Challenges for Semantic Technologies in Distributed Mobile Environments

Evan W. Patton¹ and Alexander Borgida²

Dept. of Computer Science, Rensselaer Polytechnic Institute, Troy, NY USA
 Dept. of Computer Science, Rutgers University, Piscataway, NJ USA

Abstract. We present a scenario for a mobile wine recommendation agent where semantic technologies can provide value to end users. The wine recommender uses an ontology in the $\mathcal{SHOIN}(d)$ description logic, and is extended to consider energy consumption of the device, intensional social contexts, and reasoning in a privacy-aware manner. We discuss the challenges semantic technologies, especially ones based on Description Logics, face in this scenario and formulate key issues for the mobile semantic technology community to address.

Keywords: reasoning, mobile, resource constraints, distributed, description logics

1 Introduction

Recent work has demonstrated the feasibility of reasoning on mobile phones [12,13], but resource constraints lead to poor performance of description logics (DLs). Due to space constraints, we will focus discussion on the profiles of OWL 2 (i.e., EL, QL, and RL) rather than RDF(S), and consider mostly conjunctive query answering rather than standard reasoning such as subsumption, given that many mobile applications are data/instance oriented. Specifically, we present a scenario of a mobile wine recommender system based on the $\mathcal{SHOIN}(d)$ description logic. We highlight some challenges presented when combining traditional description logics with social structures and distribution in resource constrained devices.

2 Contextual peer reasoning in a Recommender System

Consider a mobile wine agent (e.g., [7]), which is a semantic recommendation engine. The user enters a restaurant as part of a group, and the agent, running on the phone of the user, is tasked with recommending wines to go with the meal(s) chosen by the group. The agent uses its GPS together with search engines to identify the restaurant and retrieve its menu and wine list. In addition, it obtains other information about the restaurant from social media (e.g., reviews). The agent has access to a global knowledge base of foods and wines in an expressive DL (e.g., $\mathcal{SHOIN}(d)$), with recommended pairings. The agent

also has access to a personal knowledge base consisting of the likes/dislikes and past experiences of the specific user. This personal knowledge base also contains private information concerning the health status of the user, which could affect the choice of wines. Note that it is not necessary for the recommender agent to return all possible wine pairings for the desired food, or even the best one; a wine that is available locally is sufficient. Due to the use of description logics, which can describe concepts intensionally not just extensionally (i.e., by enumeration), it is possible for the agent to return an answer that describes appropriate wines, such as "a light red wine from Spain," which could be communicated to the waiter or sommelier in the absence of machine-readable wine descriptions or in case no instances on the wine list match the given class expression. Intensional information also allows the agent to be told via DLs things about the group, like the fact that they are celebrating someone's birthday (the identity of the person need not be known), or an important visitor/superior is present, in which case the user's personal preferences should be discounted. The incomplete information that can be modeled by DLs is useful, for example, if the GPS information is not sufficient to identify just one restaurant (GPS resolution is insufficient in case the restaurants are located above one another or in dense urban areas with limited access to open sky). Note therefore that recommendation is very contextual (based on both the location and the group eating together). Throughout, the system will need to balance the benefit of generating recommendations with the amount of energy used to do so.

3 Discussion

First, let us observe some of the key features of this recommender system:

- 1. The recommender need not give the best answer, nor must it give complete answers as patrons cannot try every wine/food pairing combination.
- 2. Recommendation context comes by both intensional and extensional means. For example, GPS or other geolocation techniques can extensionally describe user location. Individuals attending the meal can be described by concept expressions, e.g. $\exists hasAttendee.(clientOf.\{user1\})$.
- 3. Private data may not be transmittable due to non-technological (e.g., legal) reasons. For example, health data (e.g., allergies) used to make a recommendation cannot be transmitted under the HIPAA law in the United States. This information can only be used in a distributed inference scenario.
- 4. The agent's distributed query answering can exploit advances in both distributed/mobile databases as well as techniques from federated SPARQL. Further, using information about classes and role hierarchies, as well as least common subsumers in DL, we could gain further knowledge about which nodes are likely to have information relevant to answering a query.
- 5. Personal knowledge bases at each node evolve to be "egocentric" as the user makes their preferences known. This provides an inherent locality that can be exploited (e.g., user 2's device does not know user 1's preferences, so there is little need to query user 2's knowledge base vis-à-vis user 1).

6. Since queries can be answered in an intensional manner (i.e., by class expressions) under open world semantics, answers are not restricted to concrete instances and thus allow for more flexibility in query answering compared with closed world approaches such as mobile databases.

We now briefly discuss some challenges related to the aforementioned features and highlight some related work for the interested reader.

Challenge 1: Pervasive energy awareness. Due to significant resource requirements, mobile semantic technologies will need to be aware of available space and energy for computation and communication. Predictive models of energy use will enhance query cost estimation and planning. Intelligent migration of computation will also be useful for balancing computation with user requirements to maintain privacy or reserve sufficient energy in case of emergencies. Early work has been done by [8,11] to measure power consumed by semantic technologies but this area is still underexplored.

Challenge 2: Query, data, and knowledge migration. During query evaluation the engine may generate one or more states relevant to other nodes. [5] explores using ontology metrics to select an appropriate reasoner at runtime to minimize T-box classification time. If the cost (e.g., time, energy) of computing these states is greater than the cost to transmit, sharing them with other nodes could save resources. Another case for migration is when the device is at a point where computing a solution will require more than its available energy, but sending a portion of its T-box or A-box (e.g., sending most specific concepts [1] or summarizing [2,3]) might allow other nodes to answer sufficiently well. Energy limits and privacy constraints may be defined by the user (e.g., always ensure that I have at least 30 minutes of battery life left). [9] gives a sound algorithm for query answering in an \mathcal{EL} KB with secrecy.

Challenge 3: Query, data, and knowledge partitioning. In a highly distributed world, partitioning semantic queries so that nodes only receive portions appropriate to the local knowledge base, especially under security and privacy constraints, will be challenging. Traditional approaches have included publishing link-sets between nodes or making statistics about the underlying RDF data available as a part of a SPARQL service description [4]. However, publishing such information may expose users to data-harvesting by malicious agents. Knowledge and data may be naturally partitioned/modularized based on mobile application design, such as wine preferences for a user stored on a device versus living in the cloud. What are alternate techniques for planning semantic queries over partitioned knowledge bases and can we take advantage of the semantics with respect to the advances made by the mobile database community?

Challenge 4: Knowledge summarization and compression. Sharing knowledge in a mobile environment costs time and energy, especially if network coverage is

spotty or a high speed, low power network such as WiFi is unavailable. Minimizing the energy required to share knowledge between nodes will improve our ability to parallelize inferences and reach consensus across many nodes.

Challenge 5: Optimizing tableaux concurrency as nodes enter/exit the network. Techniques to parallelize tableaux reasoning include having different nodes classify different concepts or explore non-deterministic choices introduced by disjunction and maximum cardinality constructs in parallel.

Challenge 6: Reasoning in the face of contradictory information in a dynamic network. Paraconsistent logics provide alternatives to the traditional description logics used in the semantic web. Due to their ability to avoid deducing everything in the presence of contradictory information, they are useful for reasoning over large datasets curated by large groups (e.g., crowdsourced data about disasters [6]) starting from different base assumptions about the world. In our mobile scenarios, clearly different people may have different preferences – something that would have to be modeled in a careful manner, possible using beliefs.

Challenge 7: Resolving updates that are locally consistent but globally inconsistent. In a similar vein to challenge 6, updates consistent at a mobile node may not be globally consistent considering all nodes. While this is not specifically a challenge to mobile deployments of semantic technologies per se, one must consider the cost of performing this task from an energy perspective.

Challenge 8: Anytime/approximate reasoning for low energy. Another approach to limited energy resources is heuristics. If we can predict that an operation is going to require too much energy to compute (but not too much energy to communicate), the node could ask a peer to perform the calculation on its behalf. Approximate reasoning through less expressive DL reasoners will also increase throughput on mobile platforms when complete answers are not required.

Challenge 9: Dynamic cost functions based on context changes. Intensional descriptions of context brought by knowledge representation techniques may help reduce costs. For example, rather than having to have a user identify all of their clients, once could use class expressions to infer them. This can reduce the cost to transmit and store this information where memory and communication costs are at a premium. If we extend this further to location-based context, the savings of not enabling the GPS or WiFi to obtain user location data will improve battery duration over the course of the user's day.

Challenge 10: Data Replication/Caching. As we have already mentioned, caching is an important technique in linked data. [14] provides a model of data replication of a knowledge base using contextual information. However, such approaches often do not include a cost model with respect to the device's energy reservoir. It is possible that a sufficiently large enough cache would require so much energy to download, that not enough energy would remain to use it effectively.

Table 1. Feature summary of mobile, distributed knowledge bases and the challenges they present to reasoner designers, knowledge engineers, and application developers.

Feature	Challenges
Security & Privacy	 Preserving user privacy when performing distributed reasoning and query answering [9] Sharing generalized class expressions to hide user preferences
Query processing & planning	g
Distributed inference	\bullet Limited resources prevent "pulling all data" for inferences
Preserving/forgetting history	• Context changes may require frequent truth maintenance; how much can be deferred?
Unreliable connections	• Truth maintenance when a node leaves the network
Summarization	 Reduce T-box or A-box size for limited resources [1,2,3] Cost to summarize versus compress and transmit knowledge base elsewhere
Energy-awareness	 Different reasoning techniques result in different rates of energy consumption [8,11] Cost to transmit portions of the T-box, A-box
Concurrency	• Reuse of partial models when answering multiple queries simultaneously
Replication	 Intermediate joins to reduce redundancy [10] Semantics-driven data replication and caching [14]
Updates	• Simultaneous updates on devices may be locally consistent, but not globally consistent

4 Summary

Table 1 presents a summary of different capabilities mobile knowledge base systems might include for various application domains. We encourage the community to look at these challenges through the lens of four different resources: 1) Memory, which can be reused if free, otherwise it is limited by the amount of heap provided by the operating system; 2) Time, which can be reduced by parallelization locally (multicore) or remotely (radio); 3) Energy, which is monotonically decreasing until user connects phone to a power source; and 4) User Attention, whereby if the application is unresponsive for a period of time the user will lose interest.

This leads us to a number of open questions that may be of interest to the research community. What are techniques for efficiently migrating data to one or more nodes in the event the current node is going to run out of energy? How can we partition queries for distributed evaluation when reasoning over

private information? How can semantic descriptions be used to improve caching techniques between nodes? Can we use knowledge in addition to statistics to better partition data and query parts than has been accomplished in the mobile database community?

References

- Baader, F.: Least common subsumers and most specific concepts in a description logic with existential restrictions and terminological cycles. In: Proc. 18th IJCAI. pp. 319–324. Morgan Kaufmann Publishers Inc. (2003)
- Dolby, J., Fokoue, A., Kalyanpur, A., Kershenbaum, A., Schonberg, E., Srinivas, K., Ma, L.: Scalable semantic retrieval through summarization and refinement. In: Proc. 22nd AAAI Conf. vol. 7, pp. 299–304 (2007)
- 3. Fokoue, A., Kershenbaum, A., Ma, L., Schonberg, E., Srinivas, K.: The summary abox: Cutting ontologies down to size. In: Proc. 5th Int. Semantic Web Conf., pp. 343–356. Springer (2006)
- 4. Görlitz, O., Staab, S.: Splendid: Sparql endpoint federation exploiting void descriptions. COLD 782 (2011)
- Kang, Y.B., Krishnaswamy, S., Li, Y.F.: A meta-reasoner to rule them all. In: Proc. 23rd Int. Conf. on Information and Knowledge Management. pp. 1935–1938. ACM, New York, NY, USA (2014)
- Li, W., Adebayo, J., Shih, F., Kagal, L.: The role of mobile technologies in humanitarian relief. In: Proc. 12th Int. Conf. on Inf. Syst. for Crisis Response and Management (2015)
- 7. Patton, E.W., McGuinness, D.L.: The mobile wine agent: Pairing wine with the social semantic web. In: Proc. 2nd SDOW Workshop (2009)
- 8. Patton, E.W., McGuinness, D.L.: A power consumption benchmark for reasoners on mobile devices. In: Proc. 13th Int. Semantic Web Conf. (2014)
- 9. Tao, J., Slutzki, G., Honavar, V.: Secrecy-preserving query answering for instance checking in EL. Tech. rep., Iowa State University (2010)
- 10. Urbani, J., Kotoulas, S., Maassen, J., Van Harmelen, F., Bal, H.: Webpie: A webscale parallel inference engine using mapreduce. J. Web Semantics 10, 59–75 (2012)
- 11. Valincius, E., Nguyen, H., Pan, J.Z.: A power consumption benchmark framework for ontology reasoning on android devices. In: Proc. 4th ORE (2015)
- 12. Van Woensel, W., Haider, N.A., Ahmad, A., Abidi, S.S.R.: A cross-platform benchmark framework for mobile semantic web reasoning engines. In: Proc. 13th Int. Semantic Web Conf. pp. 389–408 (2014)
- 13. Yus, R., Bobillo, F., Bobed, C., Mena, E.: The OWL reasoner evaluation goes mobile. In: Proc. 4th ORE (2015)
- 14. Zander, S., Schandl, B.: Context-driven rdf data replication on mobile devices. Semantic Web Journal Special Issue on Real-time and Ubiquitous Social Semantics 3(2), 131–155 (2012)