RAD-NLQ: A REST API RESOURCE
DISCOVERY FRAMEWORK SUPPORTING
NATURAL LANGUAGE QUERIES

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Thesis submitted to the Office of Research and Graduate Studies in partial fulfillment of the requirements for the degree of Master of Science in Engineering

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Santiago de Chile, January 2017

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To humanity
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ABSTRACT

A great amount of functionality available on the Web is nowadays provided through Web APIs. Some of them follow the REST design guidelines, characterized by a consistent use of the HTTP methods and the identification of resources with URIs that do not include the media type, among others. REST design empowers APIs and allows them to achieve massive scalability and evolvability. This capability coupled with the introduction of a standardized semantic API description would facilitate machine-clients to discover and use REST Web API dynamically, creating customized ecosystems tailored to the user’s needs. In this thesis we present RAD-NLQ, based on the the RAD REST API description, which allows us to implement API discovery through natural language queries. We implemented and tested our approach comparing it with Google Web search engine with promising results.

Keywords: Web API, REST, Service discovery, Natural language.
RESUMEN

Gran parte de las funcionalidades disponibles en la Web es accedida por medio de APIs Web. Algunas de ellas sigue las directrices de diseño de REST que promueven un consistente uso de los métodos HTTP y la identificación de recursos con URIs que no incluyen el media type, entre otros. REST empodera a las APIs, y permite que logren gran escalabilidad y evolucionen fácilmente. Ésto, junto con la introducción de una descripción semántica de APIs Web estándar, facilitaría el descubrimiento y consumo de APIs Web REST de forma dinámica, permitiendo la creación dinámica de ecosistemas personalizados a las necesidades del usuario. En esta tesis presentamos RAD-NLQ, un framework basado en el modelo de descripción RAD que permite el descubrimiento de pares recurso-método que satisfagan consultas de usuarios expresadas en lenguaje natural. Nuestra implementación de RAD-NLQ fue probada contra el motor de búsqueda de Google arrojando resultados prometedores.

Palabras Claves: API Web, REST, Descubrimiento de Servicios, Lenguaje Natural.
1. INTRODUCTION

The Web was initially conceived as a pull-based content delivery platform. In the past decade we have witnessed a dramatic evolution of its capabilities from its ability to support dynamic content, to customization, rich interfaces, and its support of B2B applications. In the latter case, the evolution of complex traditional services with limited scalability and proprietary platforms have given place to Web APIs that fully comply Web standards and are massively scalable allowing the creation of new business ecosystems and transforming the Web into a marketplace of applications.

The main characteristic that differentiates Web APIs is its underlying architectural style. In our research we focus on the REST (Representational State Transfer) (Fielding, 2000) architectural style. It provides massive scalability, independent evolvability and extensibility, among other benefits to the Web. A REST Web API is a collection of identified resources, which are manipulated though its representations (a snapshot of the resource’s state in a moment in time) via a set of self-contained methods, such as those in the Hypertext Transfer Protocol (HTTP) (Fielding et al., 1999). Hypermedia controls (e.g. links) provided in the representations allow clients to discover related resources. REST Web APIs have experienced notorious growth in the developer community: in ProgrammableWeb\(^1\), one of the most important Web APIs repositories, most developers declare their APIs as REST-based; Google Trends\(^2\) also shows an overwhelming and increasing interest in REST Web APIs.

Nowadays, an additional revolution is pervading various technological fields by enriching technology with cognitive capabilities. This evolution have been studied in the Web community through efforts such as Semantic Web, though it was not considered in the design of REST Web APIs. One of the advantages of providing semantic support for REST Web APIs is the facilitation of APIs discovery and hence, its composition.

\(^1\)Programmable Web http://www.programmableweb.com/
\(^2\)Google Trends https://www.google.com/trends/explore?q=rest%20api,soap%20api
giving rise to the dynamic creation of new ecosystem customize to the user needs. A fundamental limitation for such case is the lack of a standardized machine-readable API description. REST Web APIs expose their resources and underling semantics in natural language documents destined to human consumption. Machine clients cannot understand such semantics, and therefore cannot determine the intended business goal achieved by executing a method on a resource. As a direct consequence, the reverse problem exists: resource discovery. A machine client cannot determine which REST APIs, resources, or methods should be executed in order to achieve a business goal. Therefore, the discovery of REST web APIs is most commonly done through manual search on large API repositories (e.g. ProgrammableWeb) through keywords, tags, or category-based searches; or simply through a Web search engine (e.g. Google, Bing, or Yahoo!) followed by manual exploration of the returned links.

In a previous publication we have presented the REST API Description (RAD) (Alarcón, Saffie, Bravo, & Cabello, 2015) and showing its capabilities to organize REST API’s methods by exploiting a semantic layer associated with the API description. In (Saffie, 2016) we exploited these characteristics to implement an automatic service composition approach. In this thesis we present RAD-NLQ, a framework based on RAD for the discovery of resource-method pair that achieve a specific business goal through natural language phrase queries. In order to validate our approach we implemented a prototype including 6 popular REST Web APIs, which outperformed the Google Web search engine in our tests.

This thesis is organized as follows: Chapter 2 presents related work on REST Web API descriptions and REST Web API discovery. Chapter 3 presents RAD, its underlying metamodel, its implementation as a JSON document, and its representation as a graph. Chapter 4 presents RAD-NLQ, our RAD-based approach for REST web API discovery through natural language, while Chapter 5 presents our prototype’s implementation, and Chapter 6 our evaluation. Finally, Chapter 7 presents our conclusions.
2. RELATED WORK

2.1. REST Web API description

A REST Web Service is a collection of resources, each resource having a unique identifier (e.g. a URI), which can be manipulated by a well defined set of methods (e.g. HTTP methods) (Fielding, 2000) and representations. A representation contains information of the resource’s state in a particular format (e.g. HTML, JSON, XML, etc.) at a particular time which can be retrieved (e.g. through an HTTP GET operation) or used to modify the resource state (e.g. an HTTP POST operation). Additionally, REST requires that its architectural components (e.g. clients, servers, caches, etc.) interact between each other through self-descriptive messages (e.g. the correct use of HTTP methods). Finally, a REST system must be hypermedia-centered, meaning that a resource’s representation must contain the necessary controls and links that allow the client to identify the available actions at any point in the client-server interaction. These four characteristics constitute REST’s Uniform Interface constraint, which characterizes the Web and as such the design of REST Web APIs. REST also facilitates service evolvability by leveraging Web standards (e.g. data formats, network protocols, etc.), and service scalability by exploiting REST architectural constraints (e.g. layers, caches, etc.).

Multiple proposals exist in order to describe REST Web APIs. The Web Application Description Language (WADL) (Hadley, 2009) is the REST equivalent of the Web Services Description Language (WSDL) (Chinnici, Moreau, Ryman, & Weerawarana, 2007). WADL describes a REST API in terms of resources, media types, schemas of the expected request and response, and representations containing parameters with links to other resources. However, it does not offer support for link discovery, ignoring the dynamic nature of REST itself. As a result, it gravitates to being operation-centric, and introduces additional complexity without yielding any clear benefits for either human or machine-clients. These descriptions are maintained independently from the service itself, also arising maintainability issues (John & Rajasree, 2013).
Other approaches include the Hypertext Application Language (HAL)\(^1\) (Kelly, 2016), a lightweight description language, implemented as a JSON document, focusing on hypermedia in order to make the API explorable, but limited only to the HTTP GET method. Google also presents an interesting proposal, the API Discovery Service\(^2\). It offers an API which serves machine-readable discovery documents for its own set of supported APIs, including information regarding resources, their JSON Schema\(^3\), methods available for each resource, and their parameters.

Semantic descriptions have been also proposed for REST services. RESTdesc\(^4\) (Verborgh et al., 2011) (Verborgh et al., 2013) represents REST API functionality in RDF, including a request’s qualified pre and postconditions. Though it is flexible, compact, and able to handle complexity, it requires previous knowledge of the resources’ URIs in order to execute more advanced queries. SA-REST\(^5\) (Lathem, Gomadam, & Sheth, 2007), and hRESTS (Kopecky, Gomadam, & Vitvar, 2008), are simpler approaches; both propose the creation of a new resource describing API resources’ URIs, methods, input, and output parameters written either as RDFa property-value pairs (Adida, Birbeck, McCarron, & Pemberton, 2008) (SA-REST), or Microformat annotations (Khare & Çelik, 2006) (hRESTS). Both approaches, SA-REST and hRESTS, support links but do not support dynamic resource discovery by following such links. ReLL (Alarcón & Wilde, 2010) is fully compliant on REST’s principles and has shown its hypermedia capability when fully crawling a REST service’s resources. However, ReLL only supports the HTTP GET method assuming only one semantic action: reading the resource’s state. Finally, Hydra (Lanthaler & Gütl, 2013) is based on JSON-LD (Sporny, Longley, Kellogg, Lanthaler, & Lindström, 2014), which adds lightweight semantics to the service’s description. Hydra models resources, operations, and hyperlinks as link templates, but its underlying RDF model adds significant complexity to the proposal.

\(^1\)HAL http://stateless.co/hal_specification.html
\(^2\)Google API Discovery Service https://developers.google.com/discovery/
\(^3\)JSON Schema http://json-schema.org/
\(^4\)RESTdesc http://restdesc.org/
\(^5\)SA-REST https://www.w3.org/Submission/SA-REST/
Industry approaches have been rapidly and steadily growing, especially among Web developers, as the need to standardize descriptions among REST Web API providers increases. Swagger⁶, among the most popular proposals in this category, has been adopted into the Open API Initiative⁷ specification. A Swagger description is a JSON or YAML document which describes an API’s resources, methods, parameters, and responses and their schemas. The RESTful API Modeling Language (RAML)⁸ is a similar proposal, where descriptions are implemented as YAML documents, providing additional support to rich data type definitions as well as URI parameters. RAML is more expressive than Swagger, but as a consequence is more complex and less intuitive. Lastly, API Blueprint⁹ uses its own Markdown-based format, and supports resources, methods, parameters, data types, and responses superficially as HTTP codes with an associated example. Though it is easy to understand, it is not intuitive to write, and can not be considered flexible or expressive. The company backing API Blueprint, Apiary¹⁰, has recently began supporting Swagger in their own services, suggesting the future suspension of support of the former. All the industry-driven approaches mentioned before have a common limitation: the lack of any type of associated semantics, limiting any kind of automated resource discovery.

2.2. Natural Language for Web service and REST API discovery

Various approaches have been proposed for the discovery of functionality available in the Web using natural language techniques, mainly for traditional SOAP/WSDL-based Web Services, in stark contrast with the lack of approaches for REST Web APIs. A SOAP/WSDL Web service exposes functionality on the Web that is described in a WSDL document (Box et al., 2000). It contains a set of endpoints (URLs), user defined methods (e.g. BuyApples), input and output parameters (e.g. Price, Quantity) as well as certain rules (e.g. security related). REST Web APIs differ in that methods are limited to the

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⁶Swagger http://swagger.io/
⁷Open API Initiative https://www.openapis.org/
⁸RAML http://raml.org/
⁹API Blueprint https://apiblueprint.org/
¹⁰Apiary https://apiary.io/
network protocol (e.g. HTTP operations) so that not out-of-band information due to am-
biguous definition -which is often the case- is required.

In order to address this ambiguity most proposals are based on Semantic Web tech-
niques, where functional aspects of service elements (e.g. operations, input and output
parameters) are associated to concepts that are part of a semantic network. These ap-
proaches tend to support schema-agnostic natural language keyword-based queries as their
input. For instance, (Lakshmi & Dhas, 2013) proposes an improved Semantic Web Service
Discovery method by combining functional and textual similarity matching, by means of
matching a keyword-based user query to semantic OWL-S (Martin et al., 2004) annota-
tions. (Sangersa, Frasincara, Hogenboom, & Chepeginb, 2013) also matches keyword-
based user queries to semantic annotations in its WSMO Web Service description. Sim-
ilarly, (Gunasri & Kanagaraj, 2014) extracts annotated keywords in the Web Service’s
OWL-S description, and groups them into clusters which are later matched, using similarity
algorithms, against a natural language keyword-based user input.

For the case of REST API designers, the main focus has been on defining resources
rather than user-defined operations. This capability combined with stateless interaction
and caches (due to the proper use of HTTP operations) provide APIs with massive scal-
ability. For REST discovery, efforts mainly come from the industry and focus on the
discovery of specific resources called root resource (API home page, API directory, API
description, API documentation, etc.) which represent a catalog of resources for a spe-
cific API. Most proposals come in the form of large Web API repositories or directories:
Mulesoft’s ProgrammableWeb\textsuperscript{11}, Mashape’s PublicAPIs\textsuperscript{12}, APIs.io\textsuperscript{13}, and APIHound\textsuperscript{14}.

\textsuperscript{11}\url{http://www.programmableweb.com/}
\textsuperscript{12}\url{https://www.publicapis.com/}
\textsuperscript{13}\url{http://apis.io/}
\textsuperscript{14}\url{http://apihound.com/}
ProgrammableWeb has the largest hand-curated API directory which can be queried by category, the API’s name, or through text to be matched against each API’s text description. This has the disadvantages of APIs having to be curated by a human, the keyword-style search not supporting natural language phrases, and the fact that search results are returned at the root resource and not the specific resources that are semantically related to the query. Since the root resource is a catalog of the API’s resources, users must manually navigate the ad-hoc documentation in order to find what they need.

Similarly, PublicAPIs is also hand-curated, and drops the category hierarchy in favor of more flexible tags, but still suffers from most of ProgrammableWeb’s issues. APIs.io indexes APIs through an Apis.json\textsuperscript{15} document, a machine readable document that API providers can use to describe their API resources through a name, a human-readable description, a set of tags, and external links which could include a Swagger description document of the API. APIs.io allows users to search their directory through the API’s name and tags, and the search response is also limited to the root resource.

APIHound constantly crawls the Web for new APIs, which they index and assign relevant categories and keywords to. The system is designed to be queried through the API’s name or keywords, and even though querying using natural language phrases is not explicitly unsupported, they are still executed as keyword-based searches, and as such, results yielded from these queries are often inconsistent and unreliable. APIHound’s contribution resides in indexing APIs by directly crawling the Web without direct intervention from the API’s developers, but as stated in their blog\textsuperscript{16} on January 5 2015, sometimes non-API related material is mistakenly also indexed. Results are also returned at the root resource, this being the main weakness of all large Web API directories, as the user must manually search the response (most commonly a documentation Web page) in order to find the resource, HTTP method, and parameters they need to achieve their intended business goal.

\textsuperscript{15}Apis.json http://apisjson.org/
\textsuperscript{16}APIHound’s Blog http://apihound.com/blog.jsp
Another way to discover APIs’ resources is through generic Web search engines such as the Google, Bing, or Yahoo! search engines, which are typically designed to support short (Spink, Jansen, Wolfram, & Saracevic, 2002) verbal and non-verbal phrases (Barr, Jones, & Regelson, 2008), allowing much needed flexibility on the end users’ queries. However, unlike previous approaches, the limitation of generic search engines resides in its search space, causing results to often be cluttered with irrelevant and non-API related material. Even though if the search space is restricted to the Web API domain, the quality of the result is directly related to the quality and granularity of the API’s description (i.e. the root resource content and its links). For example, for an API where each resource’s description has its own URL (and is indexed by it), the search engine may return the exact URL with the documentation the user is looking for; whereas if only the API’s root resource is indexed, the accuracy of the result is lost, and since such URL is returned to the user, they must keep searching for what they need in the API’s documentation resource. Thus, Web search engines response quality is highly dependent on the quality of the documentation’s webpage, and as the latter is inconsistent across the Web, so are the search engine’s results.
3. RAD

As previously mentioned, REST API descriptions are key to facilitate API discovery. In a previous work (Alarcón et al., 2015), we introduced an approach called RAD to describe REST Web APIs and allow the automatic creation of workflows (Saffie, 2016). In this chapter, we briefly summarize RAD since it is the basis of our approach. RAD is presented as a metamodel, a graph model and an implementation. The RAD metamodel (Figure 3.1) separates REST web API elements into a semantic and an activity layer.

![Figure 3.1. RAD metamodel](image)

In the semantic layer, Resource, Parameter and Action are abstract concepts in the business domain. They convey the semantics of activity layer elements, but are not bound to its implementation. The activity layer represents the REST Web API itself. Resource elements are identified by their URI, and are associated with at least one Method (e.g. GET, POST, DELETE, etc. under the HTTP protocol). Requests performed over Resources may require input Parameters (e.g. in the header, body,
or the URI). Upon the execution of the Request, a Response could be received, containing the Resource’s state in the form of a Representation, which itself could include output Parameters and a set of Hypermedia Controls (e.g. a hyperlink). Hypermedia Controls refer to a Resource-Method pair, which could potentially be executed through another Request.

### 3.1. RAD Concept Vocabulary

As discussed in the previous section, resources, parameters and methods are all individually referenced to single unambiguous concepts in the business domain. These concepts, as well as their relationships, are declared in a separate vocabulary document. This vocabulary corresponds to the semantic layer in the RAD metamodel, and could consist of a simple vocabulary or even a full-fledged ontology.

We based our vocabulary on Schema.org\(^1\), a specification backed by companies such as Google, Microsoft and Yahoo to enrich search result snippets through annotations in HTML documents. The Schema.org specification comprehends entities with their own URI, such as items, objects and actions. In this work we chose to extend the current specification by adding properties to a concept through the URI pattern `Concept/newProperty` (which has since been deprecated since May 2015), in which the new property is nested in the original concept’s URI. It is important to mention that Resource Concepts are represented in upper camelcase, while its Parameter Concepts are notated in lower camel case. We also saw the need for more specific concepts than those already present, so we added new ones to the vocabulary following the previously mentioned URI pattern, and creating relationships to link them to existing concepts.

Our vocabulary file is implemented as a JSON document. Figure 3.2 and Figure 3.3 portray snippets of such document. The required keys in this document are `name`, `version`, `baseUri`, `prefixes`, and `relationships`. Prefixes are prepended with

---

the '@' character, and are abbreviations of the vocabulary’s concepts, and as such are associated with a URI formed by concatenating the vocabulary’s baseUri and the reference value for each Resource Concept or Action Concept, as well as the Parameter Concept’s name in the case of one. RAD descriptions should reference the vocabulary’s concepts through these prefixes in order to increase the document’s maintainability. Finally, relationships between Resource Concepts, and between Parameter Concepts are specified under relationships key (Figure 3.3). Such relationships

```json
{
    "baseUri": "http://schema.org",
    "name": "RAD-Schema.org",
    "codename": "rad-schema-1.1",
    "version": "1.1",
    "created_at": "3/9/2015",
    "updated_at": "10/10/2016",
    "description": "Extension and adaptation of Schema.org's dictionary for RAD.",
    "prefixes": {
        "actions": {
            "@AchieveAction": "/AchieveAction",
            "@ActivateAction": "/ActivateAction",
            "@AddAction": "/AddAction",
            "@AssessAction": "/AssessAction",
            ...
        },
        "resources": {
            "@Place": {
                "parameters": {
                    "@placeAddress": "/address",
                    "@placeIdentifier": "/identifier",
                    "@placeDistance": "/distance",
                    ...
                },
                "reference": "/Place"
            },
        },
        "relationships": {
            ...
        }
    }
}
```
Figure 3.3. Associated Schema.org based vocabulary: relationships

are normally those of a specific concept to its generalization, or between a collection of concepts and its individual concepts. Vocabulary entities, through their relations to more general and abstract concepts, form a tree, with http://schema.org/Thing at its root.

3.2. RAD as a JSON document

This section presents an overview of the RAD metamodel implemented as a JSON document. This document’s purpose is twofold: it must not only serve as documentation, but it also must be machine readable. In Figure 3.4, fields which only serve as human-targeted documentation are presented in italics (e.g. name for human-friendly names, description for human-friendly descriptions, additional_doc for links to further documentation, and example with example values), and their presence is optional. Additionally, semantic references from Resources, Methods and Parameters to their
Figure 3.4. JSON implementation schema of RAD
corresponding concepts are done through the reference field, seen in blue in the figure. Further explanation of each portion of the JSON document will be accompanied by a snippet of an example JSON description.

Figure 3.5 presents a snippet of the document at it’s highest level, including general API information, as well as metadata regarding the description itself. Required keys at this level are baseURI, version, vocabulary and resources. baseURI refers to the invariable and common root portion of the URI preceding the resource’s unique path (Webber, Parastatidis, & Robinson, 2010), version allows for API versioning,
Figure 3.5. Spotify Web API described as RAD-JSON: API, description metadata, and resources

vocabulary specifies the unique name of the semantic vocabulary to be used across this whole document, and the resources key lists the paths to all the API’s resources.

Resources listed in resources can have their URI formed by appending the key upon which they are listed to the API’s baseURL. Semantic references to parameters in the resource’s URI template itself can be annotated directly in the path by directly including the relevant Parameter Concept’s prefix (see the /v1/users/{@userSpotifyIdentifier}/playlists resource in the example). Moving into a resource itself, two keys are mandatory: reference links the Resource in the activity layer to its corresponding Resource Concept in the semantic layer, while methods lists all available methods (e.g. GET, POST, DELETE, etc. for the HTTP protocol) available to be executed upon the resource.

Figure 3.6 explores the contents of a resource’s methods key. A method’s identifier is used as the key (see HTTP ”get” and ”post” in the example). An individual method’s required keys are reference, required_params, parameters, and responses. Once again the reference links the Method in the activity layer to its corresponding Action Concept in the semantic layer. The required_params key determines all
possible parameter combinations that could be used to execute the method through the evaluation of a logical expression (supporting AND, OR, XOR, and the use of parenthesis). Finally parameters and responses keys list all the method’s parameters and responses respectively.

Figure 3.7 explores the contents of a method’s parameters key, where all available parameters for that method are listed. Each parameter is listed by the name it must have in the request itself, and may be prepended by a symbol depending on their location in it: ’!’ for the header, and ’#’ for the body. If the parameter is present as a query parameter no symbol is prepended, while if the parameter is part of the resource’s URI template it is listed in the resource’s key and not in this section. The required keys for each parameter are: reference which references the activity layer’s Parameter to its corresponding semantic layer Parameter concept, and type which represents the parameter’s data type (e.g. ”string”, ”integer”, ”boolean”, ”array”, etc.). A parameter’s value could also have restrictions: enum indicates the list of values the parameter can take, default states the value the parameter will take if it is not included in the request, and maximum and minimum respectively limit the maximum and minimum values a number-based data type parameter is allowed to have.
Figure 3.7. Spotify Web API with RAD in JSON: parameters

Lastly, Figure 3.8 explores the contents of a method’s responses key, where all possible responses for that method are listed. Each response is listed by a unique ID, which in the case of the HTTP protocol would be its response code. The required keys in this case are headers and body, both of which are arrays containing expectations of the response header and body respectively. The body itself requires three keys: reference links a resource’s representation in the activity layer to a corresponding Resource Concept in the semantic layer, media specifies the response’s media type (currently limited to application/json), and type states the data type of the information in the response’s body. Accepted values for type are those defined by JSON Schema (i.e. string,
Figure 3.8. Spotify Web API with RAD in JSON: responses

integer, number, object, array, boolean, null), as well as hyperlink. The hyperlink value requires an additional target key to indicate the URI of a referenced resource in the response (Hypermedia Control).

3.3. RAD as a graph

RAD elements and their relationships are modeled as a single graph, presented in Figure 3.9, which mimics the metamodel previously shown in Figure 3.1. Nodes and edges stemming from the RAD Concept Vocabulary, form part of the metamodel’s Semantic Layer, while all other graph elements stem from each service’s descriptions, therefore belonging to the metamodel’s Activity Layer.
Figure 3.9. RAD graph model
4. RAD-NLQ: NATURAL LANGUAGE REST RESOURCE DISCOVERY

4.1. RAD-based Service Discovery

As previously stated, the semantic layer presented in the RAD metamodel could consist of a vocabulary, or even a full-fledged ontology. It is individually tied with the activity layer through its resource, parameters, and the underlying method in the request. In practice, this means that each Resource refers to a semantic Resource Concept, each Parameter refers to a Parameter Concept, and each Method to an Action Concept.

Given that resources, parameters, and methods are semantically annotated, a machine can now make sense of the underlying business goal in a method executed over a resource. For example, let’s consider the case of an API which allows users to rent apartments with a resource /apartments/4 accepting HTTP POST requests. Not much information can be extracted from this description, as the resource representing an apartment may not necessarily has a self descriptive name, and a POST method could mean anything, including buying, building, or renting the apartment. In a RAD description, the resource would be referencing the https://schema.org/Apartment concept, and the POST method would reference the https://schema.org/RentAction concept. Since both concepts are unambiguously described in the Schema documentation, it is clear that by executing a POST HTTP method over the /apartments/4 resource will allow us to rent such apartment.

Now that we know the business goal associated to a method-resource pair (hypermedia control), we may solve the reverse problem: to discover the resources and methods that allow us to achieve a specific business goal. We understand a business goal as an Action concept that has an effect on a Resource concept and is grounded through a set of instances of method, resource, and parameter concepts, optionally restricted on how the execution of the resulting request takes place.
With a resource concept (e.g. http://schema.org/MusicGroup), an action concept (e.g. http://schema.org/FindAction/), and optionally one or more parameter concepts (e.g. http://schema.org/MusicGroup/name/) we can query the RAD graph. For instance, we can search for all the resources referencing a given concept, that are affected by a given action, and optionally require the presence of certain parameter concepts. This query will return all the resources with the corresponding methods that would allow us to achieve our business goal. For example, to find out a music group by its name we shall search for methods described by a http://schema.org/FindAction/ concept associated to resources described by a http://schema.org/MusicGroup concept that accept parameters described by a http://schema.org/MusicGroup/name/ concept. Even though such search query can be executed on the RAD graph, its expression is cumbersome: the user must know in advance the syntax of the concept URLs, its meaning and the whole set of available concepts which requires out-of-band information (i.e. description documents, manuals, examples, etc.).

4.2. Supporting Natural Language Queries: RAD-NLQ

In this section we introduce RAD-NLQ, a framework allowing users to query the RAD graph through natural language queries. Such queries allow users to discover the resources and methods which achieve the business goal stated in the query. Two challenges that arise from this approach need to be solved: the extraction of relevant query concepts, and the matching of those query concepts with the appropriate concepts in the RAD vocabulary.

Based on the analysis of typical grammatical forms of user queries presented in (Barr et al., 2008) (see excerpt in Table 4.1), we designed and implemented an algorithm to extract concepts from a natural language search phrase (see Algorithm 1). Once a noun is found, all adjectives directly preceding it and the nouns directly following it are extracted and are considered as a Resource concept. Meanwhile, all verbs, and particles directly following them, are extracted and considered as an Action concept. Finally, if a preposition
Algorithm 1 Pseudo-code of the concept extraction algorithm

**Input:** tagged_words (an ordered list of the query’s words and their tags)

**Output:** The query’s extracted concepts, categorized by type

1. `concepts ←` An object containing three arrays that store resource concepts, action concepts, and parameter concepts
2. `tagged_words ←` tagged_words without apostrophes
3. `i ← 0`
4. **while** `i < length of tagged_words` **do**
5.   `tagged_word ←` tagged_words[i]
6.   **if** `tagged_word.tag` is a noun **then**
7.     `concept ←` tagged_word.word
8.     `k ← i − 1`
9.     **while** `k ≥ 0` **do**
10.    `k_tagged_word ←` tagged_words[k]
11.    **if** `k_tagged_word.tag` is not an adjective **then**
12.       break
13.    **end if**
14.    `concept ←` k_tagged_word.word + ” ” + concept
15.    `k ← k − 1`
16.    **end while**
17.    `k ← i + 1`
18.    **while** `k < length of tagged_words` **do**
19.      `k_tagged_word ←` tagged_words[k]
20.      **if** `k_tagged_word.tag` is not a noun nor an adjective **then**
21.        break
22.      **end if**
23.      `concept ←` concept + ” ” + k_tagged_word.word
24.      `i ←` k
25.      `k ← k + 1`
26.    **end while**
27.    `concepts.resources.add(concept)`
28. **else if** `tagged_word.tag` is a verb **then**
29.     `concept ←` tagged_word.word
30.     `k ← i + 1`
31. **while** `k < length of tagged_words` **do**
32.      `k_tagged_word ←` tagged_words[k]
33.      **if** `k_tagged_word.tag` is not a particle **then**
34.        break
35.      **end if**
36. **end if**
Algorithm 1 Pseudo-code of the concept extraction algorithm (continued)

36: \( \text{concept} \leftarrow \text{concept} + " " + \text{k\_tagged\_word.word} \)
37: \( i \leftarrow k \)
38: \( k \leftarrow k + 1 \)
39: \( \text{end while} \)
40: \( \text{concepts.resources.add(\text{concept})} \)
41: \( \text{else if tagged\_word.tag is a preposition, } i \geq 0, \text{ and tagged\_words}[i - 1].\text{tag} \) \( \text{is not a verb} \)
42: \( \text{concept} \leftarrow \text{null} \)
43: \( k \leftarrow i + 1 \)
44: \( \text{while } k < \text{length of tagged\_words do} \)
45: \( \text{k\_tagged\_word} \leftarrow \text{tagged\_words}[k] \)
46: \( \text{if } \text{k\_tagged\_word.tag} \text{ is a noun or an adjective then} \)
47: \( \text{if } \text{concept} \text{ is null then} \)
48: \( \text{concept} \leftarrow \text{k\_tagged\_word.word} \)
49: \( \text{else} \)
50: \( \text{concept} \leftarrow \text{concept} + " " + \text{k\_tagged\_word.word} \)
51: \( \text{end if} \)
52: \( \text{else} \)
53: \( \text{if } \text{concept} \text{ is not null then} \)
54: \( \text{concepts.parameters.add(\text{concept})} \)
55: \( \text{end if} \)
56: \( \text{concept} \leftarrow \text{null} \)
57: \( \text{end if} \)
58: \( i \leftarrow k \)
59: \( k \leftarrow k + 1 \)
60: \( \text{if } k = \text{length of tagged\_words, and concept is not null then} \)
61: \( \text{concepts.parameters.add(\text{concept})} \)
62: \( \text{end if} \)
63: \( \text{end while} \)
64: \( \text{end if} \)
65: \( i \leftarrow i + 1 \)
66: \( \text{end while} \)
67: \( \text{if length of concepts.actions} = 0 \text{ then} \)
68: \( \text{concepts.actions.add(" get"}) \)
69: \( \text{end if} \)
70: \( \text{return concepts} \)

is detected, all nouns and adjectives following the same grammatical rules as those used to extract Resource concepts are extracted as Parameter concepts. If at the end of the
execution no action concept is extracted, the default \texttt{http://schema.org/GetAction/}
(i.e. equivalent to HTTP GET) action concept is assumed.

Table 4.1. Typical grammatical structure of queries used by Web searchers
with a distribution based on a sample of 222 hand-labeled queries (Excerpt)

<table>
<thead>
<tr>
<th>Grammatical Type</th>
<th>Example</th>
<th>Freq %</th>
</tr>
</thead>
<tbody>
<tr>
<td>noun-phrase</td>
<td>free mp3s</td>
<td>69.8%</td>
</tr>
<tr>
<td>URI</td>
<td><a href="http://answers.yahoo.com/">http://answers.yahoo.com/</a></td>
<td>10.8%</td>
</tr>
<tr>
<td>word salad</td>
<td>mp3s free</td>
<td>8.1%</td>
</tr>
<tr>
<td>other-query</td>
<td>florida elementary reading conference2006-2007</td>
<td>6.8%</td>
</tr>
<tr>
<td>unknown</td>
<td>nama-nama calon praja ipdn</td>
<td>2.7%</td>
</tr>
<tr>
<td>verb-phrase</td>
<td>download free mp3s</td>
<td>1.4%</td>
</tr>
<tr>
<td>question</td>
<td>where can I download free mp3s</td>
<td>0.45%</td>
</tr>
</tbody>
</table>

RAD-NLQ inputs are verb phrases, that is, for the case of \textit{question-type} queries, our
algorithm will remove the question portion and will treat the query as a verb phrase. Noun
phrases will be treated the same way as verb phrases, as if no action concept is found a
default "get" action concept is assumed afterwards. Therefore, our approach supports a
71.65% of the query structures (see section 4.2 for a detailed explanation) used on Web
search engines. Other grammatical types are not supported since they are not appropriate
for API searches (i.e. "URI" and "unknown"), or the grammatical structure of the query
does not provide information regarding the expectations of the user (i.e. "word salad").

Once all relevant concepts have been extracted, a suitable match in the vocabulary
must be made for each one of them. Algorithm 2 presents our approach for implementing
such match. Each extracted \textit{query concept} is matched against relevant concepts in the
vocabulary and a similarity score is calculated; those scores that pass a minimum threshold
are selected as suitable candidates to be matched with. Once all suitable candidates are
selected (resource concepts, action concepts, and optionally parameter concepts), they are
permuted. Each permutation is assigned a score, consisting on the aggregated score of each
of its candidate concepts. Once again, those scores that pass a threshold are considered as
the closest to the business goal stated in the initial query.
Algorithm 2 Pseudo-code of the concept permutation matching algorithm

Input: query, vocabulary
Output: permutations

1: q_resource_concept ← The resource concept in the query
2: q_action_concept ← The action concept in the query
3: q_parameter_concept ← The resource concept in the query if any, else null
4: v_resource_concepts ← All resource concepts in the vocabulary
5: v_action_concepts ← All action concepts in the vocabulary
6: v_parameter_concepts ← null
7: if q_parameter_concept is not null then
8:     v_parameter_concepts ← All parameter concepts in the vocabulary
9: end if
10: candidate_resource_concepts ← []
11: candidate_action_concepts ← []
12: candidate_parameter_concepts ← []
13: for each rc_candidate in v_resource_concepts do
14:     rc_candidate.score ← concept similarity score between q_resource_concept and rc_candidate
15:     if rc_candidate.score ≥ resource concept score threshold then
16:         candidate_resource_concepts.add(rc_candidate)
17: end if
18: end for
19: for each ac_candidate in v_action_concepts do
20:     ac_candidate.score ← concept similarity score between q_action_concept and ac_candidate
21:     if ac_candidate.score ≥ action concept score threshold then
22:         candidate_action_concepts.add(ac_candidate)
23: end if
24: end for
25: if q_parameter_concept is not null then
26:     for each pc_candidate in v_parameter_concepts do
27:         pc_candidate.score ← concept similarity score between q_parameter_concept and pc_candidate
28:         if pc_candidate.score ≥ parameter concept score threshold then
29:             candidate_parameter_concepts.add(pc_candidate)
30:         end if
31:     end for
32: end if
Algorithm 2 Pseudo-code of the concept permutation matching algorithm (continued)

33: permutations ← List of permutations of candidate_resource_concepts, candidate_action_concepts, and candidate_parameter_concepts (if any)
34: for each permutation in permutations do
35:   permutation_score ← multiplication of scores for all two or three (with parameter concept) concepts
36:   if permutation_score < concept permutation score threshold then
37:     delete permutation from permutations
38:   end if
39: end for
40: return permutations
5. IMPLEMENTATION

5.1. RAD-QL: an API to query the RAD graph

In order to offer a simple interface to query the RAD graph we created RAD-QL as a query language-like API which enables the traversal of the RAD graph. RAD-QL can currently answer 10 different types of queries, such as obtaining all necessary elements to execute a successful REST API call, obtaining the most similar concepts in the Semantic Layer to a given input, and obtaining all Operation nodes directly related to a given Resource Concept and Action pair.

5.2. System overview

Our implementation architecture is presented in Figure 5.1. We store the RAD graph instance in a Neo4J 3.0\(^1\) graph database. The database is accessed solely by rad-core, a module written in Python 3\(^2\) which provides an API to query the RAD graph. Two modules, also written in Python3, populate the graph: vocabulary-parser parses our vocabulary JSON document and adds the Semantic Layer to the graph; while json-description-parser processes each RAD JSON document and adds the service to the graph, creating the respective Activity Layer nodes in the graph, and linking them to the Semantic Layer.

The query-engine module is the only access point for end users to query the graph, and as such it is the main module concerning this thesis. It (1) suggests RAD-QL queries based on input parameters, (2) processes and answers RAD-QL queries, and most importantly (3) can suggest RAD-QL queries based on natural language queries. This module was developed using Python3, using the Natural Language Toolkit’s (NLTK)

\(^1\)Neo4J https://neo4j.com/
\(^2\)Python 3.x documentation https://docs.python.org/3/
PorterStemmer\textsuperscript{4}, as well as the standard Part-Of-Speech tagger \texttt{pos.tag} and tokenizer \texttt{word_tokenize} functions to process the input phrase. Once the input phrase has been analyzed, and the key concepts and actions have been extracted, each of them is compared to existing concepts in the RAD graph’s semantic layer using the UMBC Semantic Similarity service\textsuperscript{5} (Han, Kashyap, Finin, Mayfield, & Weese, 2013). Finally, entities are found and replaced using the Dandelion API\textsuperscript{6}.

Finally, the web-app module is a Web application available at http://rad.ing.puc.cl/demo/query, and screenshots can be seen in Figure 5.2 and Figure 5.3. This application allows users to consume all three functionality provided by the query-engine. Depending on the query, the user will receive an interactable response in the form of: (1) a suggested RAD-QL query to execute, (2) a subgraph of the RAD graph which can be

\begin{figure}
\centering
\includegraphics[width=\textwidth]{uml_component_diagram.png}
\caption{RAD-NLQ System UML Component Diagram}
\end{figure}

\textsuperscript{3}Natural Language Toolkit (NLTK) http://www.nltk.org/
\textsuperscript{4}Porter Stemmer https://tartarus.org/martin/PorterStemmer/
\textsuperscript{5}UMBC Semantic Similarity service http://swoogle.umbc.edu/SimService/index.html
\textsuperscript{6}Dandelion API https://dandelion.eu/
traversed, or (3) a link. For further explanation and screenshots of this module see Appendix A. This module was developed with the Express\textsuperscript{7} framework over Node.js\textsuperscript{8} and AngularJS\textsuperscript{9}, and graphs are rendered using vis.js\textsuperscript{10}. 

\textsuperscript{7}Express http://expressjs.com/
\textsuperscript{8}Node.js https://nodejs.org/en/
\textsuperscript{9}AngularJS https://nodejs.org/en/
\textsuperscript{10}Vis.js http://visjs.org/
Figure 5.3. Screenshot of the RAD-NLQ interface in the Web application: query graph response
6. EVALUATION

6.1. Vocabulary and API Dataset

In order to evaluate our proposal we chose to use real, industry-standard Web APIs. Selected APIs had to adhere to REST’s constraints as much as possible, provide a comprehensive documentation website, and their business domain should be somewhat related. Due to the nature of the Web APIs we found, we were forced to relax our criteria regarding some of REST’s constraints. A total of six Web APIs were selected:

(i) **Foursquare**\(^1\): Provides *read* and *creation* methods to it’s directory of *venues* and their *events* resources, as well as a user’s private *profile* and *lists*.

(ii) **Google Travel Partner**\(^2\): Only two out of ten resources were included in our example: (1) the *Hotels API 2.0*\(^3\) provides programmatic access to a user’s *hotel list* feed, and (2) the *Prices API 2.0*\(^4\) allows users to query *pricing* and *itinerary* data for a given hotel.

(iii) **Songkick**\(^5\): Provides access to its live *music* database, including *past* and *upcoming concerts*, *artist search and suggestion*, and *concert setlists*.

(iv) **Spotify**\(^6\): Provides access to its *music* streaming service’s catalog, including *artists*, *albums*, *playlists*, and *tracks*.

(v) **Taxi Fare Finder**\(^7\): Allows a user to get an *fare estimate* for a given taxi ride, retrieves a list of *registered taxi companies* in a given city, and searches for supported *cities*.

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\(^1\)Foursquare API https://developer.foursquare.com/docs/
\(^2\)Google Travel Partner’s API https://developers.google.com/hotels/hotel-ads/api-reference/
\(^3\)Google Travel Partner’s Hotel API https://developers.google.com/hotels/hotel-ads/api-reference/hotels-api-v2
\(^4\)Google Travel Partner’s Prices API https://developers.google.com/hotels/hotel-ads/api-reference/prices-api-v2
\(^5\)Songkick API http://www.songkick.com/developer
\(^7\)Taxi Fare Finder API https://www.taxifarefinder.com/api.php
(vi) **Uber**

Allows users to obtain information and estimates of Uber rides as well as cancel requested Uber rides. It also provides access to a user’s profile and history, as well as the ability to retrieve all available products for a user.

These Web APIs were described by a RAD JSON document as described in section 3.2 and then parsed into the RAD graph presented in section 3.3. Table 6.1 presents a general overview of the resulting graph. Table 6.2 details the vocabulary subgraph composition, and Table 6.3 details the activity layer nodes by API. Finally, Table 6.4 details the use of distinct semantic layer concepts across all APIs.

**Table 6.1. Nodes and edges in the graph database**

<table>
<thead>
<tr>
<th>Concepts</th>
<th>Nodes</th>
<th>Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocabulary</td>
<td>405</td>
<td>463</td>
</tr>
<tr>
<td>Foursquare</td>
<td>612</td>
<td>1174</td>
</tr>
<tr>
<td>Google Travel Partner</td>
<td>29</td>
<td>50</td>
</tr>
<tr>
<td>Songkick</td>
<td>318</td>
<td>579</td>
</tr>
<tr>
<td>Spotify</td>
<td>611</td>
<td>1189</td>
</tr>
<tr>
<td>Taxi Fare Finder</td>
<td>47</td>
<td>82</td>
</tr>
<tr>
<td>Uber</td>
<td>175</td>
<td>304</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>2197</td>
<td>3841</td>
</tr>
</tbody>
</table>

**Table 6.2. Vocabulary subgraph composition**

<table>
<thead>
<tr>
<th>Concept Type</th>
<th>Distinct Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resource Concepts</td>
<td>106</td>
</tr>
<tr>
<td>Actions</td>
<td>11</td>
</tr>
<tr>
<td>Parameter Concepts</td>
<td>299</td>
</tr>
</tbody>
</table>

### 6.2. Input Query Dataset

We consider a use case to be a combination of one **Resource** Concept, one **Action** Concept, and optionally one **Parameter** Concept, with a clear underlining business goal. In

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8Uber API [https://developer.uber.com/docs/riders/references/api](https://developer.uber.com/docs/riders/references/api)
order to create a testbed we defined the vocabulary of concepts from the APIs documentation. That is, we retrieved all documentation websites for each RAD-indexed resource and each API, and extracted relevant keywords to act as Resource Concepts, Action Concepts, and Parameter Concepts. A total of 42 unique use cases were formed though this process.

In order to eliminate bias in the grammatical construction of the input search query phrases used in our evaluation, we automatically generated such phrases. In subsection 4.2 we analyze how and why our concept extraction algorithm supports a 71.65% of user query’s grammatical compositions across web search engine users through the direct support of only one of them: verb phrases. Therefore, we created the SimplePhraseTransform tool for generating phrases based on simplified grammatical rules constructed out of part-of-speech tags used in the Penn Treebank Project. Our input set consists of a total of 128

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9SimplePhraseTransform’s Source Code https://github.com/rad-lab/simple-phrase-transform

10Penn Treebank Project https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html
queries generated out of the original 42 use cases, and its composition can be viewed in Table 6.5.

<table>
<thead>
<tr>
<th>Query Type</th>
<th>Example</th>
<th>Freq %</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC + A</td>
<td>search for venues</td>
<td>73.44%</td>
</tr>
<tr>
<td>RC + A + PC</td>
<td>search for venues by their name</td>
<td>19.53%</td>
</tr>
<tr>
<td>E + A</td>
<td>get U2’s upcoming events</td>
<td>7.03%</td>
</tr>
</tbody>
</table>

6.3. Evaluation Criteria

We evaluated our model through the direct comparison of our system versus the Google search engine using as input the same automatically generated natural language phrase-queries, since all other API repositories search engines listed in section 2.2 do not support this kind of search queries. For a proper comparison, we used a similar rating criteria for the search results of both systems (our approach and the Google search engine). We also restricted the Google search domain to the API’s documentation through the use of the ‘site:’ command in order to eliminate results from sources not in the dataset. Equation 6.1 defines our ranking score based on the position of the item in the response (the higher the rank, the lower the value). Equation 6.2 defines a correctness score based on the content of the response: we consider that a partial answer for a query only includes some of the expected items in the response, while a tangential answer satisfies the query goal through the execution of an indirectly related action and resource (e.g. obtaining a price estimate for the taxi by canceling the request itself).

\[
\text{ranking_score} \left( \text{ranked\_position} \right) = \begin{cases} 
1.1 - 0.1 \times \text{ranked\_position} & \text{if } 1 \leq \text{ranked\_position} \leq 10 \\
0 & \text{else}
\end{cases}
\] (6.1)
correctness_score(content) =

\[
\begin{align*}
1 & \quad \text{if the response content directly answers the query} \\
0.8 & \quad \text{if the response content partially answers the query} \\
0.5 & \quad \text{if the response content tangentially answers the query} \\
0.2 & \quad \text{if the response content has a link to the query’s answer} \\
0 & \quad \text{if the response content does not answer the query}
\end{align*}
\]  

We also consider the concept_extraction_score (Equation 6.3) which is applied only to the RAD-NLQ system. This score measures the ability of the system to use all possible concepts present in the input to form a RAD-QL query. We also define the hit_score (Equation 6.4) which is applied only to the Google search engine results. This score measures the content of each link according to the number of relevant elements in the target Web page (e.g. a single URL documenting all the APIs resources will score lower than a URL that targets a specific resource directly related to the answer).

\[
\text{concept\_extraction\_score(used\_concepts, total\_concepts)} = \frac{\text{used\_concepts}}{\text{total\_concepts}}
\]  

\[
\text{hit\_score(number\_of\_elements)} = \frac{1}{\text{number\_of\_elements}}
\]  

Finally, we defined the performance scores for RAD-NLQ (Equation 6.5) and the Google search engine (Equation 6.6). These scores will be directly compared in the next section (higher is better).
\[ rad_{nlq\_score}(responses) = \sum_{r \in responses} \left( \text{ranking}_{score}(\text{ranked\_position}_r) \right. \]
\[ \times \text{correctness}_{score}(\text{content}_r) \]
\[ \left. \times \text{concept\_extraction}_{score} (\text{used\_concepts}_r, \text{total\_concepts}_r) \right) \]  
(6.5)

\[ google_{score}(responses) = \sum_{r \in responses} \left( \text{ranking}_{score}(\text{ranked\_position}_r) \right. \]
\[ \times \text{correctness}_{score}(\text{content}_r) \]
\[ \times \text{hit}_{score}(\text{number\_of\_elements}_r) \]  
(6.6)

6.4. Results

An overview of the results of our evaluation are presented in Table 6.6, and a histogram of the result’s scores can be observed in Figure 6.1. At a first glance we see that queries including entities instead of concepts are all successfully resolved by RAD-NLQ, while the Google search engine is unable to correctly answer these queries. Additionally, queries which have a parameter as a restriction are much more reliably answered by RAD-NLQ.

Further inspection on queries where RAD-NLQ was outperformed by Google reveals some limitations of our system. On 7 queries (25.92%) RAD-NLQ performed correctly, averaging a respectable score of 0.65; Google, on the other hand, did not only offer the required link in one of its top ranks, but also delivered a link to the APIs documentation homepage which included a link to the resource documentation. Thus, it obtained a higher score though it did not provide new information but redundant information. Another 9 failed queries (33.33%) are related to use cases solely involving complex resources without a unique concept representing them, but rather a collection of parameter concepts. Such

<table>
<thead>
<tr>
<th>Query Type</th>
<th>RAD-NLQ</th>
<th>Draws</th>
<th>Google</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC + A</td>
<td>67 (52.34%)</td>
<td>4 (3.13%)</td>
<td>23 (17.97%)</td>
<td>94 (73.44%)</td>
</tr>
<tr>
<td>RC + A + PC</td>
<td>20 (15.63%)</td>
<td>1 (0.78%)</td>
<td>4 (3.13%)</td>
<td>25 (19.53%)</td>
</tr>
<tr>
<td>E + A</td>
<td>9 (7.03%)</td>
<td>0 (0.00%)</td>
<td>0 (0.00%)</td>
<td>9 (7.03%)</td>
</tr>
<tr>
<td>Total</td>
<td>96 (75.00%)</td>
<td>5 (3.91%)</td>
<td>27 (21.09%)</td>
<td>128 (100%)</td>
</tr>
</tbody>
</table>

is the case of Google Travel Partner’s Price\textsuperscript{11} resource which offers a given hotel’s pricing and itinerary data, as well as Foursquare’s Venue Hours\textsuperscript{12} resource which offers exclusively a given venue’s opening and popular hours. In both cases there is no clear underlying concept for them, and as such, our concept matching performs poorly. In all other 11 failed cases (40.74%), the problem can be traced to correctly extracted concepts failing to match concepts in our vocabulary.

\textsuperscript{11}Google Travel Partner’s Prices API https://developers.google.com/hotels/hotel-ads/api-reference/prices-api-v2

\textsuperscript{12}Foursquare API’s Venue Hours resource https://developer.foursquare.com/docs/venues/hours
Figure 6.1. Result’s score histogram for RAD-NLQ and the Google Web Search Engine
7. CONCLUSIONS

In this thesis we offer further validation of the RAD description metamodel for REST APIs, which is capable of representing well-known real Web APIs. RAD is able to successfully support most common practices in Web API design, including a lightweight model of resources, methods, required parameters and their data type and location in the request (i.e. URL, header, or body), and all responses as well as their parameters.

This thesis also offers further validation of the metagraph derived from the metamodel. The metagraph allows for the discovery of services at a resource-method pair level in order to achieve a given business goal. This metagraph also allows flexibility on its implementation: we have shown in this thesis the use of a graph database and the Schema.org dictionary as our semantic layer, but any other graph-based approach is supported, including a full-fledged RDF-based ontology as the semantic layer.

Most importantly, this thesis is proof that the RAD metamodel and metagraph allow for the discovery of services at a resource-method pair level through Web search engine-like natural language phrase queries. We have presented a framework able to support natural language beyond industry-standard keywords, but rather phrases, which successfully outperforms Google’s Web search engine in most Web API discovery use cases.

An important advantage of our proposal is that the description constitutes a separate layer not only from the semantic layer itself, but also from the implementation of the API: the RAD description has no effect over data exposed by the API, its functionality, and the supported media types (e.g. JSON, XML, YAML, HTML, etc.). An important disadvantage stems from this: the description is tightly coupled to the API’s implementation. By allowing the description to be flexible and not having an effect on the implementation, coupling occurs the other way around, where any change on the API must be reflected on its documentation, decreasing service evolvability. Considering most APIs maintain a documentation website anyways, this coupling could be maintained, and not increased,
through the generation of the documentation website itself from its RAD description doc-
ument.

Another limitation appears when analyzing real industry-level Web API’s design: though
common Web API design practices are supported, special cases exist. As discussed in sec-
tion 6.4, not all resources have a clear underlying concept to be represented by, but rather
a collection of loose parameters. Another case we encountered is when the the presence
or value of a parameter directly changes the concept representing the URL. Both cases
are an inconvenience in our our discovery efforts, and though they could be attributed to
problems in the API’s design, these cases occur in well-known Web APIs, and should be
acknowledged.

Additionally, the quality and precision of our concept matching process results are
limited by the the complexity and completeness of the semantic layer in use. In this
theses we based our semantic layer on the Schema.org vocabulary, but ontologies and
other graph-based solutions could also be used. A semantic layer with more detailed
and complete relationships could be exploited in order to obtain more precise results than
those shown in this thesis. This would significantly increase the solution’s complexity, as
the underlying algorithm for the concept matching process would have to be specifically
tailored for each variation of the semantic layer.

As of future work, we will focus on improving RAD-NLQ’s results through the use of
an ontology over the Schema.org vocabulary approach, allowing us to make use of more
complex relationships between concepts. We also aim to improve our concept similarity
process which is directly linked from the previous goal. Finally, we look forward on sup-
porting both border case limitations previously discussed, through the support of virtual
one-time-use concepts composed by loosely coupled parameters.
REFERENCES


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APPENDIX
A. WEB APPLICATION SCREENSHOTS

This appendix details the user’s flow throughout the Web Application described in Chapter 5 when discovering resource.method pairs through natural language phrase queries. The demostration presented in this appendix is available at rad.ing.puc.cl/demo/query.

Figure A.1. RAD-NLQ: User’s natural language phrase input

Figure A.1 presents the data input field for the Web Application. A total of 3 queries modes are supported: Natural language, RAD-QL, and Query Suggestion. The first mode is selected and allows the user to input a natural language phrase query in the query box (e.g. ”get a concert’s setlist”). The former 2 modes will be explained further ahead.

The response to the natural language query submitted in Figure A.1 is presented in Figure A.2. The response contains a list of RAD-QL queries containing the extracted concepts from the input query, ranked by the amount of extracted concepts out of the total are used to form each RAD-QL query (the numbers on the right). Each RAD-QL query in the response is interactable, and upon clicking one the query is inputted into the query box and the query mode is switched to RAD-QL. Figure A.3 presents this scenario when selecting the suggested highest-scored RAD-QL query which allows us to discover resources and methods involving the specified resource and action concepts.
Figure A.2. RAD-NLQ: Concept extraction from user’s input

Table: Executed query:
get a concert's setlist

<table>
<thead>
<tr>
<th>TABLE</th>
<th>RAW</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUGGEST SERVICES FOR CONCEPT &quot;concert setlist&quot; AND ACTION &quot;get&quot;</td>
<td>1</td>
</tr>
<tr>
<td>SUGGEST SIMILAR ACTION CONCEPTS FOR &quot;get&quot;</td>
<td>0.5</td>
</tr>
<tr>
<td>SUGGEST SIMILAR RESOURCE CONCEPTS FOR &quot;concert setlist&quot;</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Figure A.3. RAD-NLQ: RAD-QL query to discover resource-method pairs with the extracted concepts

Figure A.4 presents the response to the query inputted in Figure A.3. A ranked list of interactable method node IDs are presented, as they serve as they are unique to a resource-method pair, as a single method node can only be associated to a single resource node. Each ID is accompanied buy a number ($\geq 0, \leq 1$) on the right representing how well the execution of that resource-method pair answers the RAD-QL query.

Upon selecting the best-ranked method node ID, the Query suggestion query mode is selected and the ID is added to the list. This mode allows users to find RAD-QL queries based on the type of parameters they have, alongside filling the returned query’s template.
Figure A.4. RAD-NLQ: Ranked method node IDs linked to the extracted concepts

Figure A.5. RAD-NLQ: Obtaining RAD-QL query suggestions for the selected method node ID

with the stated value for each parameter. This can be seen in Figure A.6, where a list of RAD-QL queries is presented which use the given parameters, alongside a number by which they are ranked representing the proportion of parameters used to form the query.

Finally, upon executing the only RAD-QL query returned in Figure A.6, which aims to retrieve the workflow for the method node’s ID, an interactable graph is returned. This graph is a subgraph of the RAD graph, and presents the method node, alongside its associated resource, parameters, and responses, as well as all relationships between
Figure A.6. RAD-NLQ: RAD-QL queries suggested for the given node ID them. All nodes and edges can be selected in order to view more detailed information about them. Additionally, all nodes can be directly added into the Query suggestion query mode as parameters, allowing users to continue exploring the RAD graph.
Figure A.7. RAD-NLQ: Interactive graph detailing the workflow for the given method node