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Declarative Design of Spoken Dialogue Systems with Probabilistic Rules

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Introduction

- Spoken dialogue systems typically rely on pipeline architectures with «black-box» components developed separately
- Each component employs ad-hoc encoding formats for their inputs/outputs and internal parameters
- Formats rarely compatible with one another!
    - Difficult to derive a semantic interpretation as a whole
    - Difficult to perform *joint* optimisations
    - Domain- or task-specific knowledge often «hardwired»

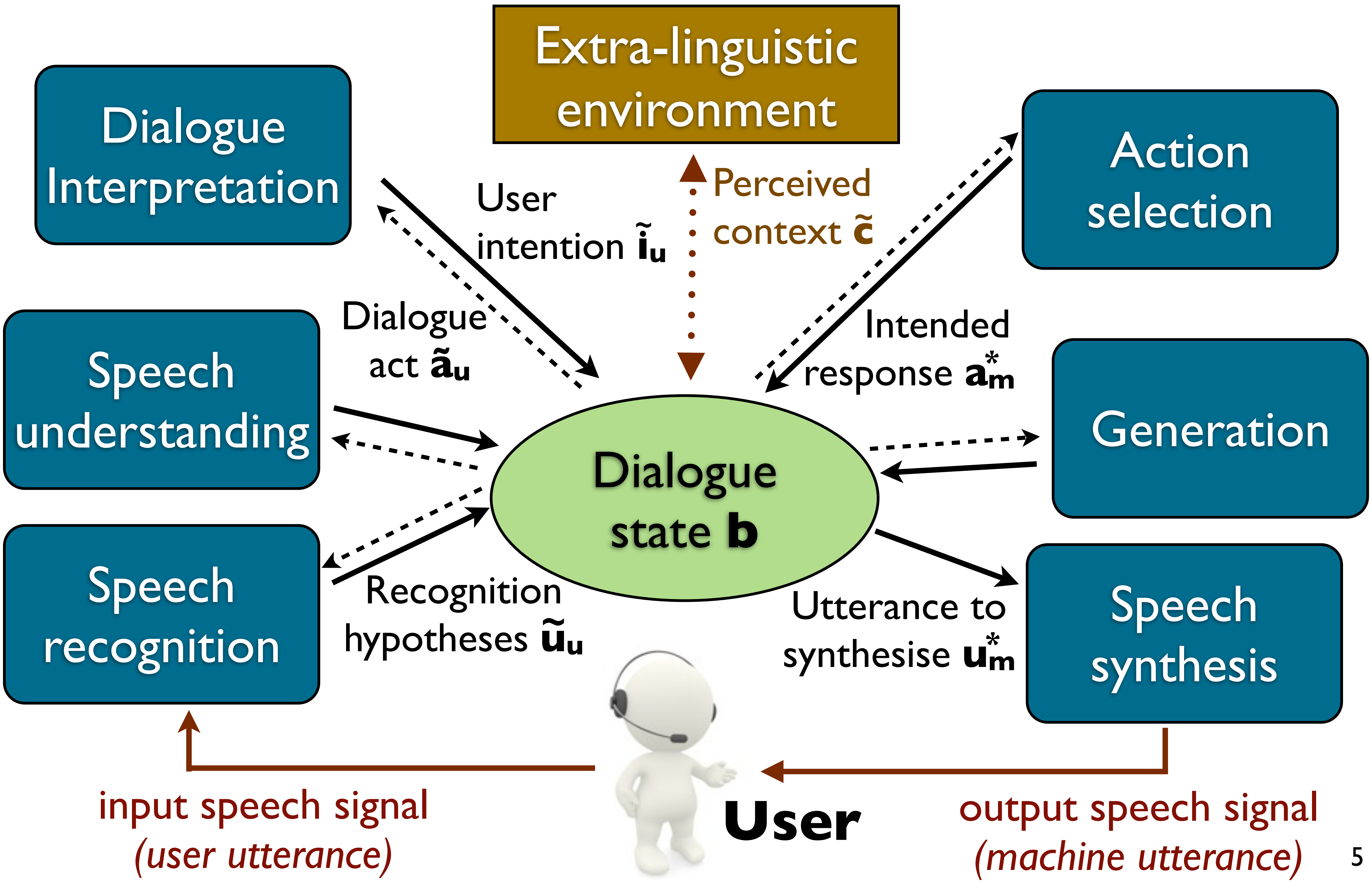
Introduction

- We adopt an alternative approach:
  - Declarative specification of all domain- & task-specific knowledge via a *common representation formalism*
  - System architecture «stripped down» to a core set of algorithms for probabilistic inference
- Advantages:
  - Domain portability
  - More transparent semantics
  - More flexible workflow

General architecture

- *Blackboard architecture* revolving around a shared dialogue state
  - Dialogue models are attached to this dialogue state, and listen for relevant changes appearing on it
  - When triggered, they read/write to this state, creating and updating the state variables
- Dialogue state encoded as a *Bayesian Network*
  - Each network node represents a distinct state variable, possibly connected to other variables

General architecture



Dialogue models

- The dialogue models are all expressed in terms of probabilistic rules
- Probabilistic rules are *high-level templates* for constructing probabilistic models
- Why use this representation formalism?
  - Take advantage of the *internal structure* of the problem while retaining the stochastic modelling
  - Abstraction mechanism (reduced set of parameters)

Probabilistic rules

- Probabilistic rules take the form of structured **if...then...else** cases
- Mapping from *conditions* to (probabilistic) *effects*:

if (condition$_1$ holds) **then**
  P(effect$_1$)= θ_1, P(effect$_2$)= θ_2, ...
else if (condition$_2$ holds) **then**
  P(effect$_3$) = θ_3, ...
...
else
  P(effect$_n$) = θ_n, ...

Probabilistic rules

- *Conditions* are (arbitrarily complex) logical formulae on state variables
- *Effects* are value assignments on state variables
- Effect probabilities are *parameters* that can be estimated from data

Example:

if (a_m = AskRepeat) **then**
  $P(a_u' = a_u) = 0.9$
  $P(a_u' \neq a_u) = 0.1$

Utility rules

- The formalism can also describe *utility models*
- In this case, the rule maps each condition to an assignment of *utility values* for particular actions:

if (condition$_1$ holds) **then**
  $Q(\text{actions}_1) = \theta_1$, $Q(\text{actions}_2) = \theta_2$, ...
else if (condition$_2$ holds) **then**
  $Q(\text{actions}_3) = \theta_3$, ...
...
else
  $Q(\text{actions}_n) = \theta_n$, ...

Rule instantiation

- How are the rules applied to the dialogue state?
- The rules are *instantiated* in the Bayesian Network, expanding it with new nodes and dependencies

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$P(V = \ldots \wedge W = \ldots) = 0.6$

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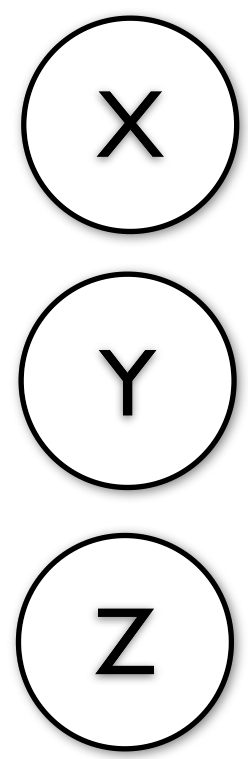

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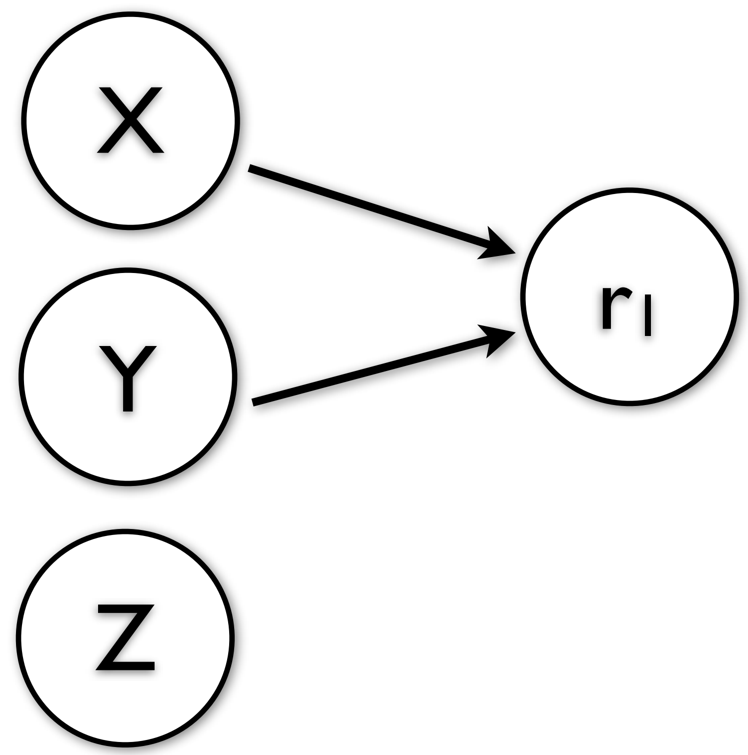

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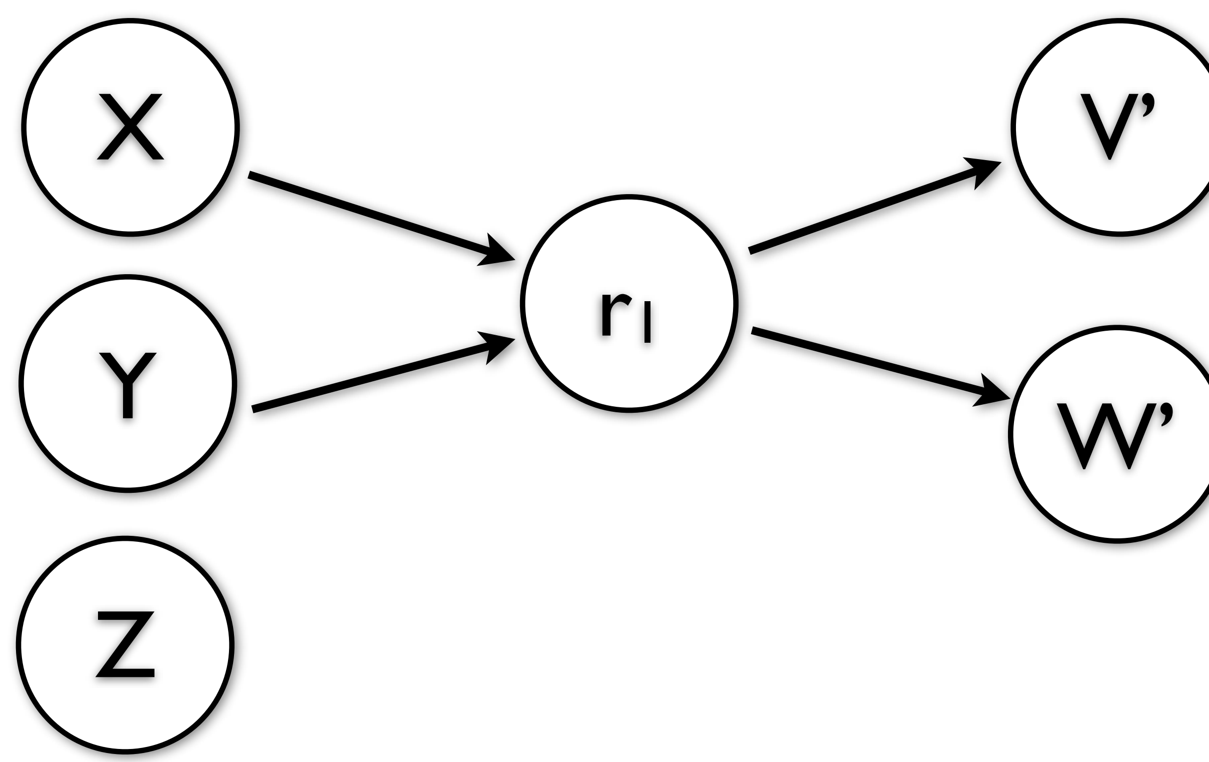

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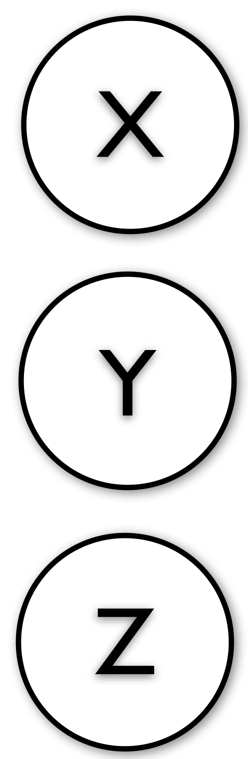

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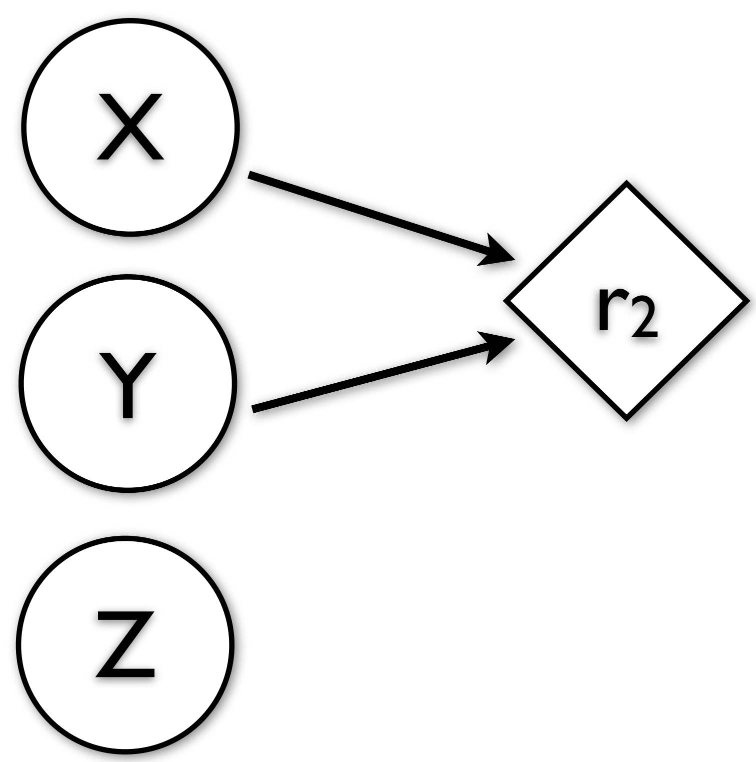

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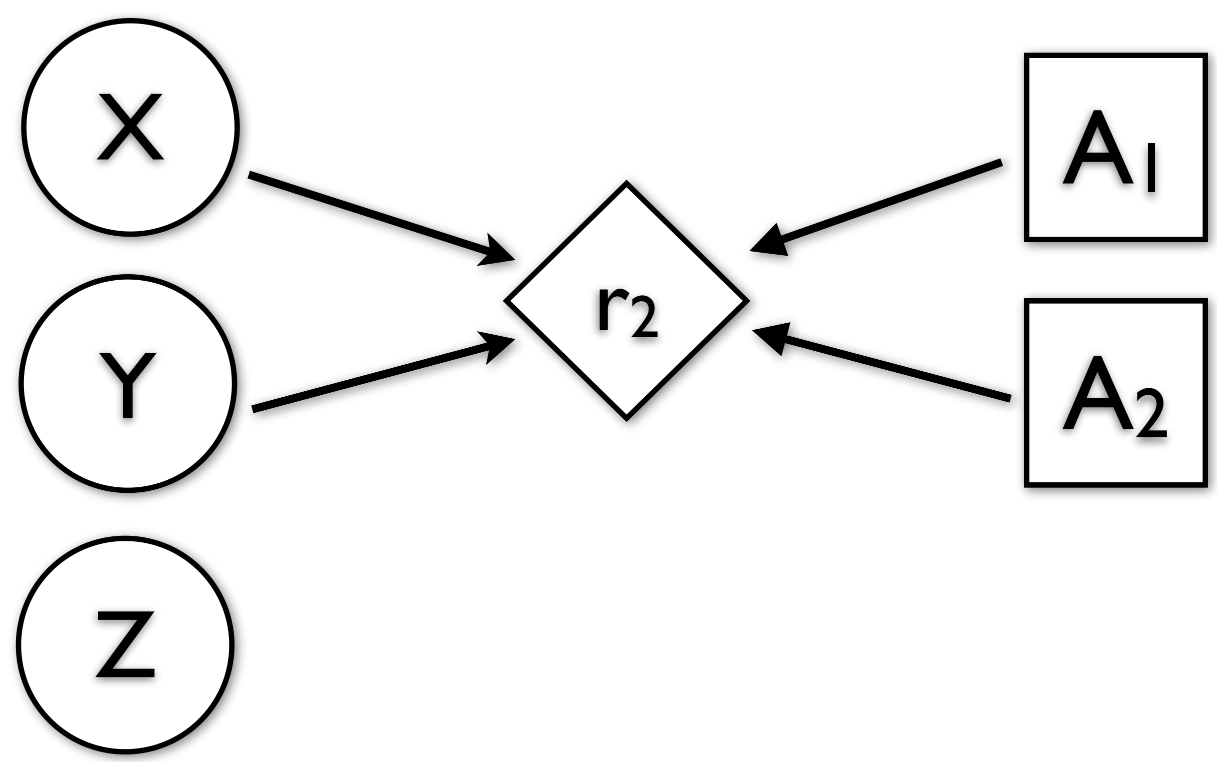

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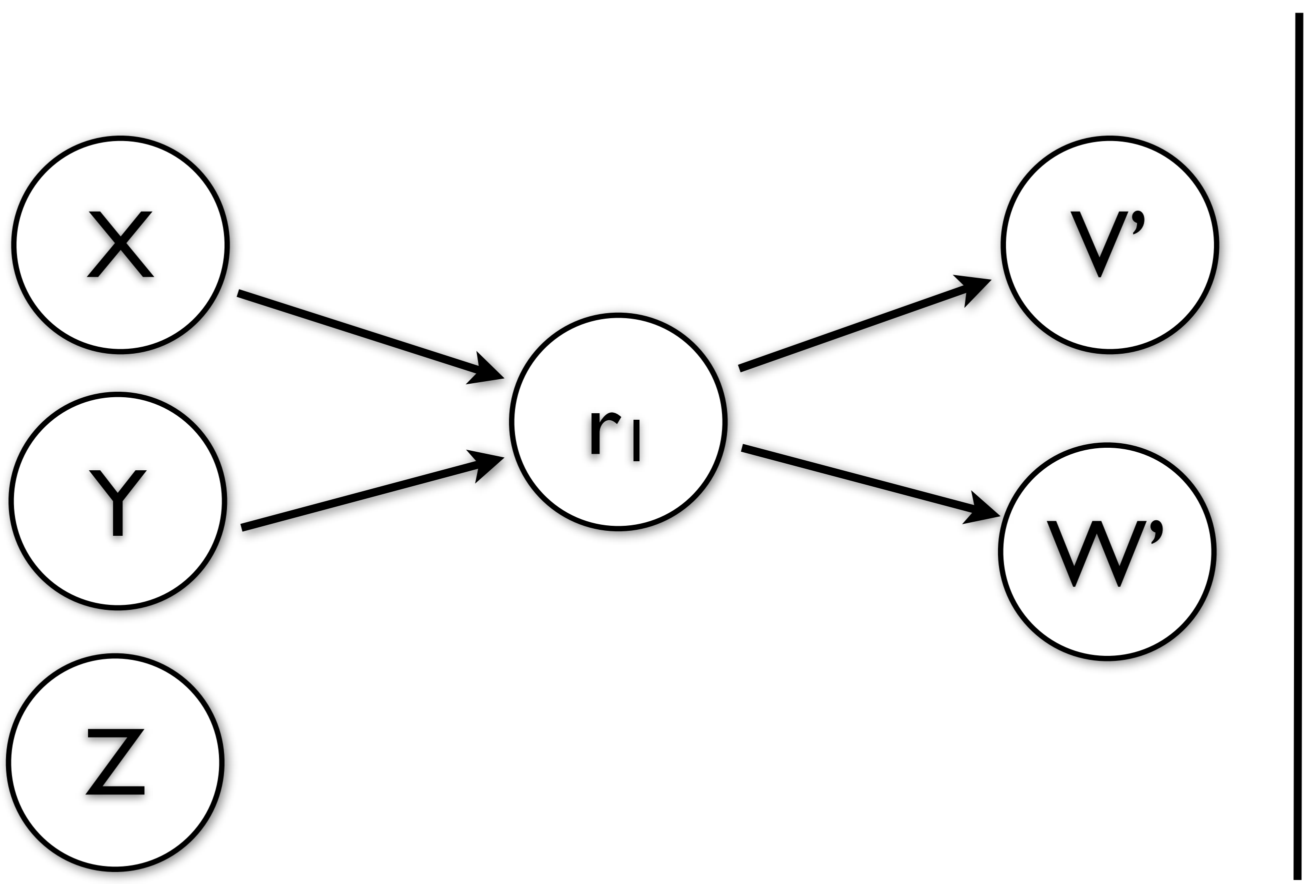

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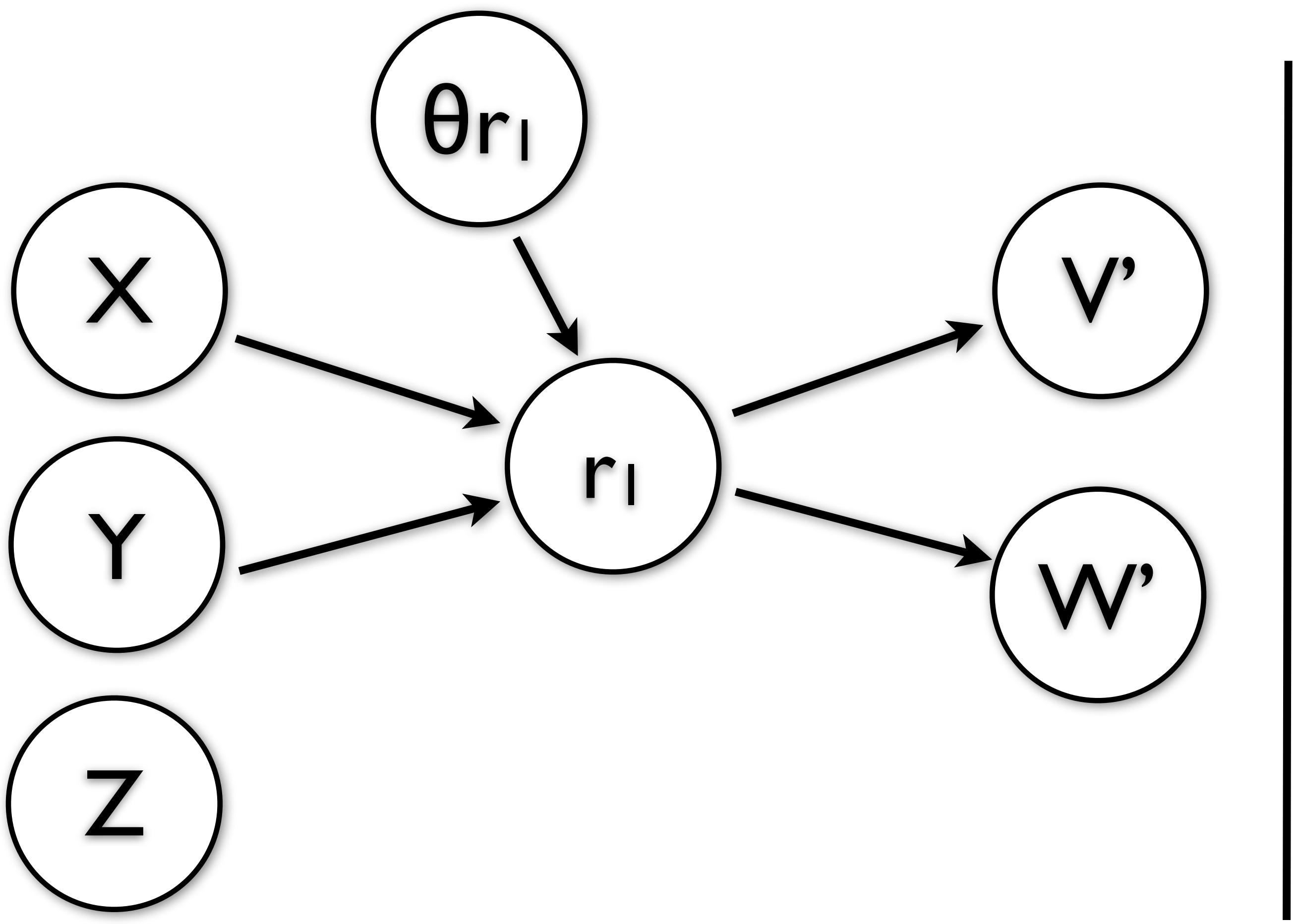

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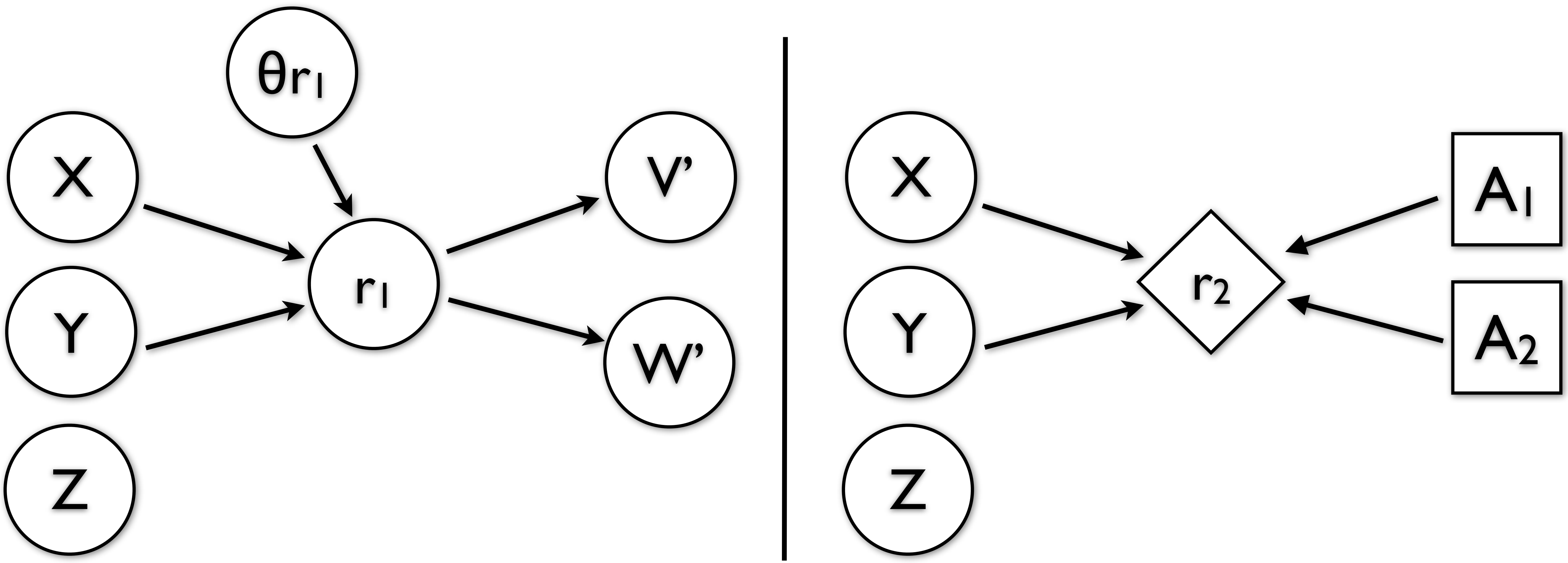

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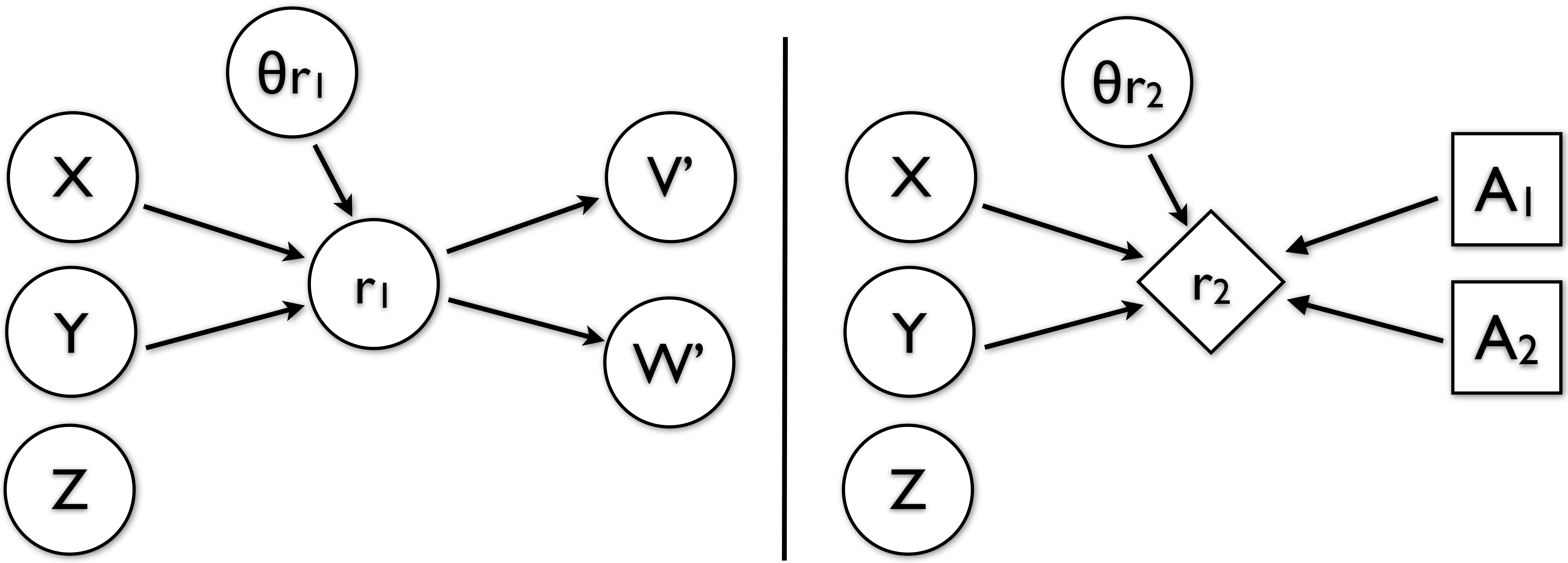

Processing workflow

- To ease the domain design, the rules are grouped into *models*
- Each model is associated with a *trigger variable* causing its activation
- When a model is activated:
  - A rule node is created for each rule, conditionally dependent on the variables used in the conditions
  - Nodes corresponding to the output variables of the rule are also created/updated, and connected to the rule node

Processing workflow (example)

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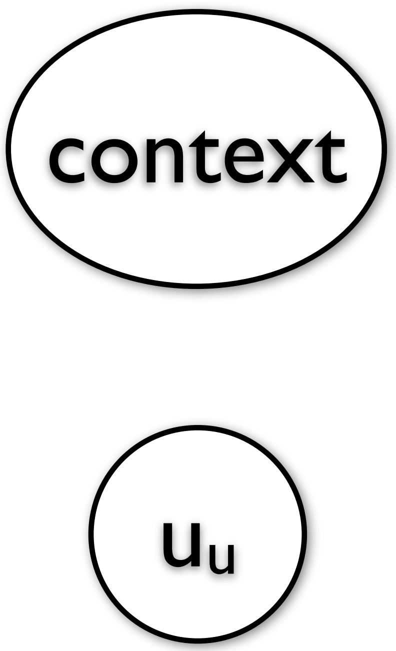

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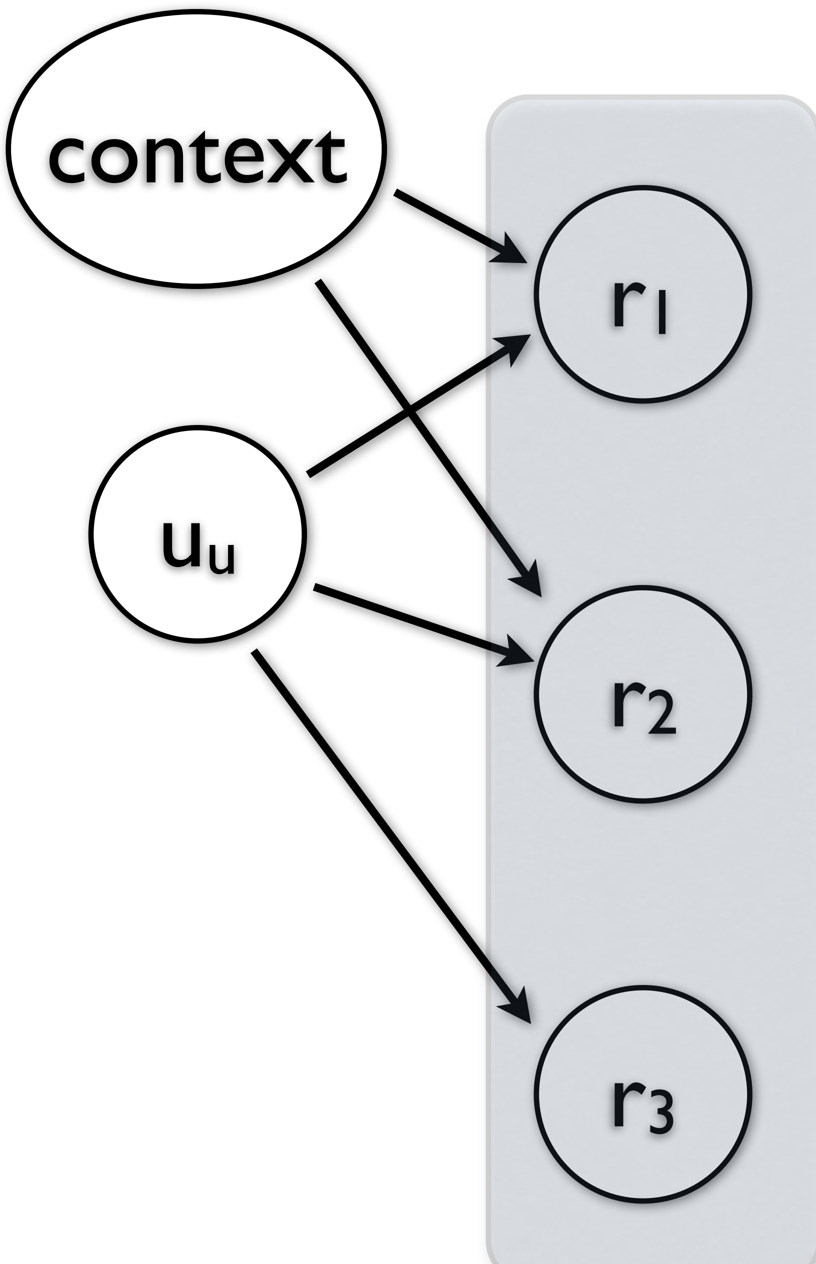

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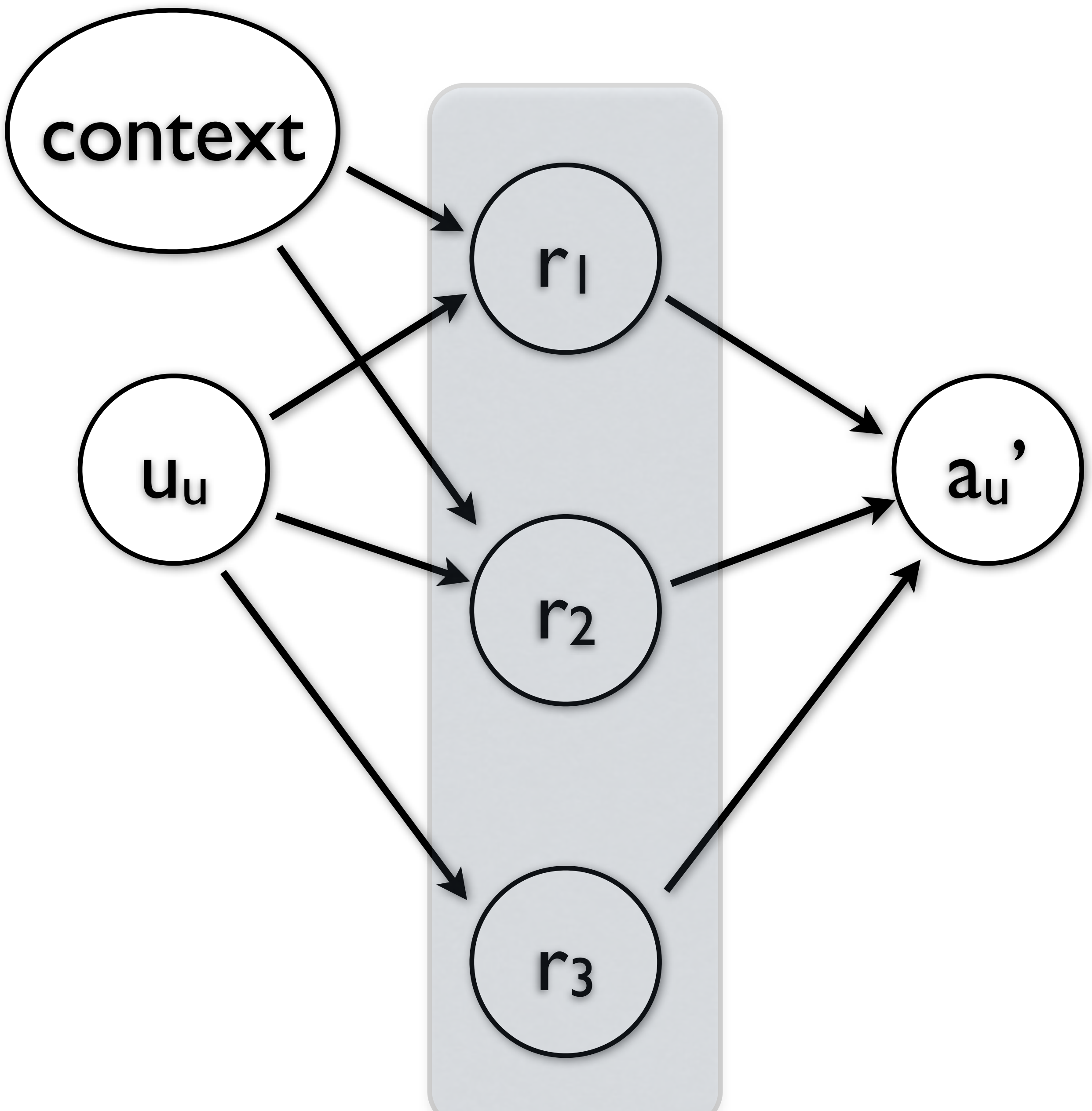

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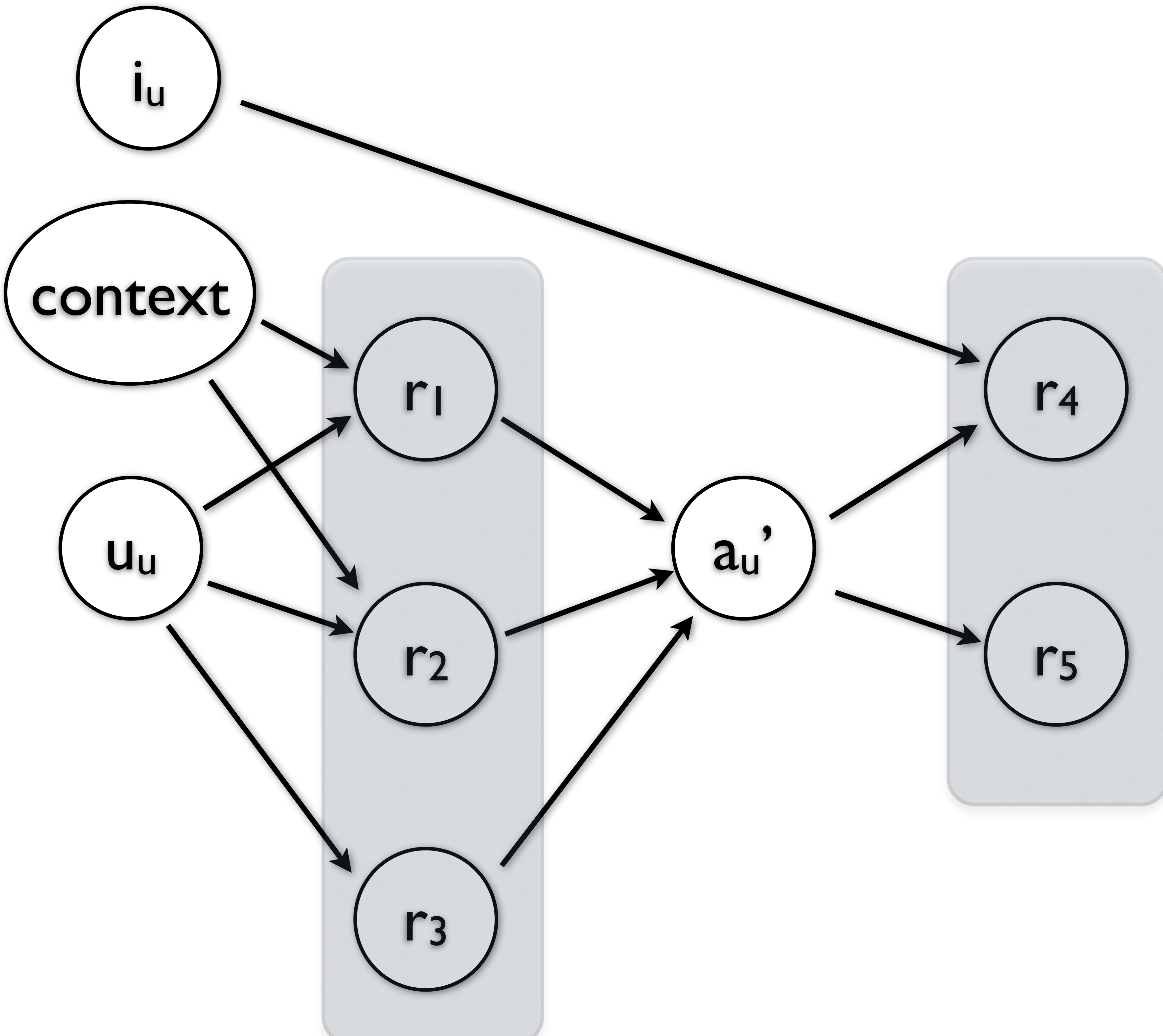

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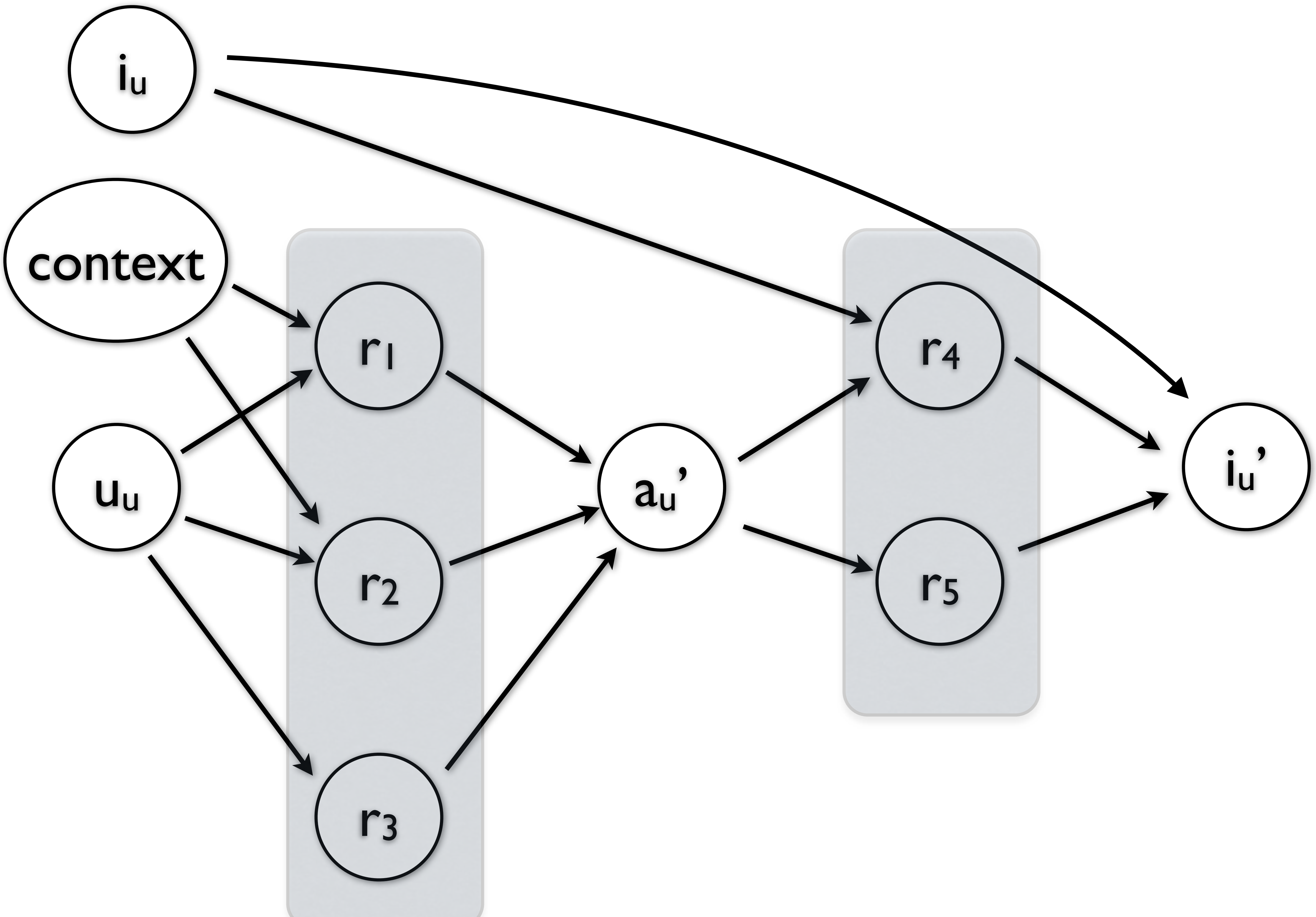

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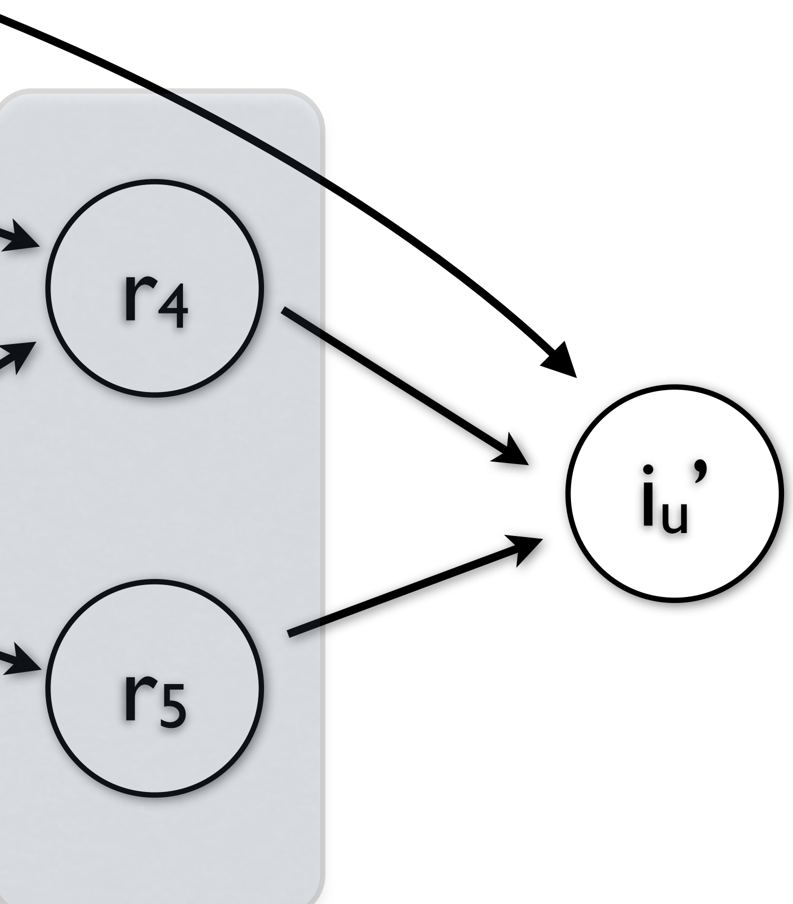

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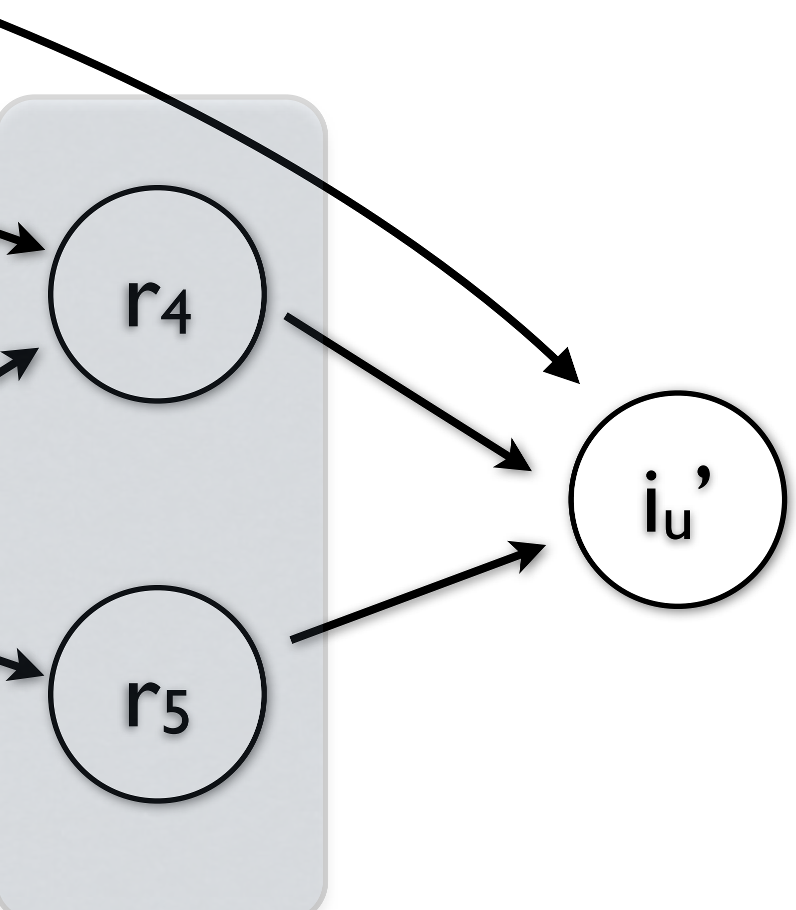

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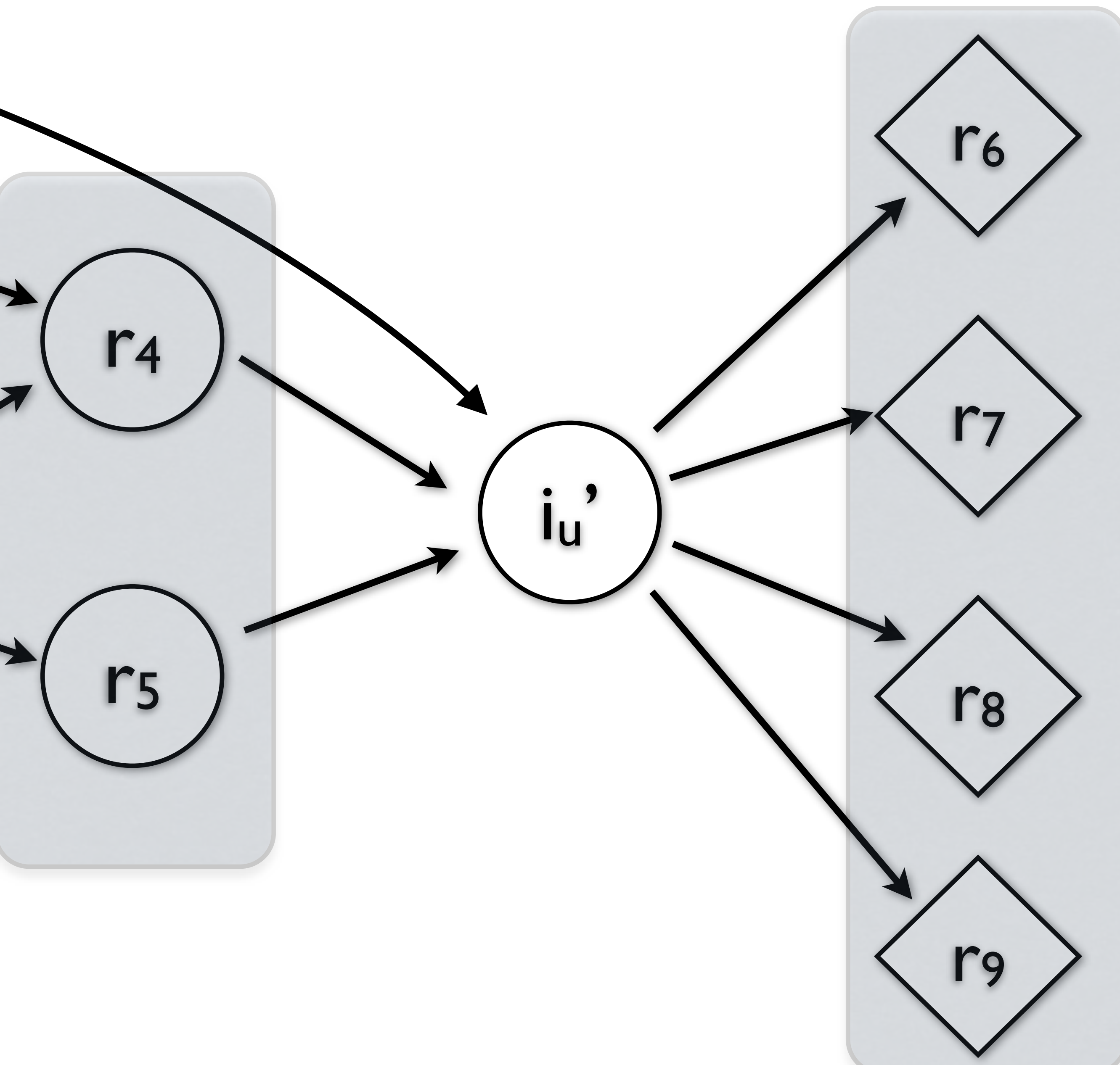

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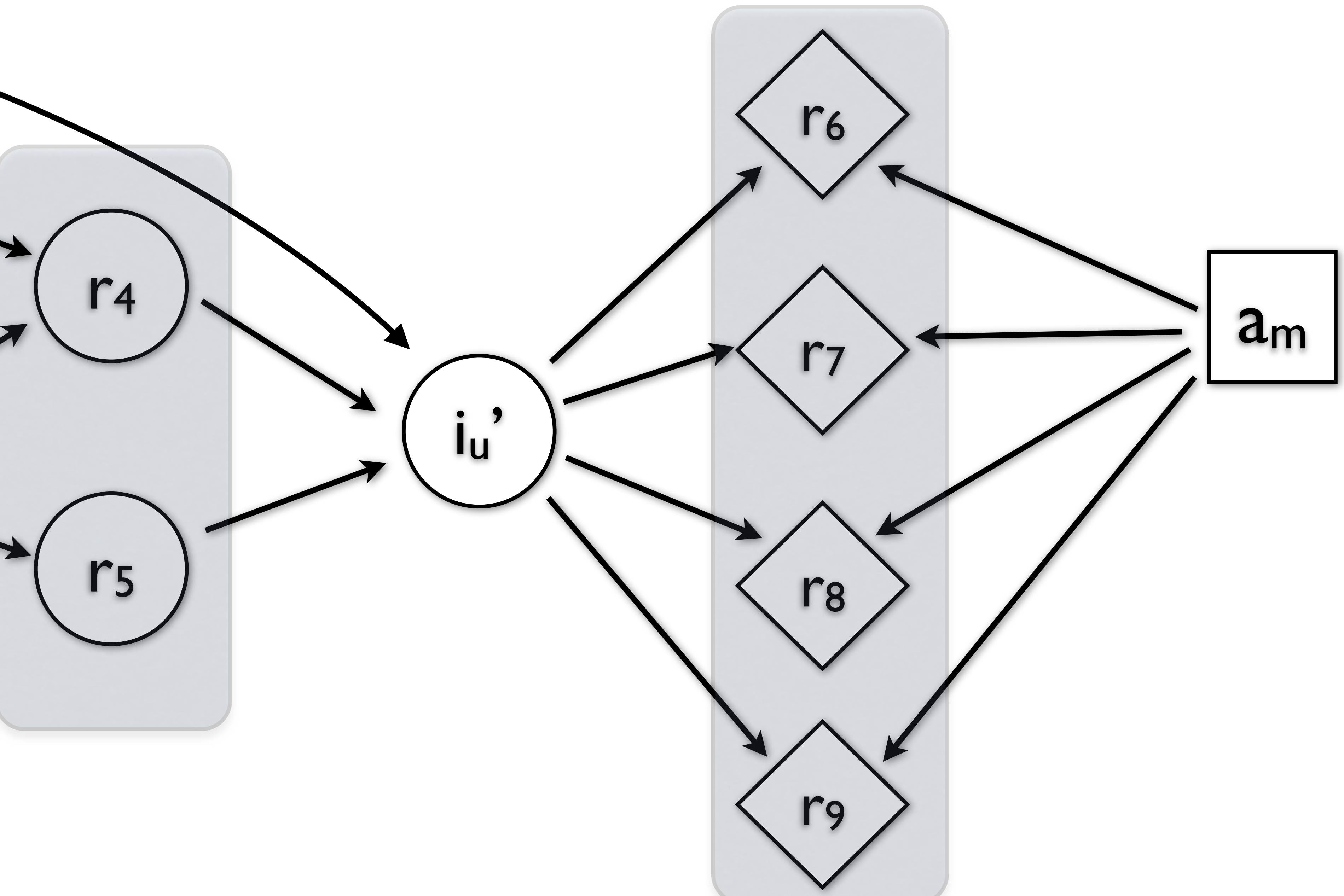

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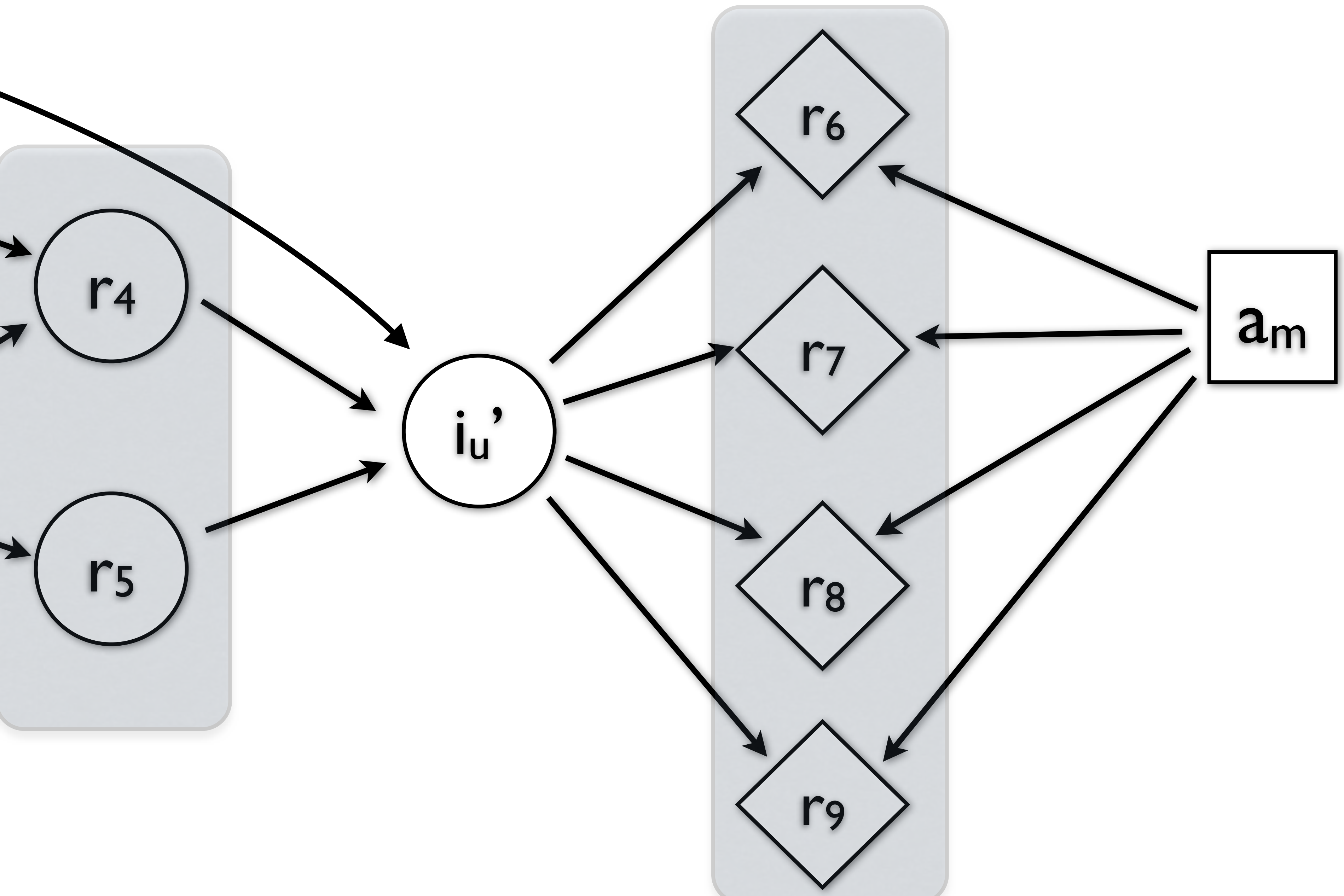

etc.

Processing workflow

- Additional details
  - No pipeline restriction: processing flow is possible
  - Decision nodes require a *decision* to be made, by selecting the value with maximum utility
  - Once the dialogue state is «stable» (no more model can be triggered), it is pruned to reduce it to a minimal size, retaining only the necessary nodes
  - The rules update existing variables or create *new* ones

Experiments

- The described formalism was implemented and tested in a simple human-robot interaction scenario
- The models for NLU, DM and NLG were encoded as probabilistic rules (total of 68 rules)

Experiments

- The utilities for the action selection rules were learned from Wizard-of-Oz data
- The other rules (NLU and NLG) were deterministic
- System also included a speech recogniser, TTS, and libraries for controlling the physical actions of the robot

[Pierre Lison, «Probabilistic Dialogue Models with Prior Domain Knowledge», SIGDIAL 2012]

Examples

- Dialogue act recognition rule:

$$
\begin{aligned}
r_1 :\ & \textbf{if } (u_u \text{ matches "left arm down"}) \\
& \vee (u_u \text{ matches "lower * left arm"}) \\
& \vee (u_u \text{ matches "down * left arm"}) \ \textbf{then} \\
& \quad \{P(a'_u = \text{LeftArmDown}) = 1.0\}
\end{aligned}
$$

- Prediction of next user action:

$$
\begin{aligned}
r_2 :\ & \textbf{if } (a_m = \text{AskRepeat}) \ \textbf{then} \\
& \quad \{P(a'_u = a_u) = 0.9\}
\end{aligned}
$$

Examples

- Action selection rules:

$$r_3: \textbf{if } (i_u = \text{RequestMovement}(\text{X})) \textbf{ then}$$
$$\{Q(a'_m = \text{DoMovement}(\text{X})) = 3.0\}$$

$$r_4: \textbf{if } (true) \textbf{ then}$$
$$\{Q(a'_m = \text{AskRepeat}) = 1.2\}$$

- Natural language generation rule:

$$r_5: \textbf{if } (a_m = \text{Ack}) \textbf{ then}$$
$$\{Q(u'_m = \text{“ok”}) = 1.0 \ \wedge$$
$$Q(u'_m = \text{“great”}) = 1.0 \ \wedge$$
$$Q(u'_m = \text{“thanks”}) = 1.0\}$$

Conclusions

- Dialogue system design based on the specification of probabilistic rules
- «Hybrid» approach combining domain knowledge and stochastic modelling
- Step towards a cleaner separation between system architecture and domain- and task-specific knowledge?

Future work

- Online estimation of the rule parameters (e.g. model-based Bayesian reinforcement learning)
- Joint optimisations of the parameters for NLU, DM and NLG models
- Incremental processing

Next interaction domain

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