

Class Responsibility Assignment as Fuzzy Constraint Satisfaction

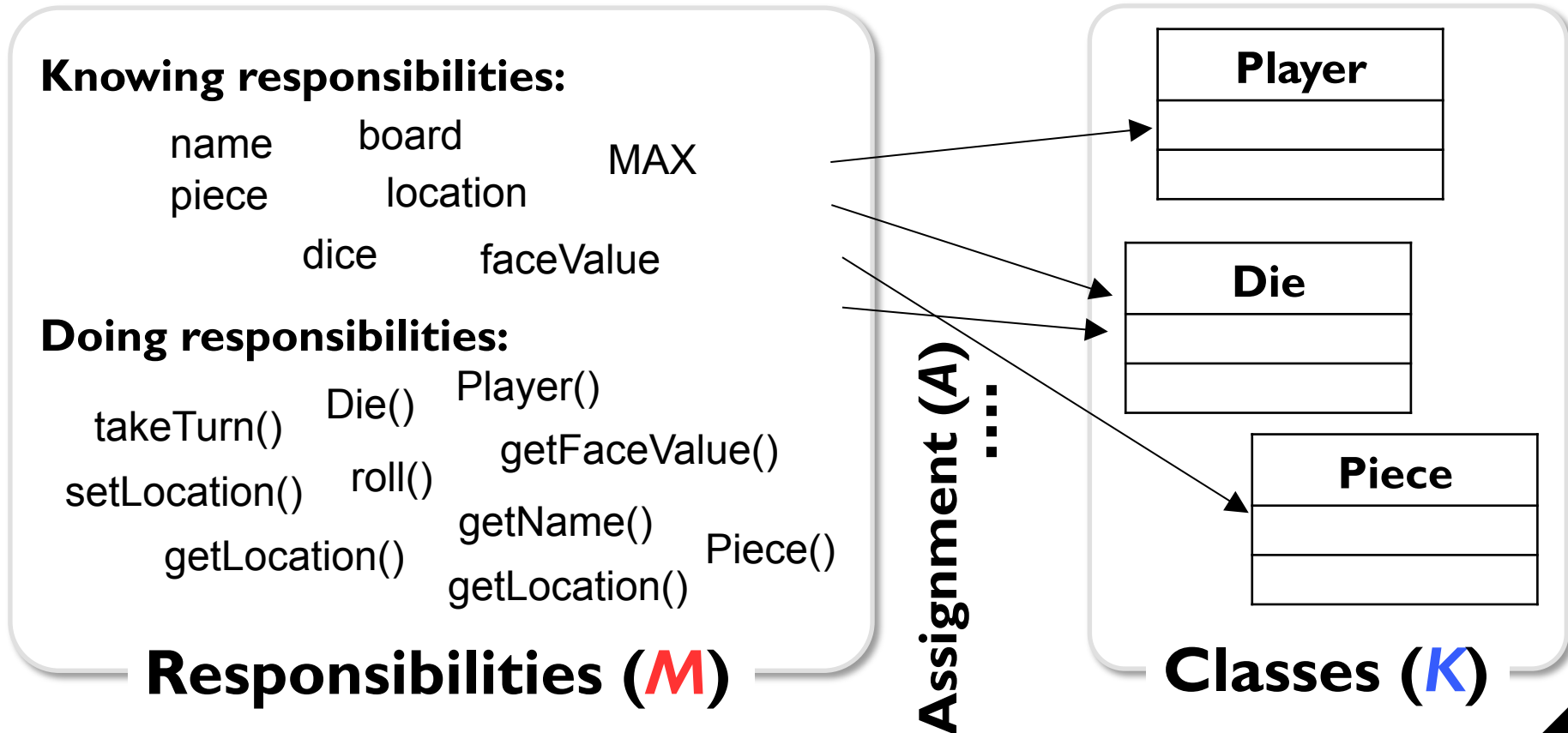
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[†]Tokyo Institute of Technology

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Class Responsibility Assignment (CRA)

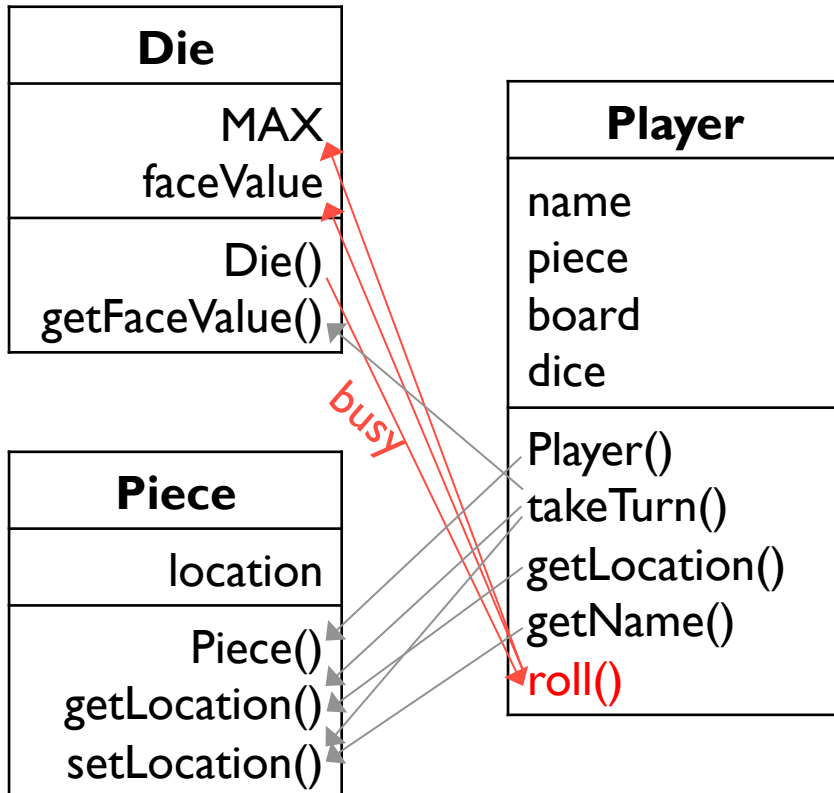
- Deciding a mapping $A : M \rightarrow K$



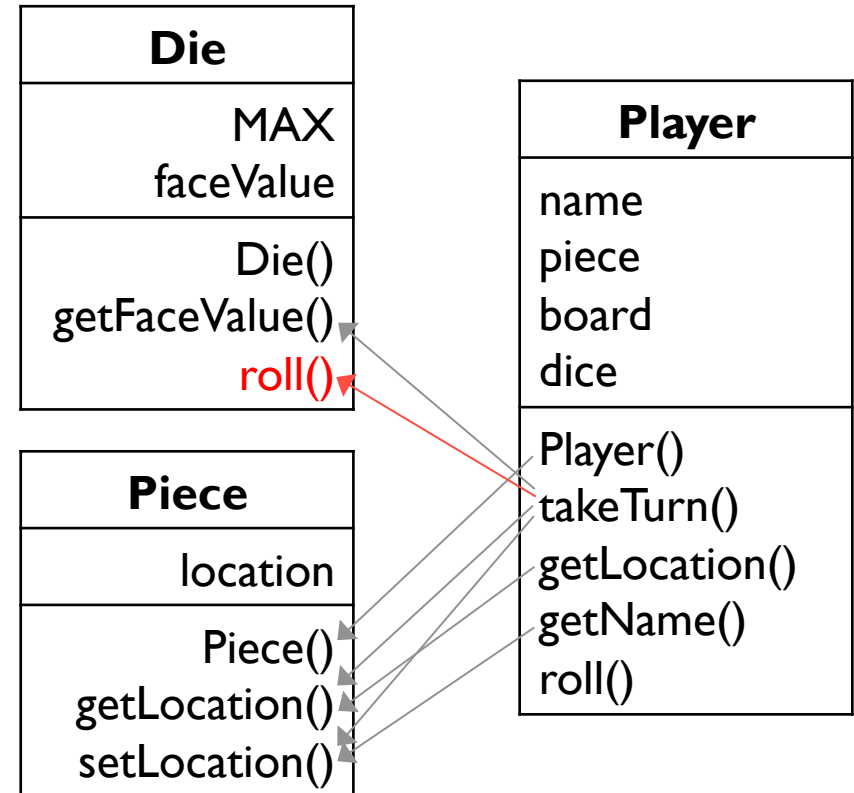
Towards Quality CRA

- Example criterion: *Low Coupling*

CRA 1



CRA 2



Challenges for Automating CRA

- CRA is over-constrained
 - **Low Coupling:** The distance between two classes having related responsibilities should be short.
 - **High Cohesion:** The relation between two responsibilities in close classes should be close.

Trade-off



A realistic solution needed,
which satisfies constraints *to some extent*

Toward Interactive Tool

- Support of trial-and-error in design process

- **Stability:**

- *"I want to improve my manually-assigned model.
Do not DRASTICALLY modify it!"*

- **Users Intention:**

- *"I found that these two responsibilities should be assigned to **the same class / different classes**"*



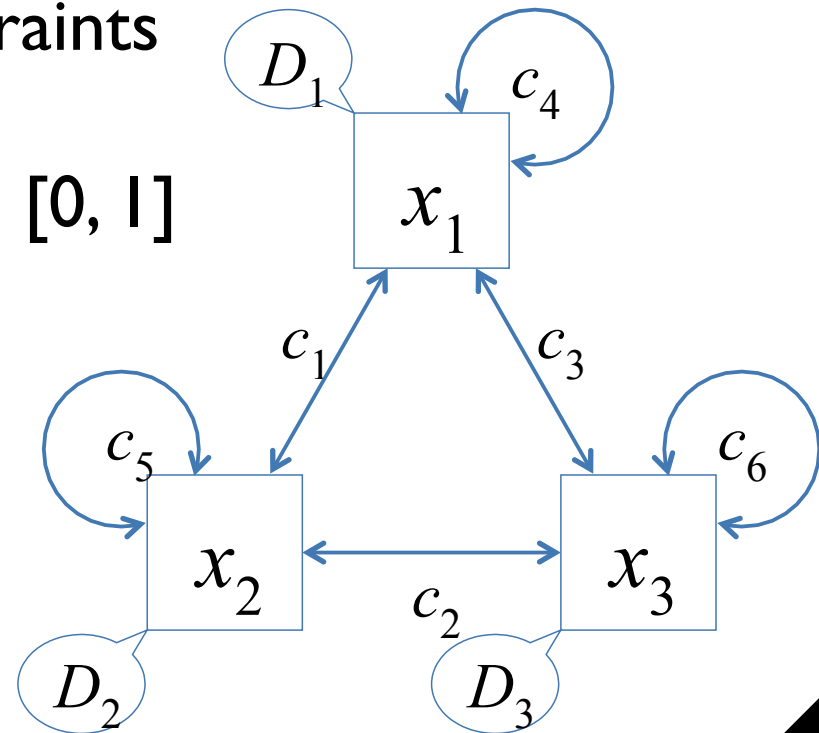
flexibly configurable technique needed

Our Approach

- Formulating CRA using ***Fuzzy Constraint Satisfaction Problem*** (FCSP)
 - Combinational search problem in AI field
 - Benefits
 - No need to define a monolithic evaluation function
 - Each criterion is naturally represented as *fuzzy constraints*
 - Usage of well-maintained solvers

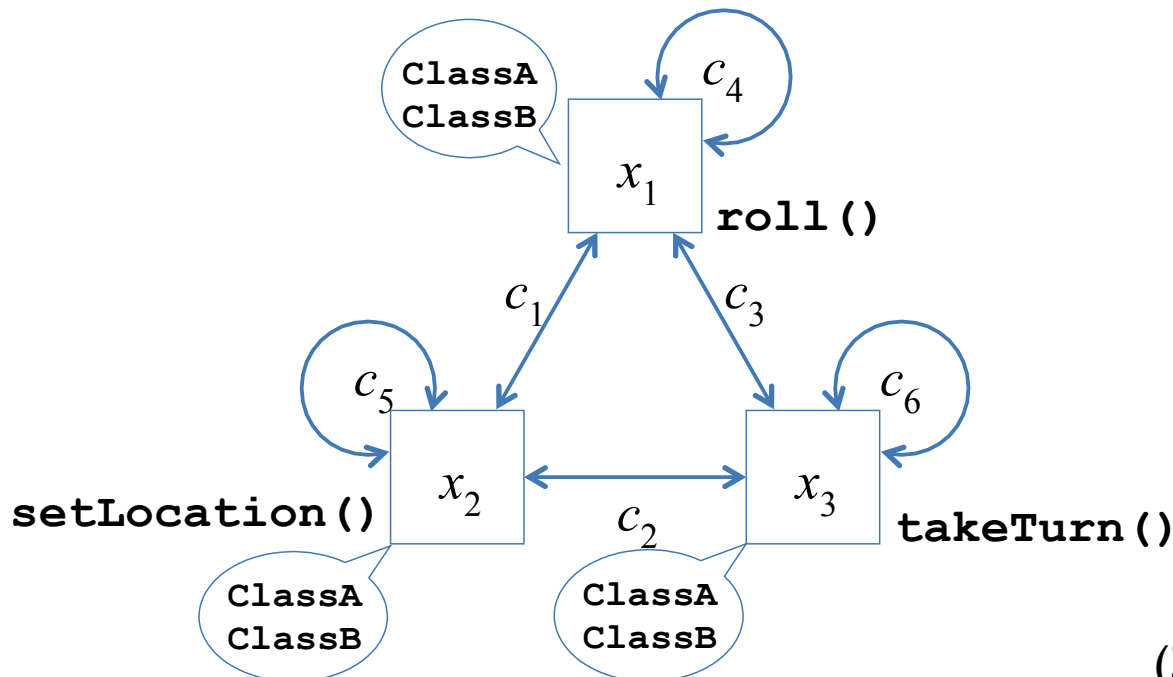
FCSP

- Variable: $X = \{ x_1, x_2, \dots, x_n \}$
- Domain: $D = \{ D_1, D_2, \dots, D_n \}$
- Constraint: $C = \{ c_1, c_2, \dots, c_r \}$
 - inc. Unary and binary constraints
 - Each constraint has its satisfaction degree (μR) $[0, 1]$
- Objective:
 - Maximizing $\min_{c \in C} \mu R$



Formulation

- Variable x \square \leftarrow Responsibility $m \in M$
- Domain D Ⓢ \leftarrow Set of classes K
- Constraint c \leftrightarrow \leftarrow Assignment strategy

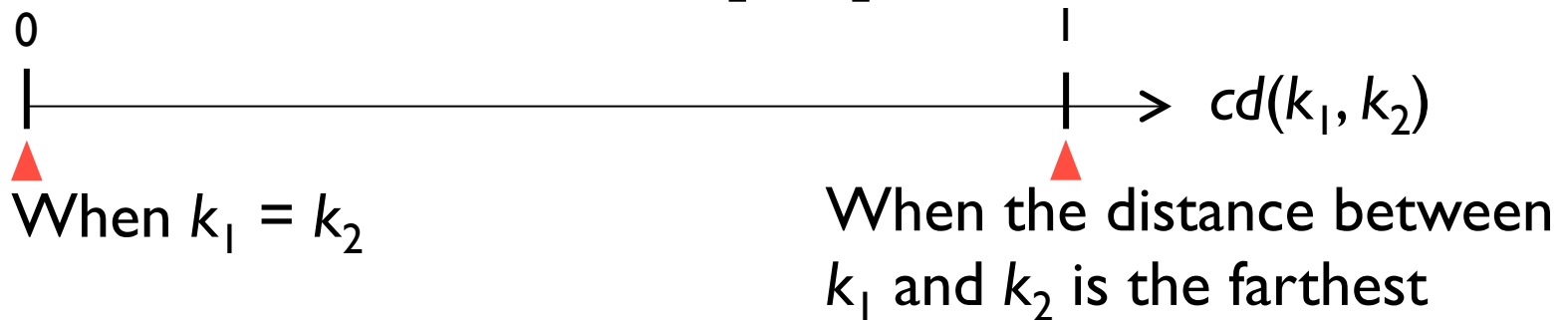


(3 responsibilities)

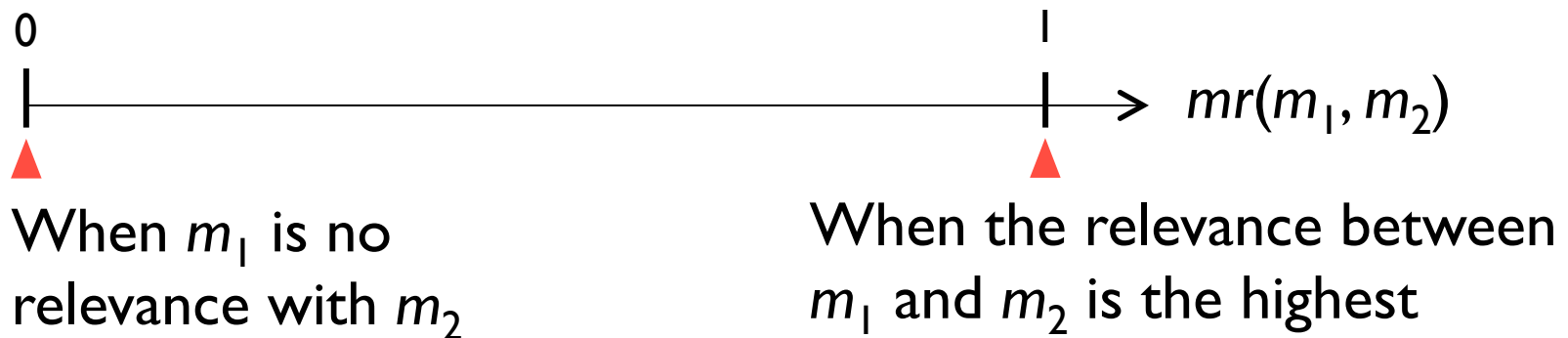
Given Information

- Normalized two measures are used

- **Class Distance** $cd : K^2 \rightarrow [0, 1]$



- **Responsibility Relevance** $mr : M^2 \rightarrow [0, 1]$



Constraints

- c^{lc} : Low Coupling



relevant responsibilities are in distant classes

- c^{hc} : High Cohesion



irrelevant responsibilities are in closer classes

- c^s : Stability



responsibilities moved from the initial assignment

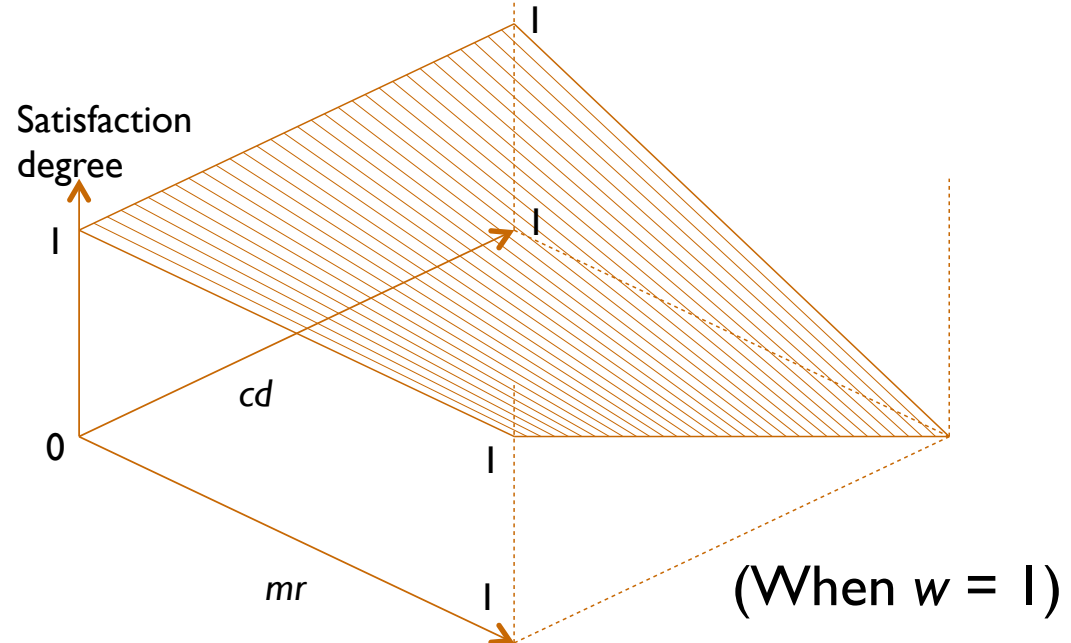
- c^{same} , c^{diff} : Users Intention



distance between the specified responsibilities does not follow

c^{lc} : Low Coupling

- Binary constraint for a pair of variables
- Satisfaction degree decreases when relevant responsibilities are in distant classes

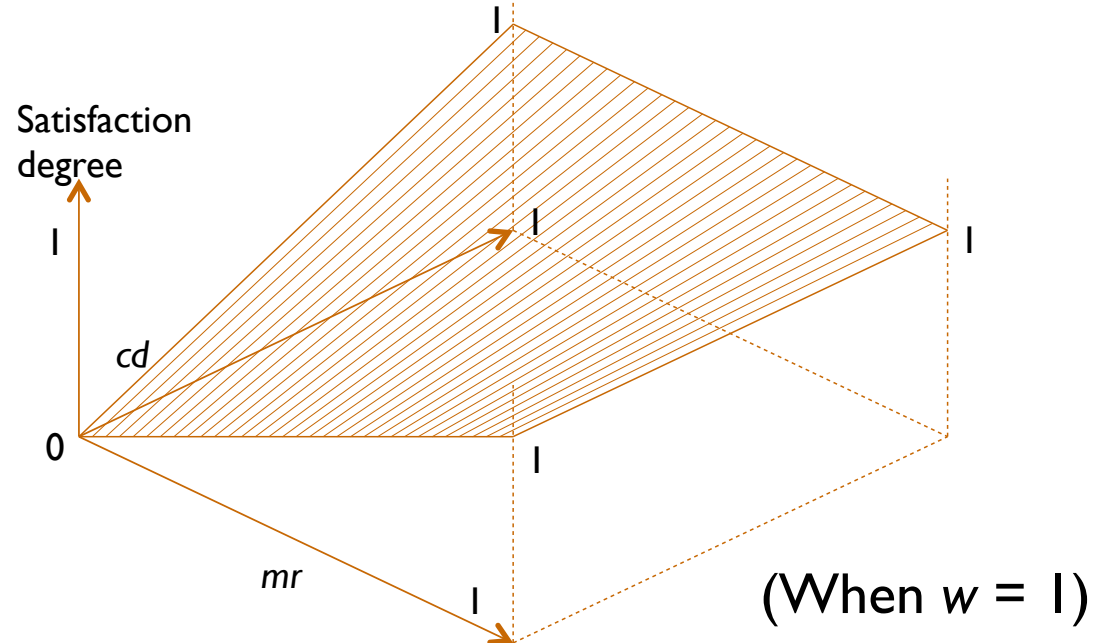


For m_1 and m_2 ,

$$\mu R_c(k_1, k_2) = \{ -mr(m_1, m_2)cd(k_1, k_2) + 1 \}^w$$

c^{hc} : High Cohesion

- Binary constraint for a pair of variables
- Satisfaction degree decreases when irrelevant responsibilities are in closer classes



For m_1 and m_2 ,

$$\mu R_c(k_1, k_2) = \{ (1 - mr(m_1, m_2))cd(k_1, k_2) + mr(m_1, m_2) \}^w$$

c^s : Stability

- Unary constraint for each variable
- Satisfaction degree decreases when the class to which a responsibility belongs in the current assignment is far from that in the given assignment

For m ,

$$\mu R_c(k) = \{ 1 - cd(k_{\text{orig}}, k) \}^w$$

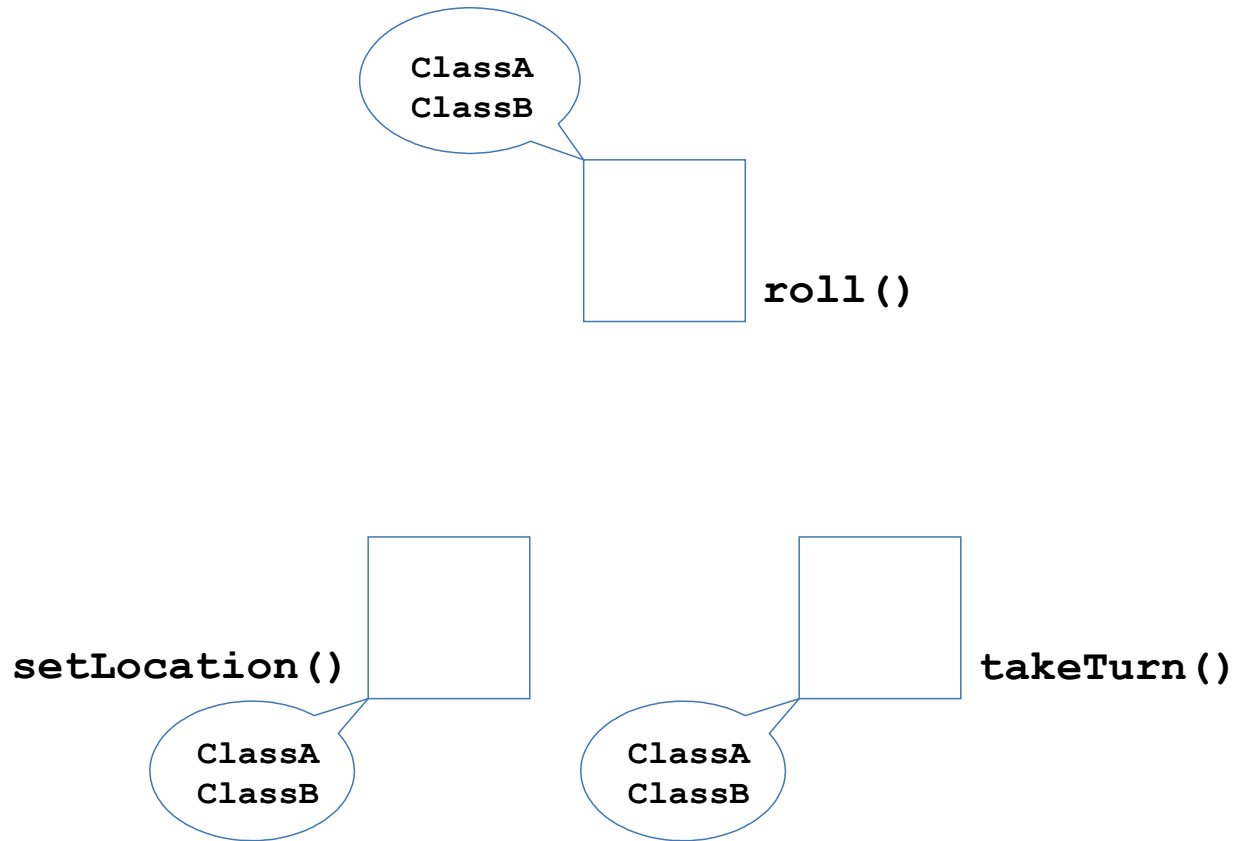
c^{same} / c^{diff} : Intention

- Binary constraint for each pair of variables
- Satisfaction degree decreases based on the distance between the target classes

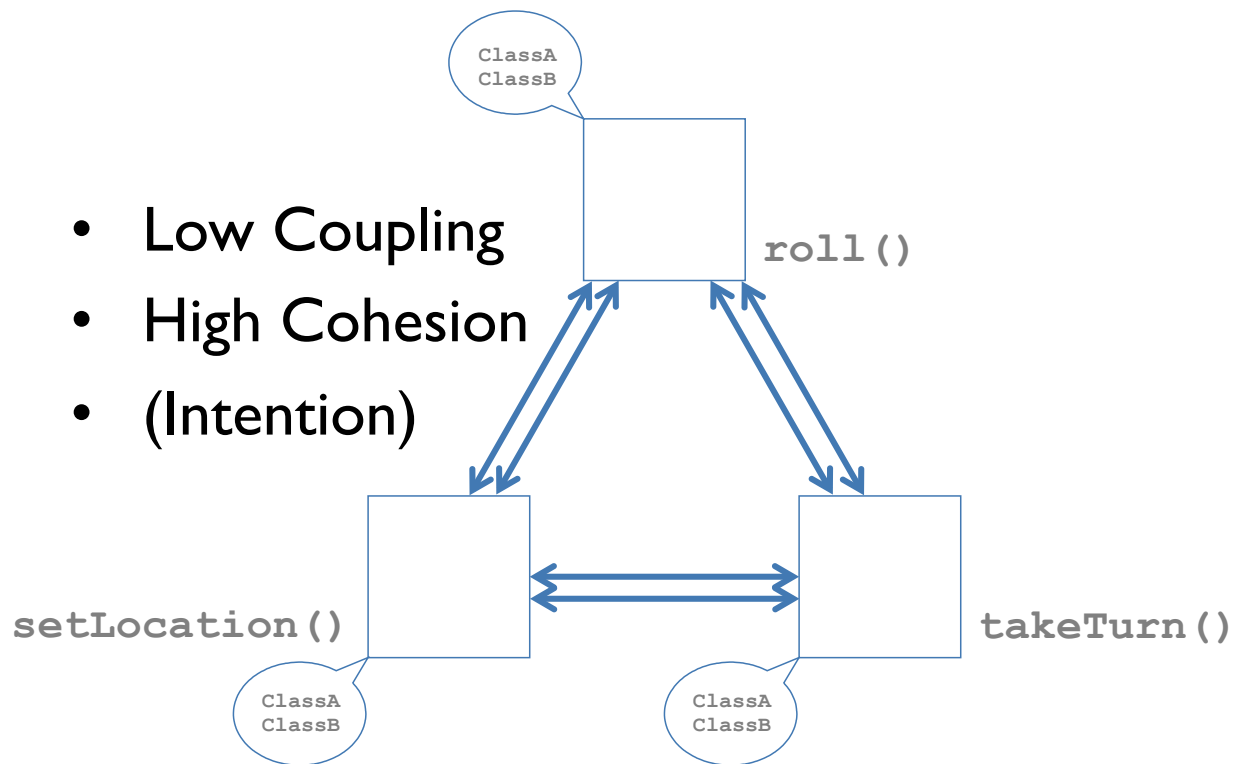
For m_1 and m_2 ,

$$\begin{aligned}\mu R_{c^{\text{same}}}(k_1, k_2) &= \{ 1 - cd(k_1, k_2) \}^w \\ \mu R_{c^{\text{diff}}}(k_1, k_2) &= cd(k_1, k_2)^w\end{aligned}$$

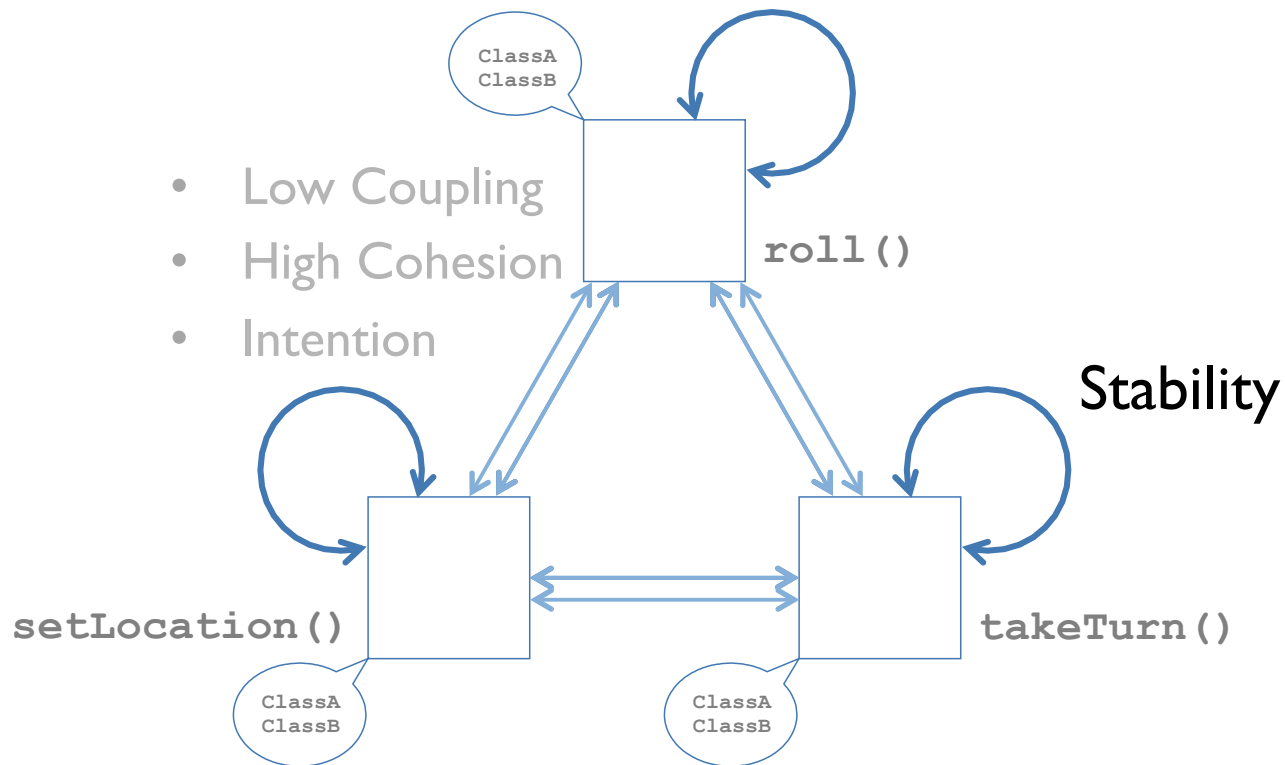
Example: Constraints



Example: Constraints



Example: Constraints



Evaluation Questions

- EQ 1:

*How accurately does our technique assign responsibilities **from scratch**?*

- EQ 2:

*How accurately does our technique fix the assignment of responsibilities **if an initial assignment is given**?*

- EQ 3:

*Does our technique fix the assignment **when users' intentions are given**?*

- EQ 4:

*Is the calculation of the assignment performed **fast enough**?*

Summary of Evaluation

- EQ 1:

*How accurately does our technique assign responsibilities **from scratch**?*

So-so.

- EQ 2:

*How accurately does our technique fix the assignment of responsibilities **if an initial assignment is given**?*

Good.

- EQ 3:

*Does our technique fix the assignment **when users' intentions are given**?*

Yes.

- EQ 4:

*Is the calculation of the assignment performed **fast enough**?*

Yes.

Summary of Evaluation

- EQ 1:

*How accurately does our technique assign responsibilities **from scratch**?*

A certain level of precision.

Monopoly: 69%

NextGenPos: 33%

- EQ 2

*How accurately does our technique fix the assignment of responsibilities **if an initial assignment is given**?*

Good level of precision.

Monopoly: 58%

NextGenPos: 73%

- EQ 3

*Does our technique fix the assignment **when users' intentions are given**?*

Yes.

2 of 3 constraints hold.

- EQ 4

*Is the calculation of the assignment performed **fast enough**?*

Yes.

e.g., Fix: < 1ms

Experimental Setup

- Example models from a CRA textbook

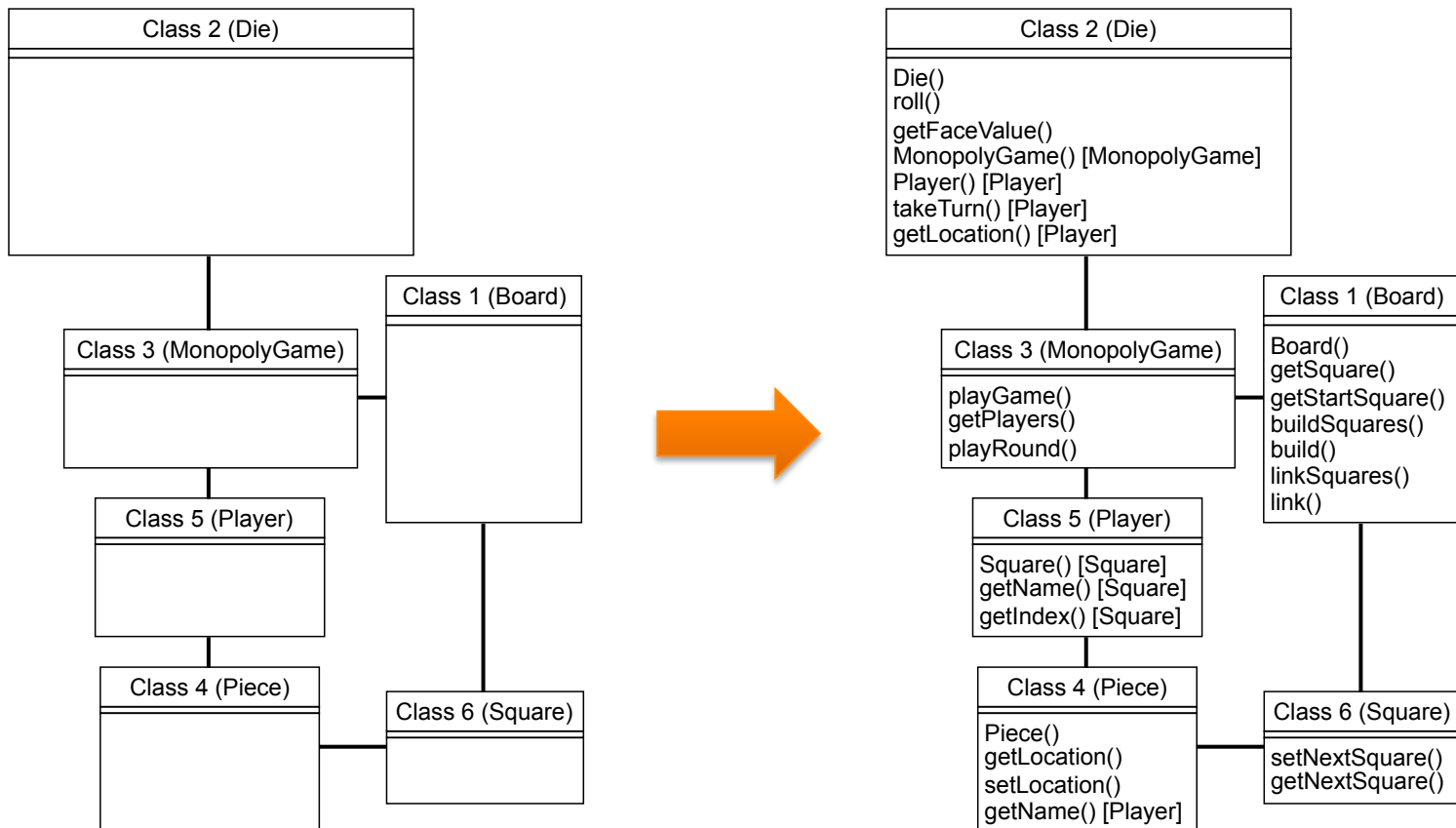
System	# classes	# responsibilities
Monopoly	6	26
NextGenPos	9	30

- Reverse engineering from source code
 - Examples and oracles were extracted from textbook
 - Class distance cd and Responsibility relevance mr were measured based on the oracle

EQ I (from scratch)

How accurately does our technique assign responsibilities from scratch?

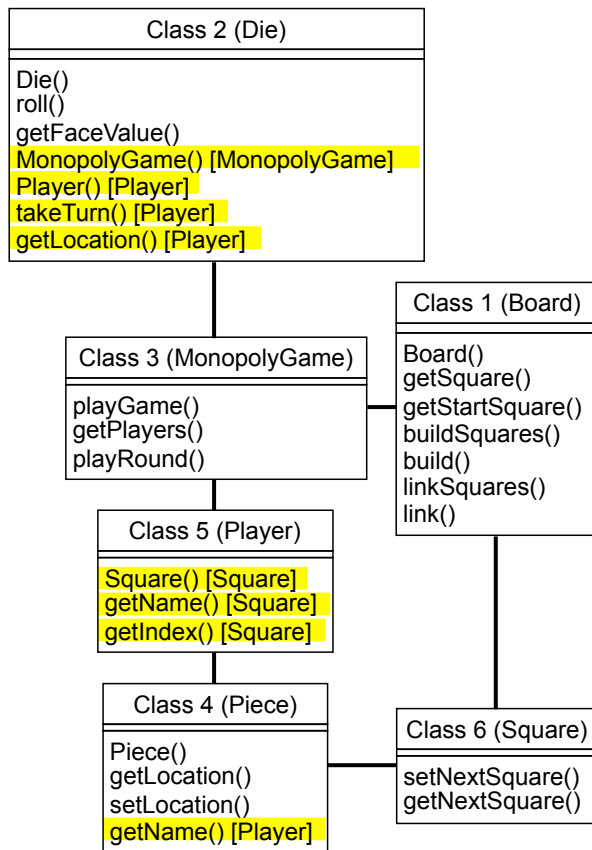
- Prepared an empty model and assigned all the responsibilities



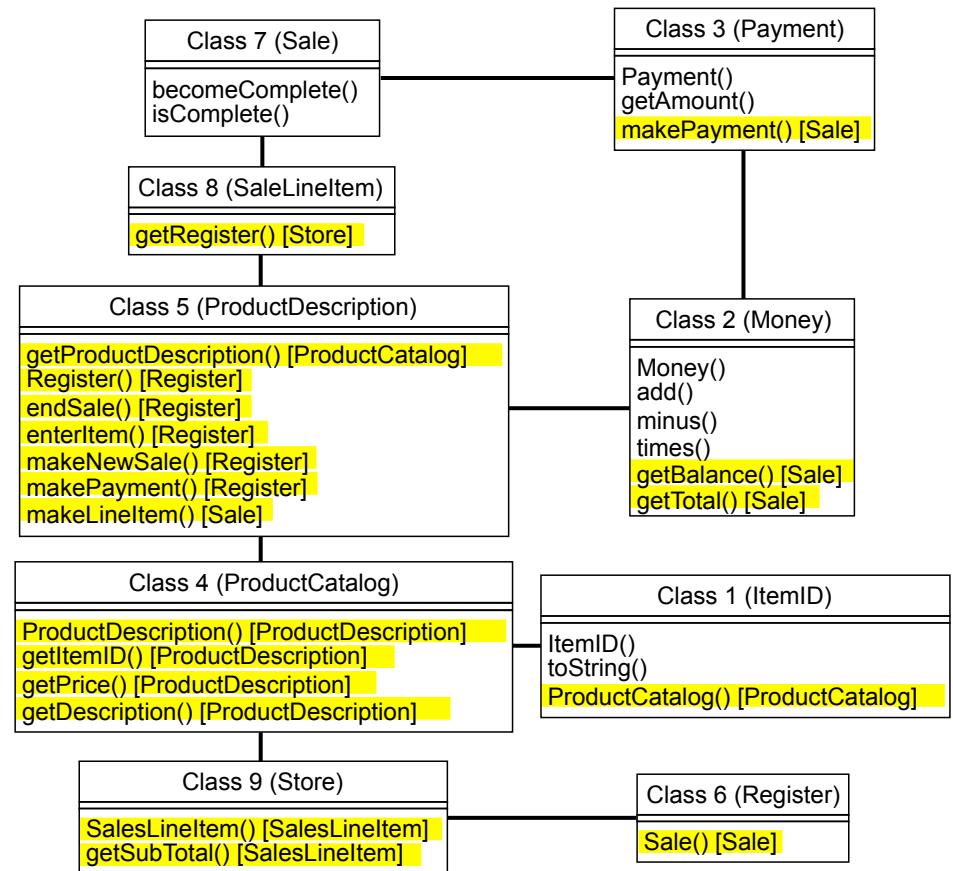
EQ I (from scratch)

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Monopoly: 69%



NextGenPos: 33%

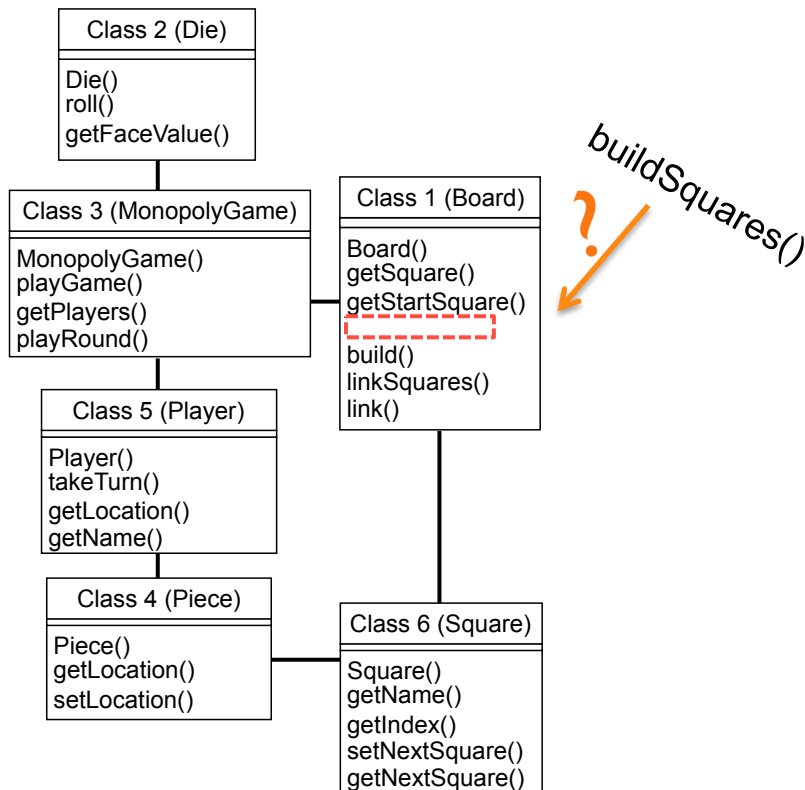


Incorrect assignment [Oracle]

EQ 2 (w/ initial model)

How accurately does our technique fix the assignment of responsibilities if an initial assignment is given?

- Detached each responsibility and re-assigned it



- **Result**

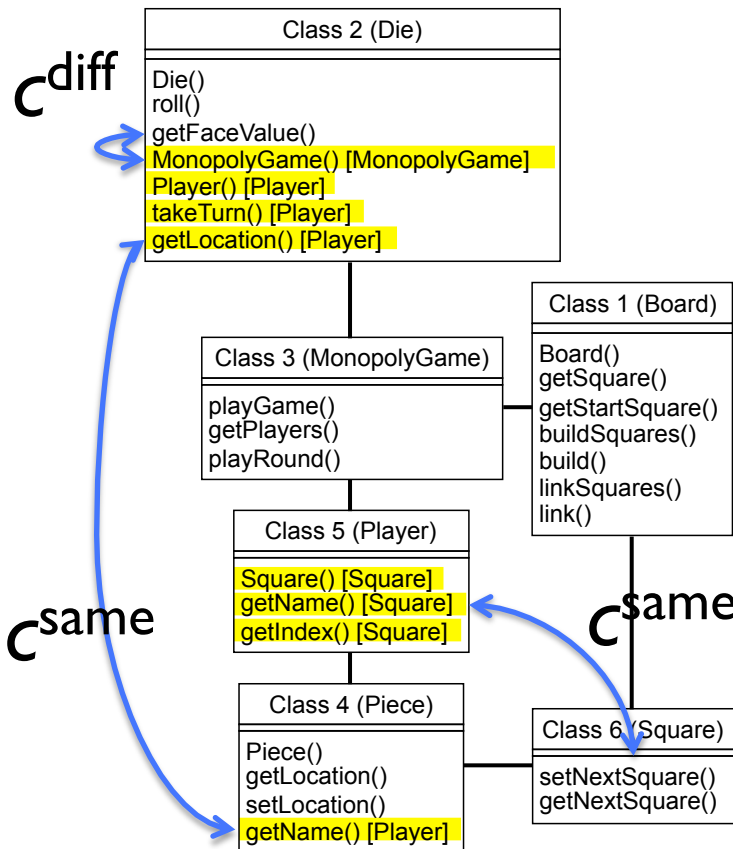
- Monopoly: **58%**
(15 resp.)
- NextGenPos: **73%**
(22 resp.)

EQ 3 (intention)

Does our technique fix the assignment when users' intentions are given?

- Added 3 intention constraints in Monopoly

→ 2 of 3 were worked well



Users intention-based constraints are feasible.

EQ 4: Execution Time

Is the calculation of the assignment performed fast enough?

● Implementation

- Our FCSP library w/ fuzzy forward checking
- on Java 7 (Window 7, Intel Core i7, 2.93GHz)

● Result

- **Experiment for EQ 1** (\neq actual usage)
 - Monopoly: 20 ms
 - NextGenPos: 8550 ms
- **Experiment for EQ 2**
 - < 1 ms
- **Experiment for EQ 3**
 - 20 ms



Yes, fast enough.

Discussion/Conclusion

EQ 2:

improvement of
existing model



EQ 3:

Addition of
users intention



EQ 4:

Execution time



Might be feasible to develop
an **interactive CASE tool** for supporting CRA



(**Flexibility** by formulating CRA as *fuzzy* CSP)

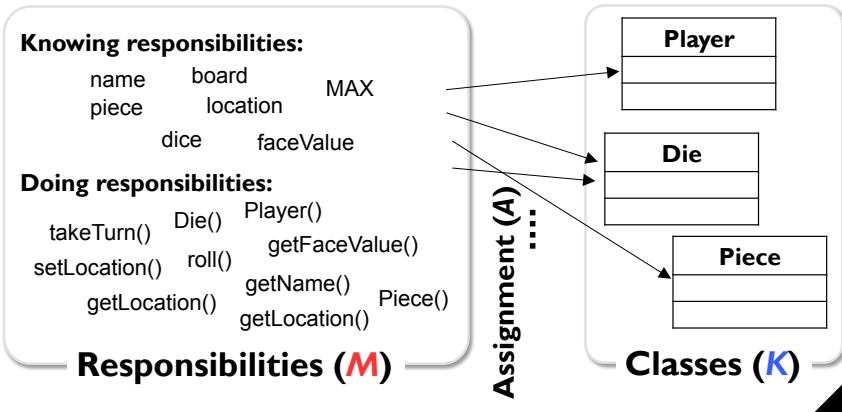
Future Work

- Richer case studies for confirming scalability
 - Applying our technique to real systems
- Use of other software metrics
 - e.g., LCOM*
- Expressing other strategies as fuzzy constraints
 - e.g., GRASP

 Implementing CASE tool for designers

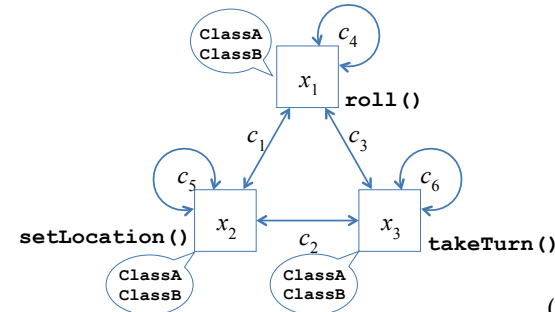
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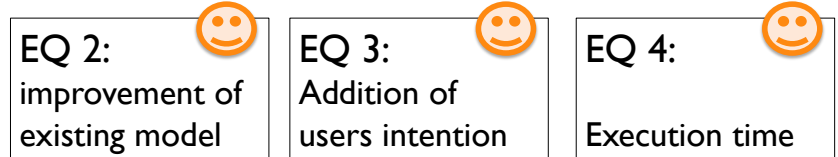
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Constraints

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Discussion



Might be feasible to develop an **interactive CASE tool** for supporting CRA

(Flexibility by formulating CRA as **fuzzy CSP**)

Credits

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