) → lineage(P:X1[3]),
lineage(P:X2[]),
lineage(P:X2[4])

$Y = [[\dots], \dots [\dots]]$

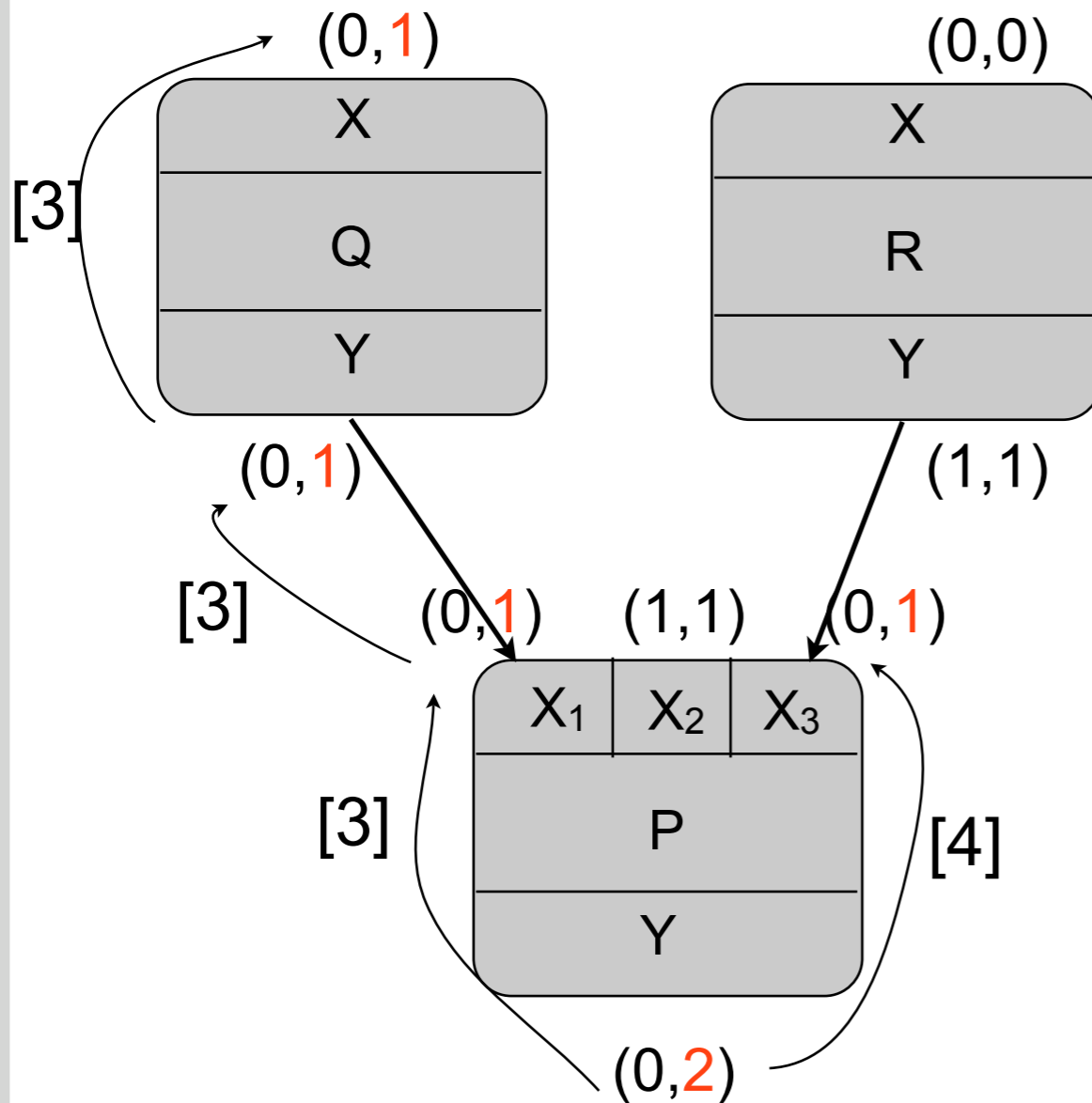
Extension to the entire workflow graph



$$Y = [[\dots], \dots [\dots]]$$

$\text{lineage}(P:Y[3,4]) \rightarrow \text{lineage}(P:X1[3]),$
 $\text{lineage}(P:X2[]),$
 $\text{lineage}(P:X2[4])$

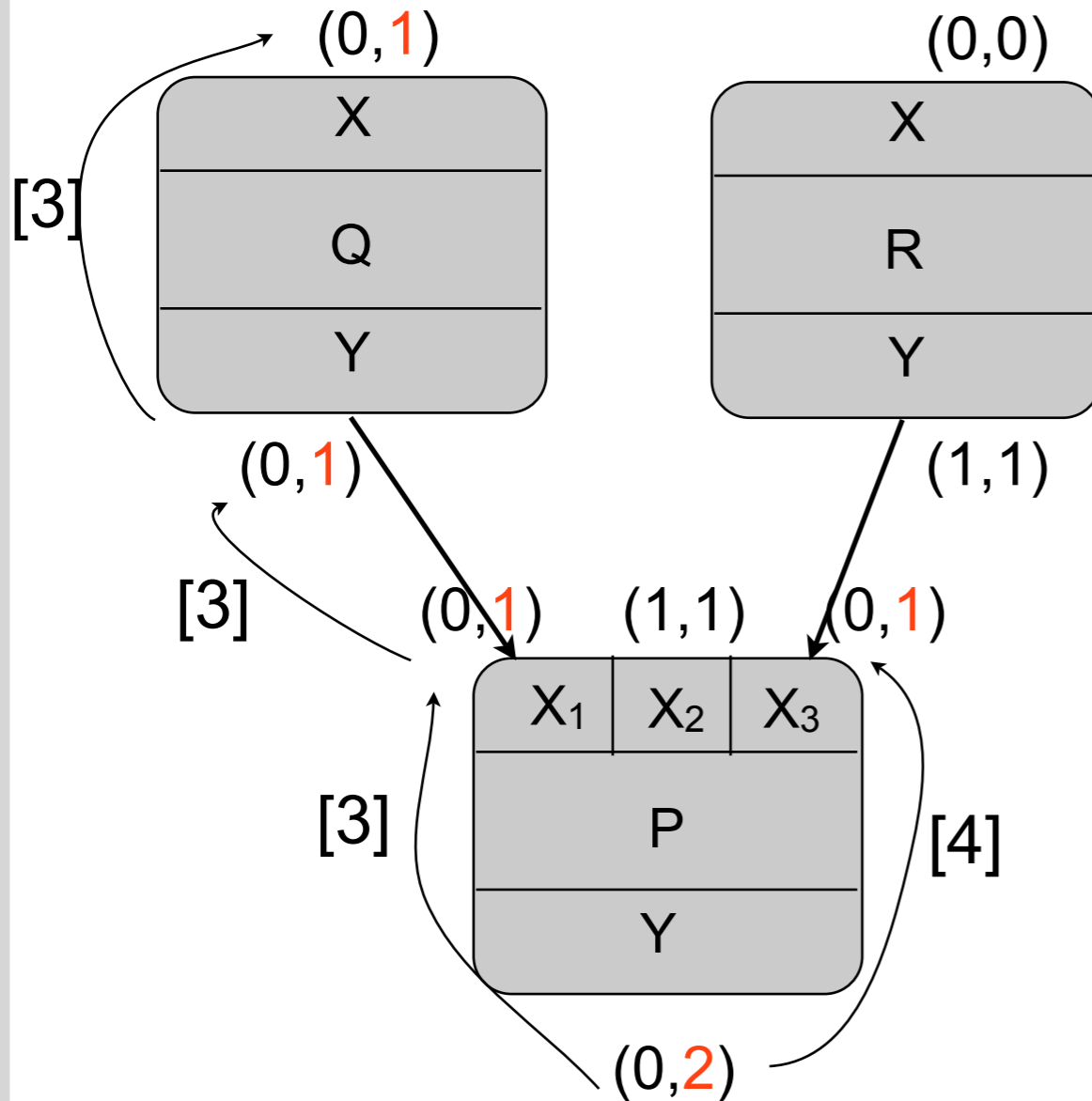
$\text{lineage}(P:X1[3]) = \text{lineage}(Q:Y[3]) \rightarrow$
 $\text{lineage}(Q:X[3])$



$$Y = [[\dots], \dots [\dots]]$$

lineage(P:Y[3,4]) \rightarrow lineage(P:X1[3]),
lineage(P:X2[]),
lineage(P:X2[4])

lineage(P:X1[3]) = lineage(Q:Y[3]) \rightarrow
lineage(Q:X[3])

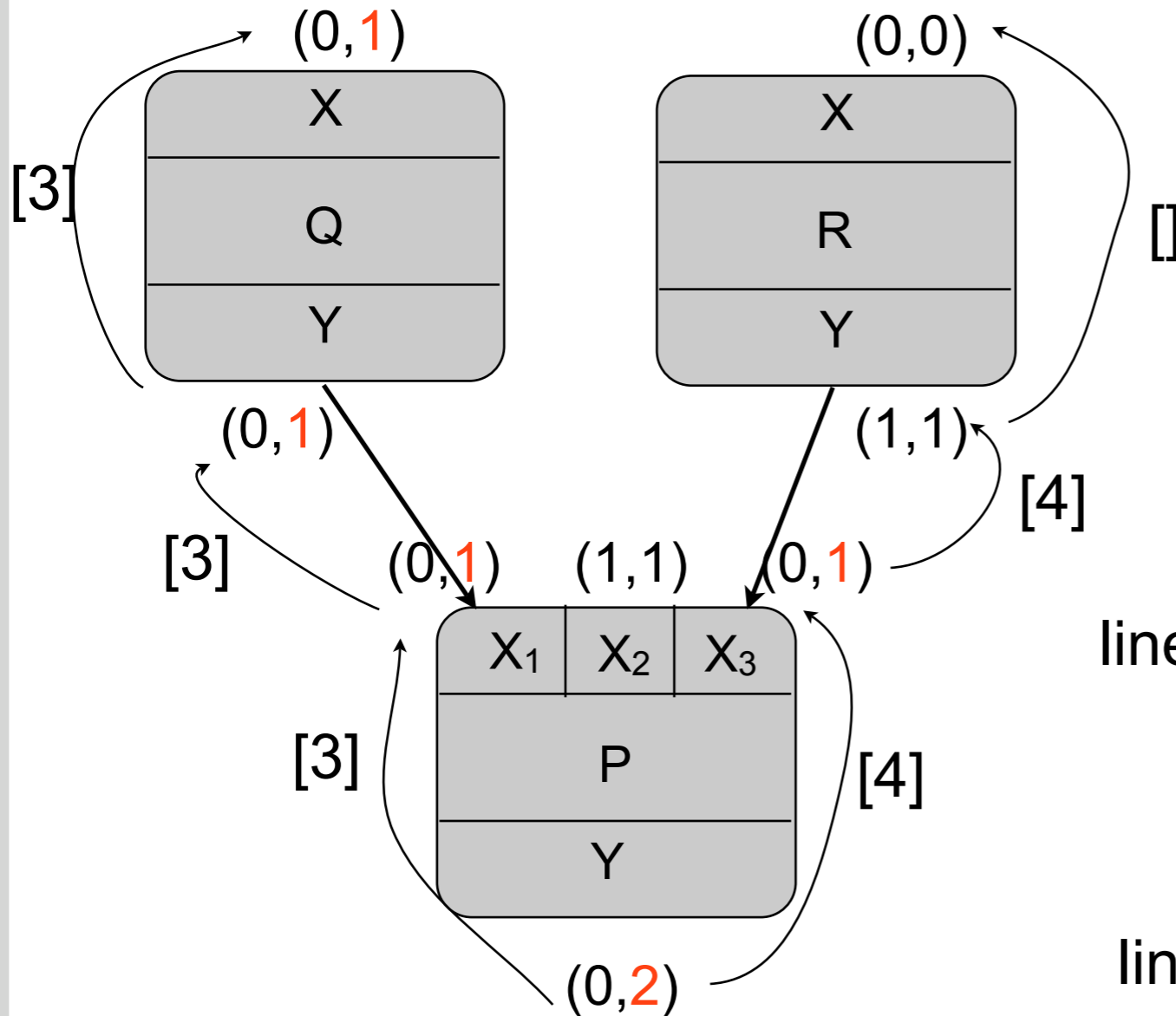


$$Y = [[\dots], \dots [\dots]]$$

$\text{lineage}(P:Y[3,4]) \rightarrow \text{lineage}(P:X1[3]),$
 $\text{lineage}(P:X2[]),$
 $\text{lineage}(P:X2[4])$

$\text{lineage}(P:X1[3]) = \text{lineage}(Q:Y[3]) \rightarrow$
 $\text{lineage}(Q:X[3])$

$\text{lineage}(P:X3[4]) = \text{lineage}(R:Y[4]) \rightarrow$
 $\text{lineage}(R:X[])$

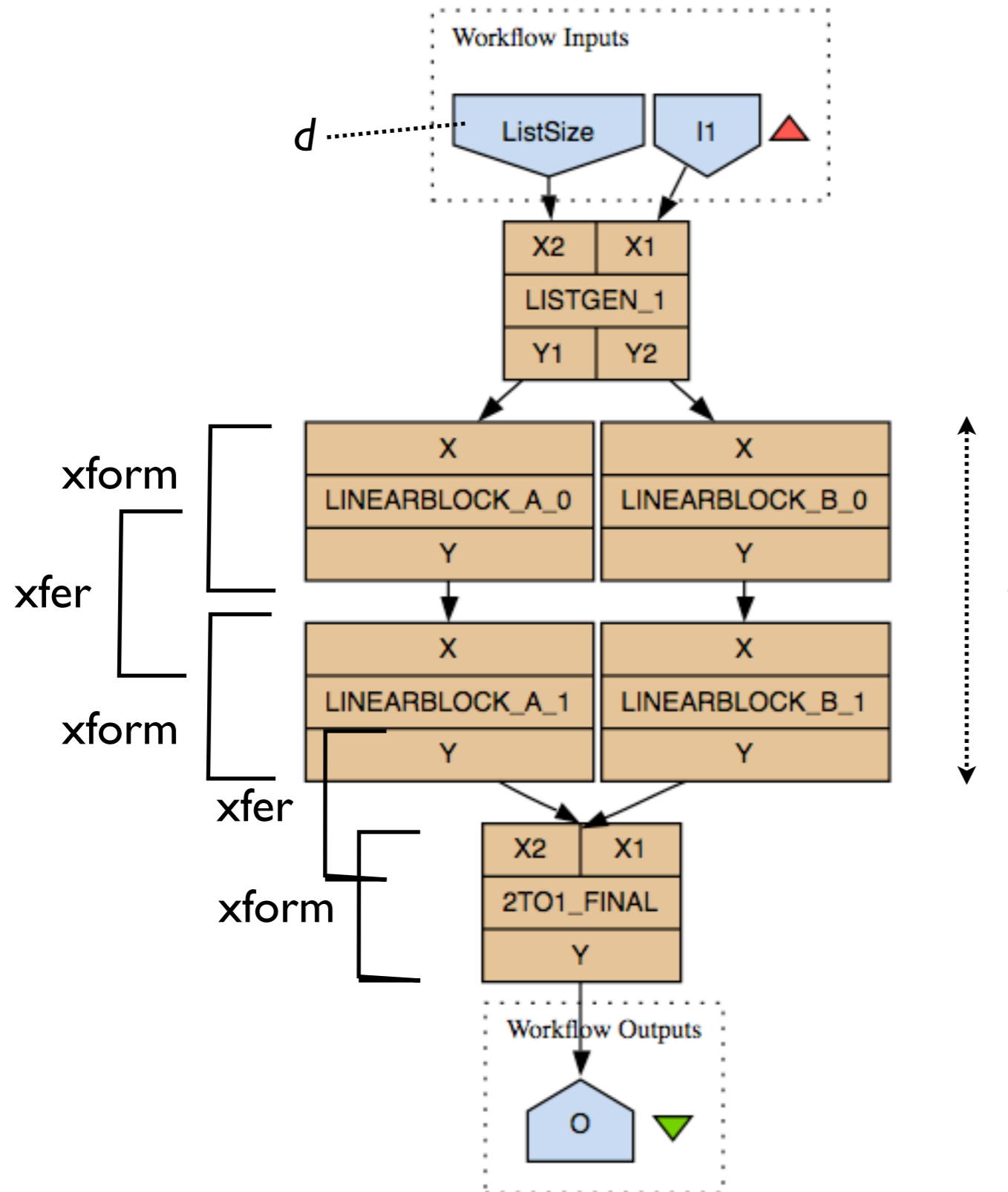


$$Y = [[\dots], \dots [\dots]]$$

$\text{lineage}(P:Y[3,4]) \rightarrow \text{lineage}(P:X1[3]),$
 $\text{lineage}(P:X2[]),$
 $\text{lineage}(P:X2[4])$

$\text{lineage}(P:X1[3]) = \text{lineage}(Q:Y[3]) \rightarrow$
 $\text{lineage}(Q:X[3])$

$\text{lineage}(P:X3[4]) = \text{lineage}(R:Y[4]) \rightarrow$
 $\text{lineage}(R:X[])$



- Query processing:
 - alternating sequence of *xform* and *xfer* steps
- apply path projection at each *xform* step
- A complete **granular** and **focused** query can be answered by traversing the workflow graph alone
 - starting from the target vars
 - one simple query for each selected processor input port

- Scalability:
 - query time depends on size of workflow graph, not size of provenance graph
 - workflow graphs are small, fit in memory, can be indexed easily, etc.
 - search over a graph at least as large as the workflow graph is inevitable -- this is the baseline cost!

- Graceful degradation:
 - worst case is a completely unfocused query
 - one query to trace at each *xform* step
 - no worse than other approaches

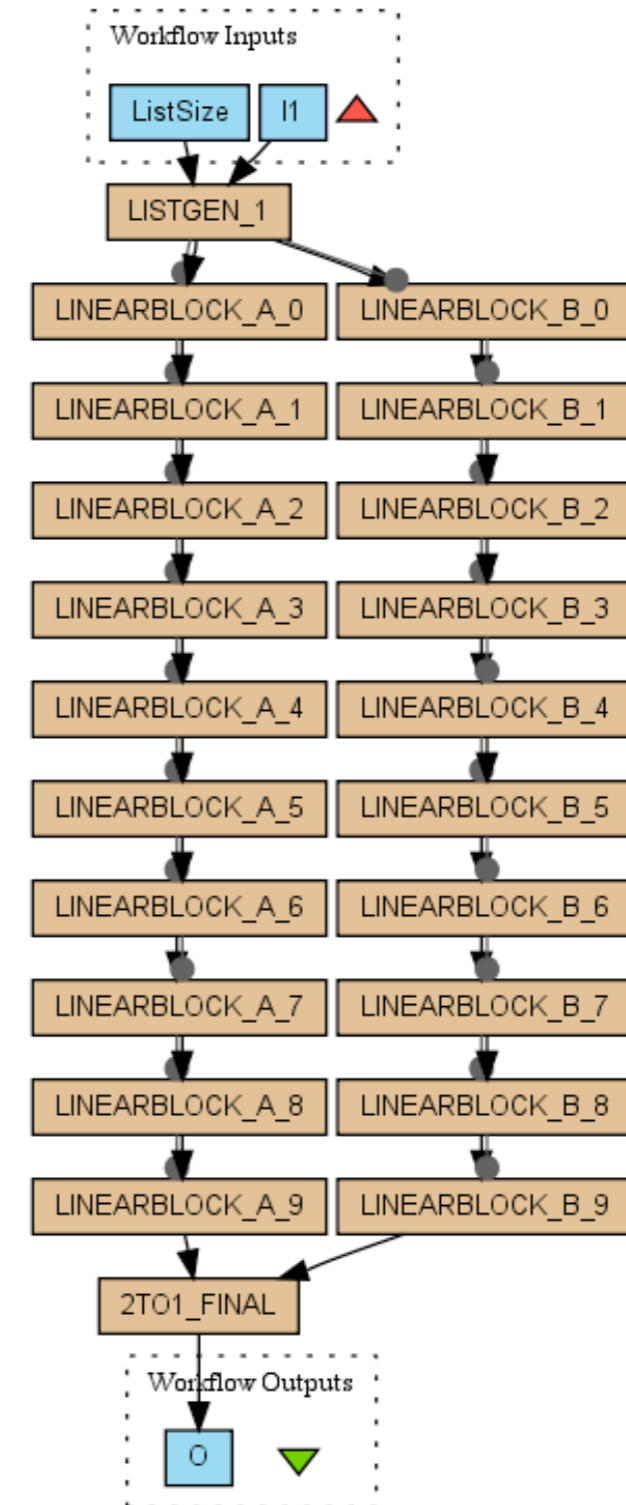
- Fine-grain answers provided at no additional cost

- Performance evaluation performed on programmatically generated dataflows

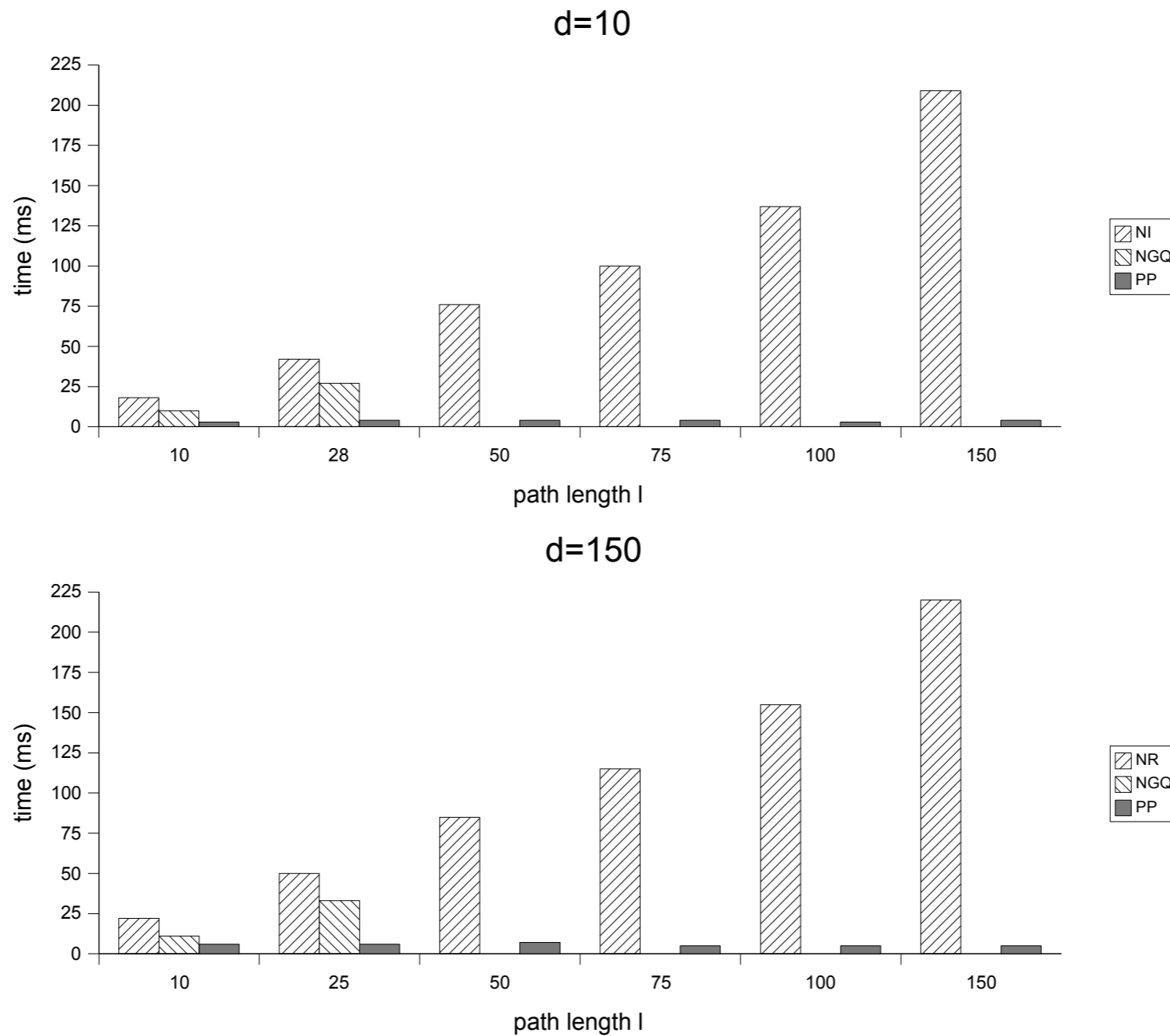
– the “T-towers”

control:

- size of the lists involved
- length of the paths
- includes one cross product

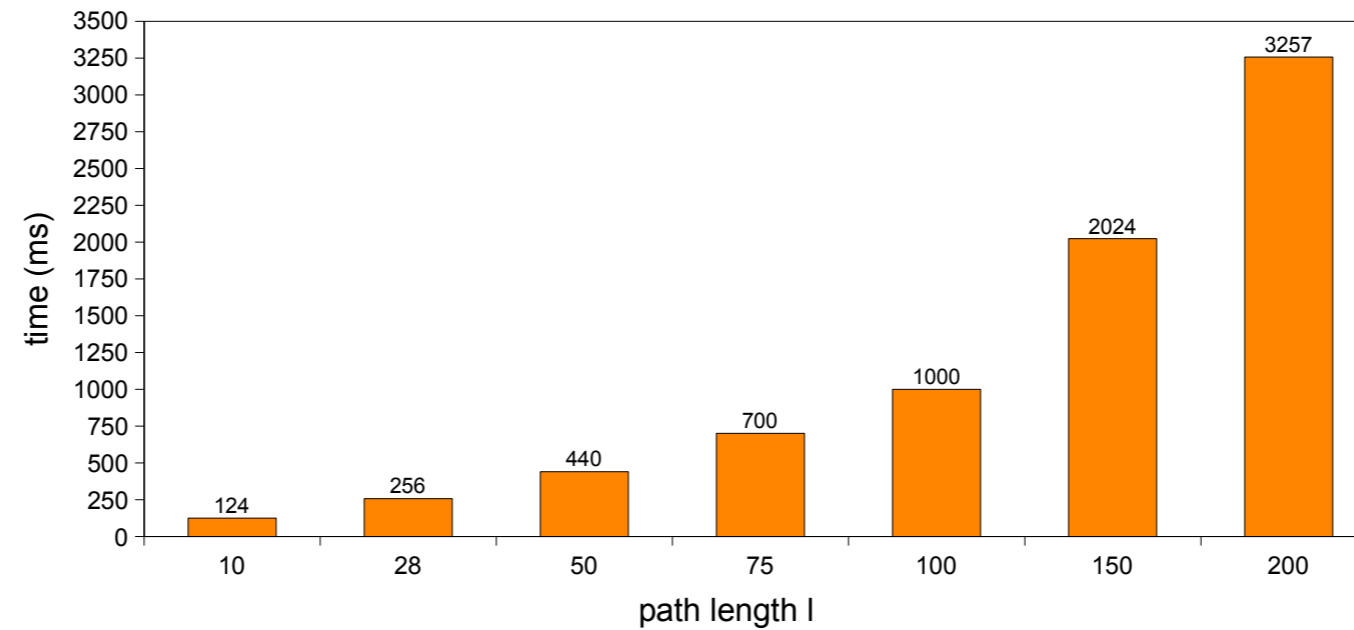


- query response time: naive vs. “path projection” approaches



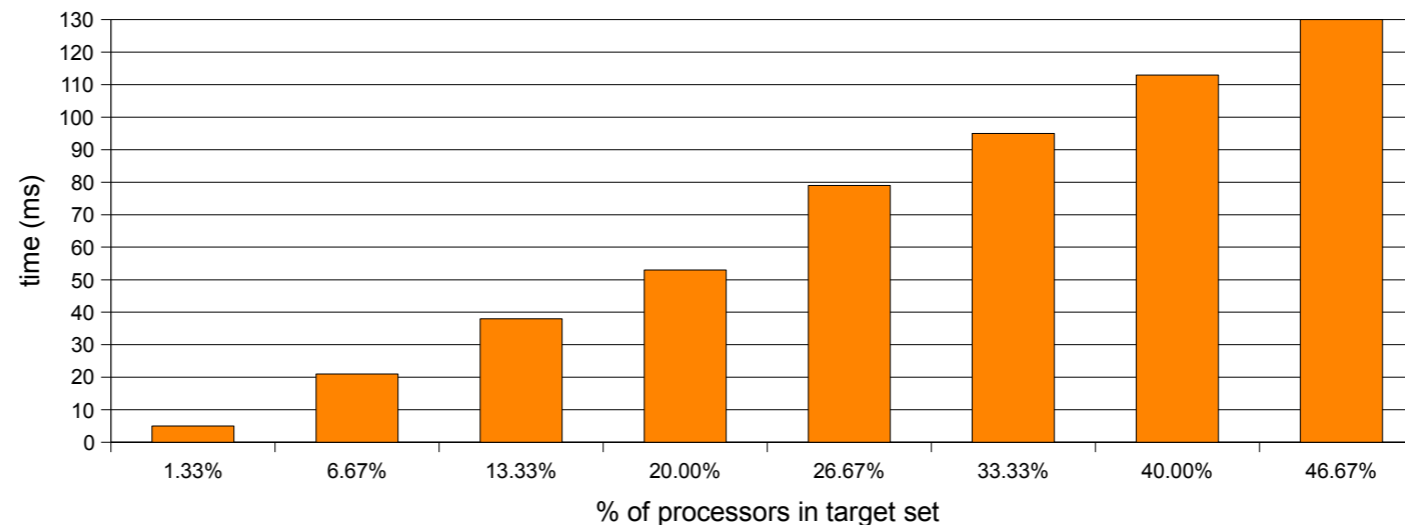
- workflow search time by path length (“tower height”)
 - common to all strategies!

workflow pre-processing time by graph size



- performance degradation on fully unfocused queries

response times for PP on unfocused queries (l=150)



- An original approach to lineage queries for Taverna that combines
 - efficiency and fine-granularity
- Relies on semantic properties of the Taverna dataflow model
- Further work:
 - visual specification of user query
 - visual presentation of query answer
 - space compression
 - semantic overlays, annotations
- To be bundled with some future version of Taverna...