Resolving Over-constrained Conditional Temporal Problems Using Semantically Similar Alternatives

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Over-constrained situations

- Commonly encountered in temporal reasoning:
  - As humans we always ask for more than what we can do.
- Existing approaches of autonomous systems have limited supports for them:
  - Either weakening and/or suspending temporal constraints[1], or removing domain requirements completely[2].
- Human experts can often resolve such situations through weakening temporal or domain requirements.
  - *Leave your work 20 minutes early.*
  - *Go to a Korean restaurant instead of a Chinese one.*

[1] Peng Yu and Brian Williams. Continuously relaxing over-constrained conditional temporal problems through generalized conflict learning and resolution. In Proceedings of the 23th IJCAI (IJCAI-13), pages 2429– 2436, 2013.
[2] Thompson, Cynthia A., Mehmet H. Goker, and Pat Langley. A personalized system for conversational recommendations. Journal of Artificial Intelligence Research 21 (2004): 393-428.

Objective

We want a system that **works with the users**

to **resolve** over-constrained planning problems

through making **trade-offs**

between **domain** and **temporal requirements**.

Uhura - A Travel Plan Assistant

Key Contributions

- We developed the Conflict-Directed Semantic Relaxation algorithm, to compute relaxations for conflicting requirements through weakening **domain** requirements descriptions, in addition to temporal constraints.

"Delay your arrival by 5 minutes."

  - **Explore alternative destinations that were not encoded in the original problem;**

"How about a Chinese restaurant instead of a Korean restaurant?"

  - **Prioritize relaxations that are likely to be preferred by users.**

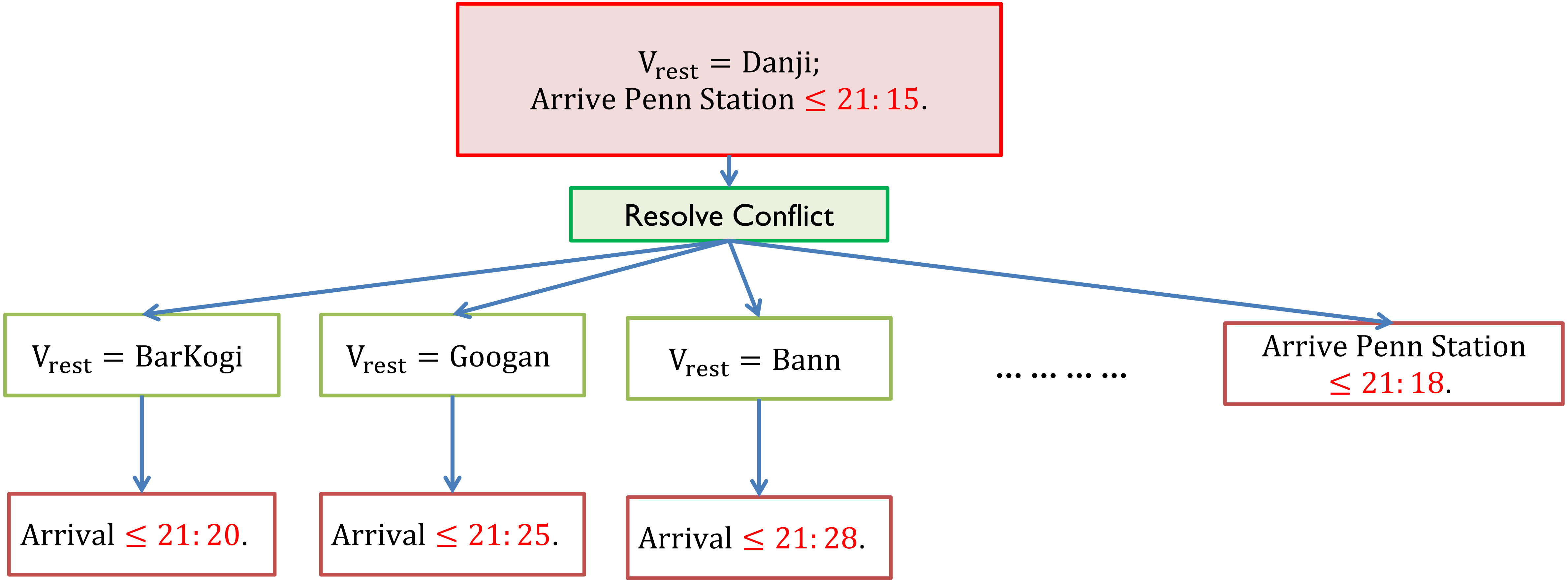
"If Korean restaurant does not work, how about Chinese? (instead of BurgerKing)"

Key Questions

- Computing domain relaxations to resolve conflicts between requirements.
- Prioritizing domain relaxations and enumerating them in best-first order.

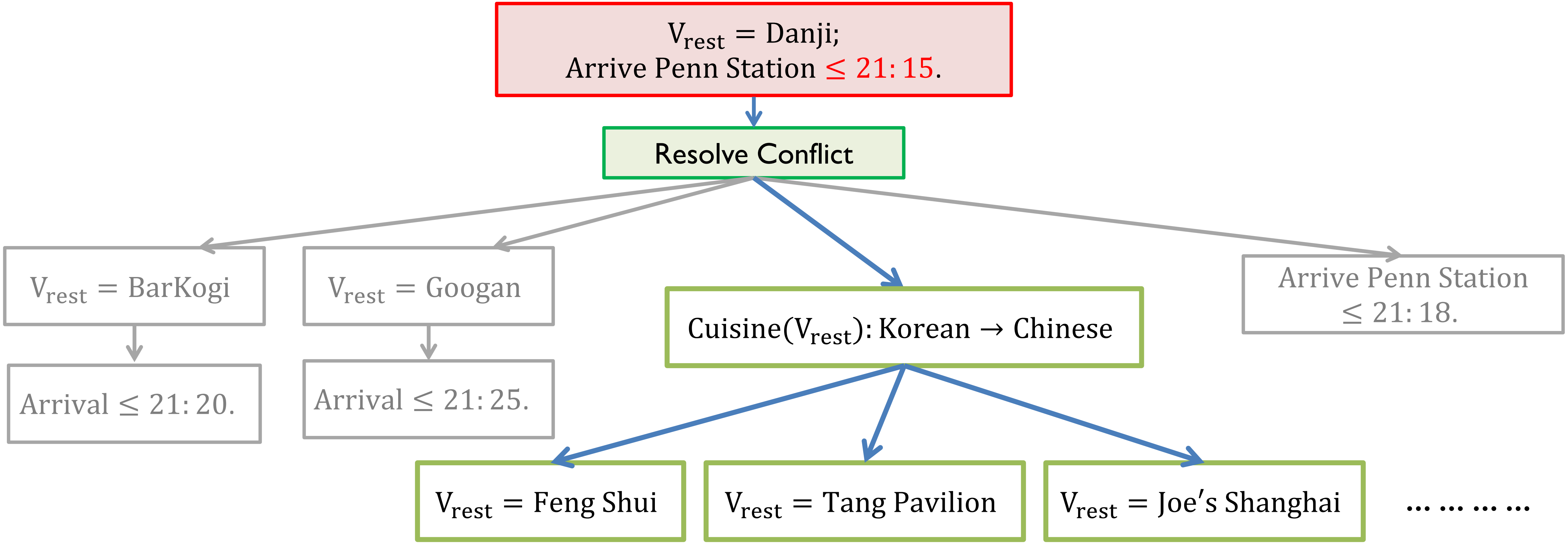
Prior Work on Temporal Relaxation

- When a conflict is discovered between constraints, previous relaxation algorithm will try to resolve it through alternative variable assignments, or continuously weakening the temporal constraints.



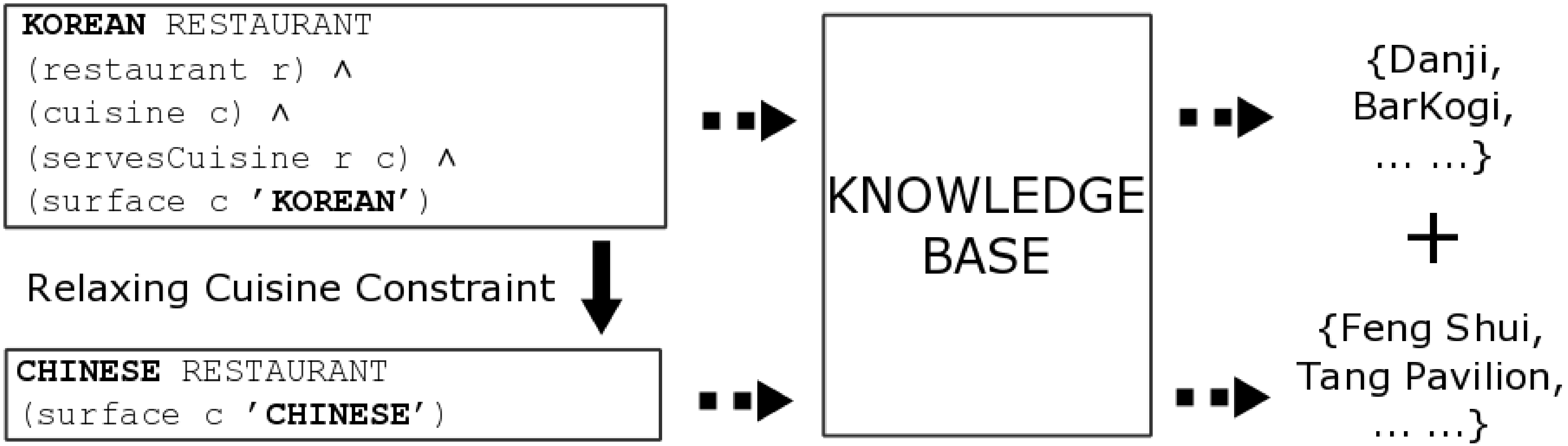
Conflict Resolution using Domain Relaxations

- In addition, we also weaken the domain descriptions, allowing more options to be considered in order to resolve the conflicts.



Retrieving Candidates for Domain Relaxations

- The domain of variables are specified by a set of semantic constraints, encoded as logical queries.
- Given a domain relaxation, we will query the knowledge base for additional domain candidates, using the weakened semantic constraints.



Similarity Measurement

- We need a measurement of the similarity between semantic constraints:
  - Supports a total ordering between alternatives.
  - Works across multiple domains.
  - Distinguishes between concepts represented by the same word: Chinese (cuisine) restaurant and Chinese (genre) movie.

- Currently, the weakening of semantic constraints are guided by a phrase similarity model[1], generated by the Word2Vec[2] package over Freebase concepts.

Cuisine KOREAN m.048vr → CHINESE m.01xw9 0.7140 → THAI m.07hxn 0.6945 → MEXICAN m.051zk 0.5169 → AMERICAN m.01z1zf2 0.3183

[1] Word2Vec: https://code.google.com/archive/p/word2vec/.
[2] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

Empirical Evaluation

- We invited 9 participants to evaluate the usefulness of CDSR, by using the travel advisor to manage their day-to-day tasks:
  - CDSR found solutions for the participants in 52 out of 54 sessions.
  - Temporal relaxation approach provided solutions in only 43 sessions.
  - The quality scores indicate that users are in general satisfied with the solution provided by CDSR.

Acknowledgements

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- The integrate trip planner tool can be accessed using this URL:

  https://uhura.csail.mit.edu

- The Amazon Echo custom skill can be downloaded using this URL:

  https://github.com/yu-peng/uhura-echo-interface

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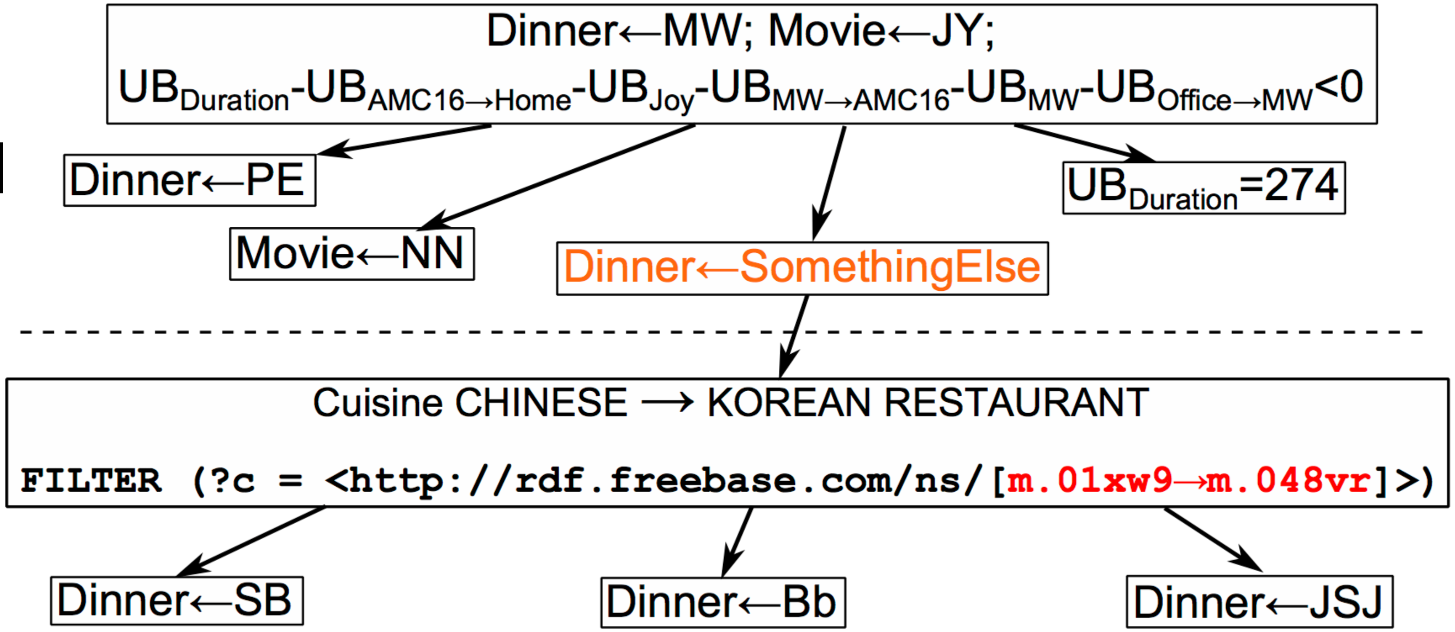
- Details on CDSR's best-first enumeration procedure with domain relaxations.
- Experiment and user study results, implementation issues and limitations.
- A deeper look into the integrated travel advisory system built on top of CDSR.

Questions

Simultaneous Enumeration of Temporal and Domain Relaxations

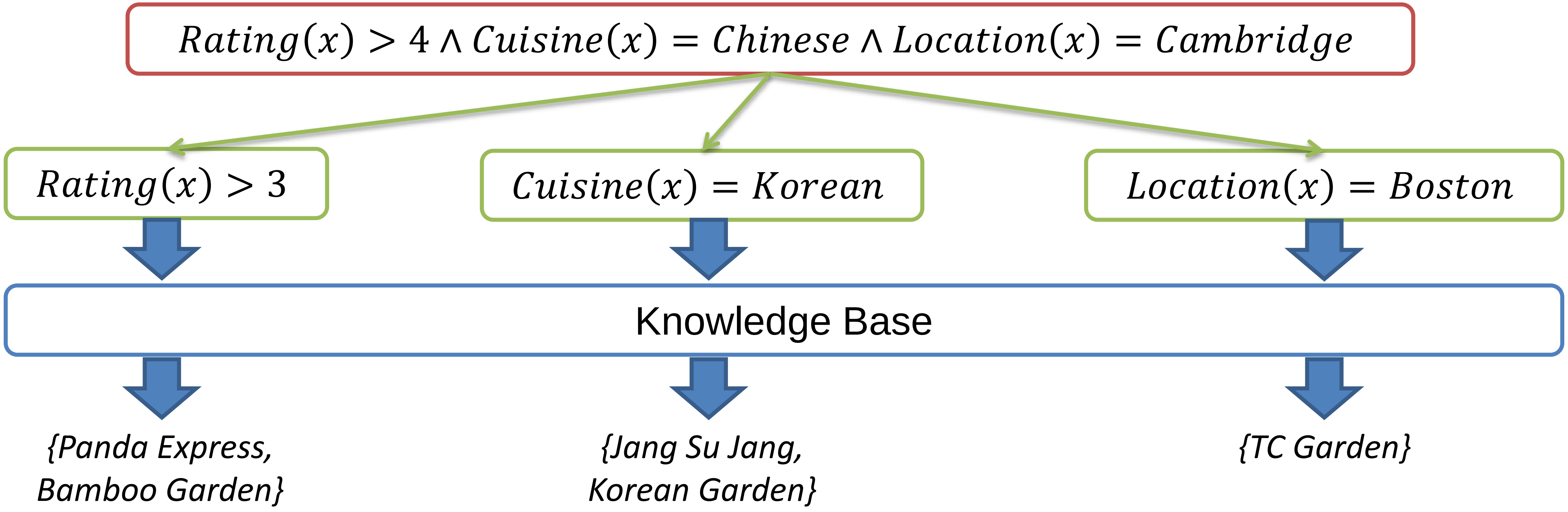
- We developed the Conflict-Directed Semantic Relaxation (CDSR) algorithm for enumerating relaxations to over-constrained temporal problems in best-first order.

- CDSR resolves conflicts by continuously relaxing temporal constraints, as well as adding additional values to the variable domains through weakening their semantic constraints.

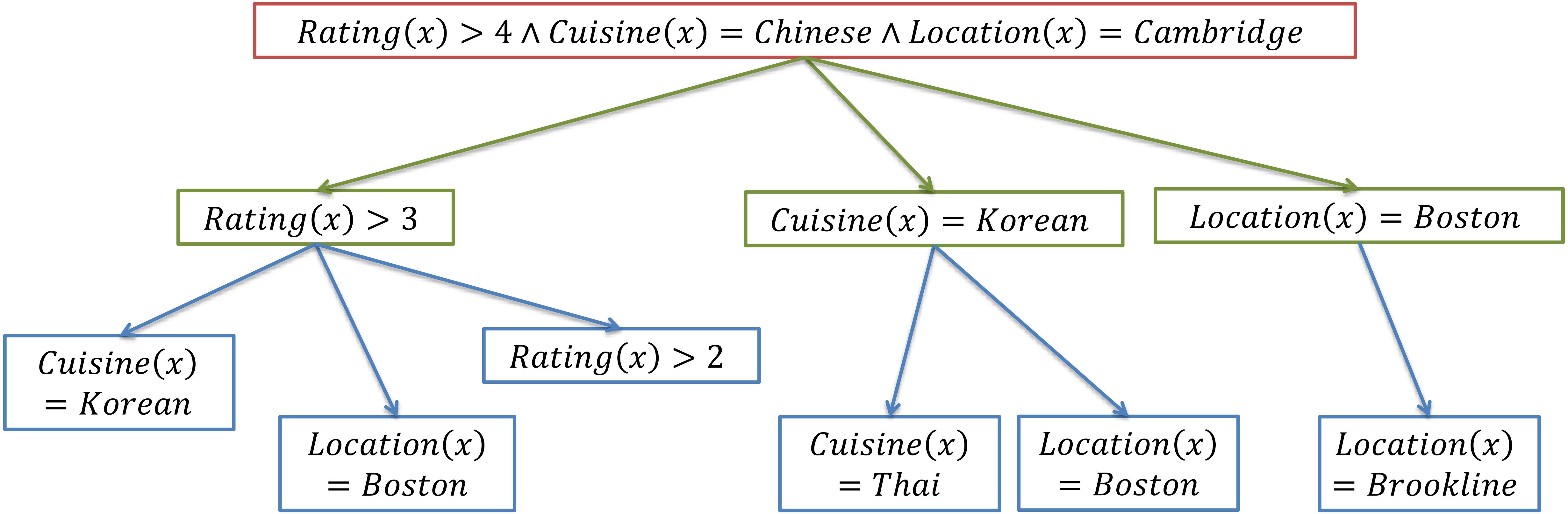


Domain Relaxations

- The domain of some variables are specified by a set of semantic constraints, encoded as SparQL queries for querying the .
- CDSR relaxes the semantic constraint and then queries the knowledge base for additional candidates.



Relaxing Multiple Domain Constraints



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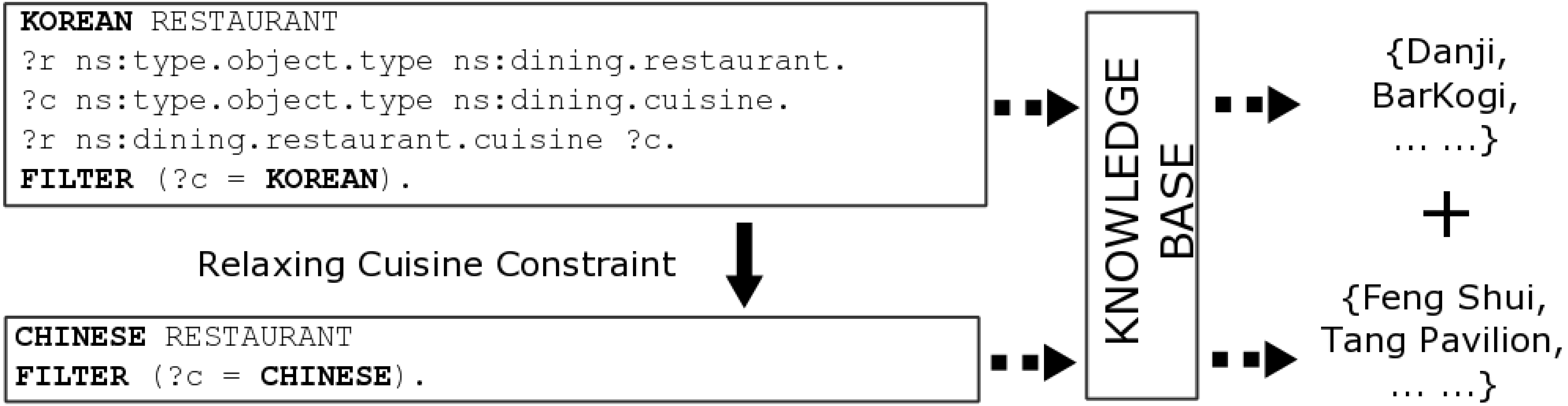

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  - The quality scores indicate that CDSR's solutions are acceptable in most scenarios, users are in general satisfied with the solution provided by the system.

Session	Quality Score	Temporal Relaxation	Domain Relaxation
1	3.3 (1.4)	2.0 (2.6)	2.1 (2.7)
2	2.4 (1.5)	1.3 (2.9)	3.0 (3.3)
3	2.7 (1.5)	2.9 (3.0)	3.1 (2.8)
4	3.7 (1.6)	0.3 (0.7)	1.7 (3.4)
5	3.2 (1.4)	1.9 (2.6)	1.7 (3.0)
6	3.3 (1.5)	0.6 (1.1)	0.0 (0.0)