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SEMI-SUPERVISED MACHINE LEARNING OF INTENT DATA MODELS BASED ON GROUP BASED POLICY

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ABSTRACT

Techniques are described herein for using semi-supervised machine learning to simplify an intent interface for end users by allowing a user to specify key network features in which they are interested. A continual learning based approach better adapts to a continuously changing intent interface and simplifies the experience for end users. The semi-supervised learning algorithm learns the reverse mapping (stored in an intent cache database) of Group-Based Policy (GBP) policy templates expressed using data models (e.g., as Yang models) as well as user network feature key words given a set of existing network configuration use cases provided as topology network maps, device configurations, and manually crafted GBP policy objects. A new user starts by specifying key intent features of interest, picks the closest mapping GBP template, and configures their network.

DETAILED DESCRIPTION

Today, users want to enable business processes for deploying networking services using a declarative intent based interface. The intent based interface describes what must be done without requiring the knowledge of "how" at the level of business processes. Programming using lower-level models is cumbersome and error-prone, and often intent is lost. GBP based interfaces have been developed to simplify user experience. However, given that the network configuration landscape is a continually changing landscape and given that GBP based User Interface (UI) tools still require significant user input, the intent interface is still challenging and cumbersome. There is a need to leverage a continuous learning environment that not only achieves the goal of simplifying intent specification but adapts dynamically.

An intent based user North Bound Interface (NBI) uses abstractions such as tenants, endpoints, endpoint groups, contracts, a subject, clauses, classifiers, and actions. Tenants are users and groups of users. Endpoints are user client applications on a server, server applications on a remote server, etc. Endpoint groups are groups of endpoints. Contracts

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indicate how sets of endpoints communicate. The subject is an ordered list of rules to match traffic and actions that must be taken upon a match. Clauses are conditions, etc. under which a contract's subject is chosen. A classifier is a traffic match criterion. An action is applied on a communication (e.g., Quality of Service (QoS) policy).

Some examples of intent based NBIs include: enabling tenant/endpoints on site A access to applications on site B; specifying bandwidth guarantees and/or real time performance Service Level Agreements (SLAs) for tenants/endpoints on site A when accessing services on site B; specifying security and isolation for a tenant on site A desired when accessing applications on site B; creating a Data Center Interconnection (DCI) and provide the SLA for that DCI; applying a Service Function Chain (SFC) for a tenant's Internet access from their Virtual Data Center (vDC); etc.

GBP provides a customer facing NBI that uses abstractions such as the tenant, network Layer 2 (L2) and/or Layer 3 (L3) service contexts, the applications a tenant wants to use, the SLAs that a tenant needs, etc. The customer facing intent NBI drives service level abstractions. Recursively, service level abstractions drive device level Application Programming Interfaces (APIs).

New techniques are described herein that leverage semi-supervised machine learning to augment existing GBP intent NBI based solutions/tools. Using semi-supervised learning methods are provided for creating an intent mapping of key network services keywords to pre-cached GBP intent templates. This mapping is made available as an intent cache database to customers via the augmented GBP NBI. The customers themselves may further enhance the intent cache database using the same semi-supervised learning methodology that was used to create it. The augmented GBP NBI provides a more simplified interface for the customer than exists today.

The cache database of intent templates is developed by performing a semi-supervised machine learning based training on existing network topologies. An input data set instance comprises an existing network topology (specified as a network map) for a specific use case, existing device configurations (CLI or Yang model based), an existing GBP graph that was manually crafted to match that network configuration, and a set of starter input network feature keywords describing a use case (supervised component of learning). The semi-supervised machine learning approach is used to train on a large number of such data set instances and determine key intent features (including those that were not specified, which is why this is a semi-supervised approach rather than fully supervised approach). The semi-supervised machine learning approach is then used to train on an additional set of data set instances (also referred to as a test set) to test the accuracy of mapping of key intent features to a GBP graph template. The premise of this technique is that key intent features are sufficient to select a good starter GBP graph template for a given use case. As part of the intent interface, a user may specify the key features in which they are interested and a close-distance match based GBP graph is chosen as the starting policy intent for that user. The user may then modify the match to match intent more closely for their use case.

Figure 1 below illustrates a semi-supervised learning approach to learn policy intent models using existing topologies.

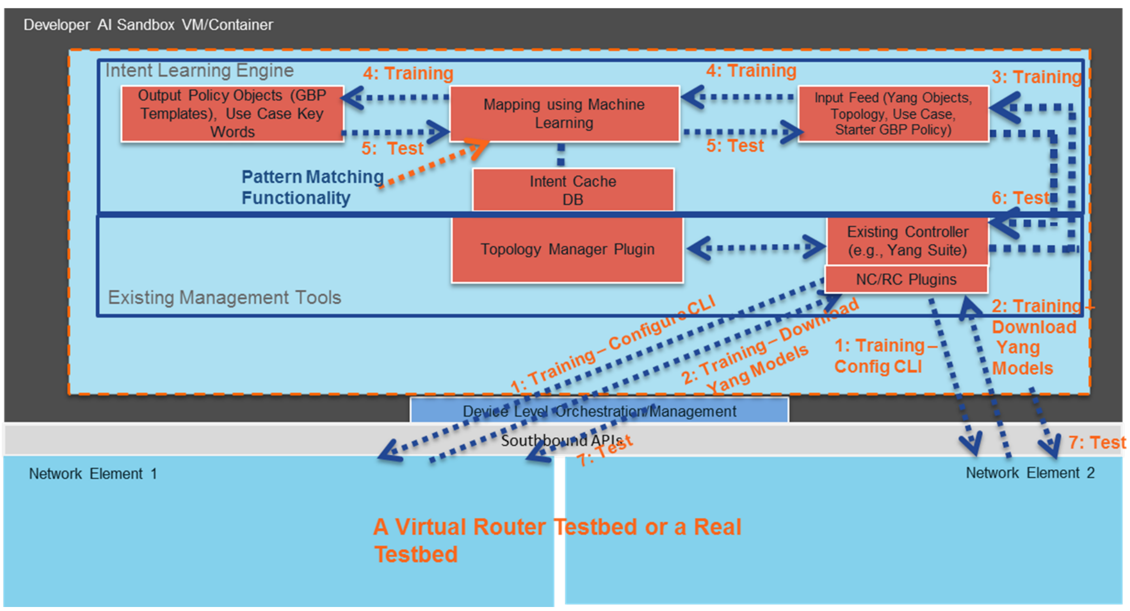

Figure 1

Figure 2 below illustrates a next generation architecture leveraging aforementioned techniques to improve/simplify intent based NBI.

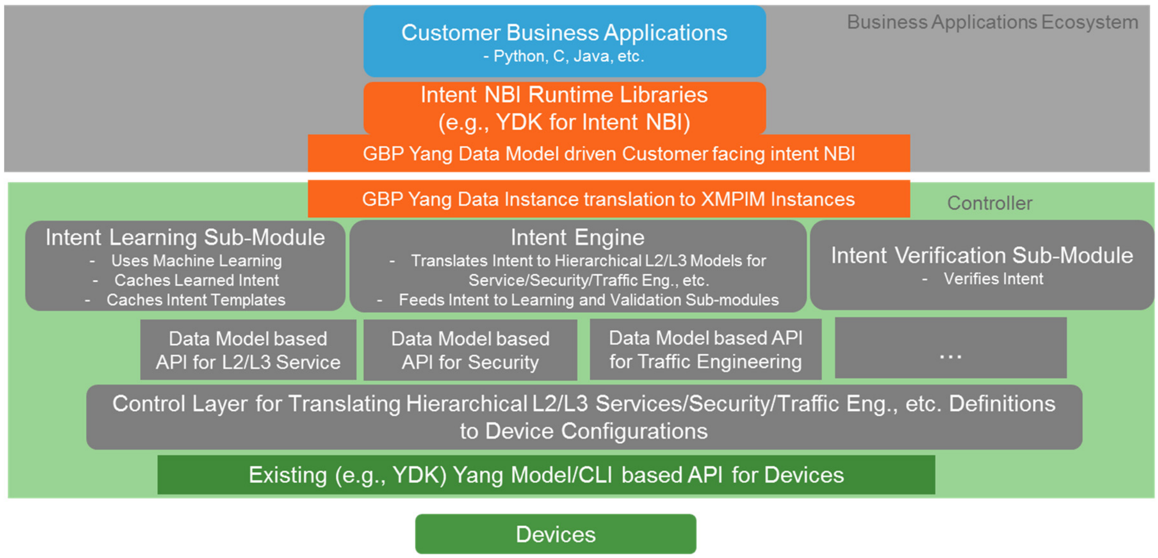

Figure 2

The above techniques help augment existing GBP based solutions/tools by simplifying the intent user interface. Additionally, intent realization testing/validation may be improved across platforms / operating systems by adding ready-to-consume validated intent templates for key networking use cases.

A key question one must ask when leveraging these techniques is if a machine learning based approach is necessary and if one can create a one-time deterministic mapping of use case keywords to GBP graph templates. Given that the intent scope is quite large, the task of creating a deterministic mapping that covers all use cases as well as handles the evolution of intent NBI is actually quite onerous. As a business entity that is specifying intent, the entity has the task of figuring out how to create policy constructs for that organization. The intent definition may simply specify, for a set of applications, what scale and resiliency to target, what users can use it, the level of security to enable, etc. Some mechanism should translate that intent to the policy objects that need to be provided in GBP (e.g., which ports (or port ranges) those applications use). It may not be fully bounded since an organization could be using little-known ports. A pre-trained database may provide a good starter set for that which is desired to be enabled by an organization in that organization's network. Through a large set of use cases spanning across many organizations, the starter policies may be provided to an organization on the fly, based on simple intent matches. The machine learning plugins may help the organization dynamically update the policy objects to adapt to their day zero needs as well as day one changes as they introduce new applications.

Feature keywords may refer to business entity intent keywords (e.g., what applications, what level of scale, performance, security, etc.). This may be a more simplified intent interface over GBP learned over time. The machine learning approach is a good candidate due to the scope involved with the large number of required policy objects that are more or less auto-generated. Because machine learning is not completely accurate, it may be required to tweak the auto-generated policy sets. They serve the purpose of removing the barrier to learning and building GBP policy objects for a large network.

In summary, techniques are described herein for using semi-supervised machine learning to simplify an intent interface for end users by allowing a user to specify key network features in which they are interested. A continual learning based approach better adapts to a continuously changing intent interface and simplifies the experience for end users. The semi-supervised learning algorithm learns the reverse mapping (stored in an intent cache database) of GBP policy templates expressed using data models (e.g., as Yang models) as well as user network feature key words given a set of existing network configuration use cases provided as topology network maps, device configurations, and manually crafted GBP policy objects. A new user starts by specifying key intent features of interest, picks the closest mapping GBP template, and configures their network.