ServeNet: A Deep Neural Network for Web Service Classification*

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Abstract. Automated service classification plays a crucial role in service management such as service discovery, selection, and composition. In recent years, machine learning techniques have been used for service classification. However, they can only predict around 10 to 20 service categories due to the quality of feature engineering and the imbalance problem of service dataset. In this paper, we present a deep neural network ServeNet with a novel dataset splitting algorithm to deal with these issues. ServeNet can automatically abstract low-level representation to high-level features, and then predict service classification based on the service datasets produced by the proposed splitting algorithm. To demonstrate the effectiveness of our approach, we conducted a comprehensive experimental study on 10,000 real-world services in 50 categories. The result shows that ServeNet can achieve higher accuracy than other machine learning methods.

Keywords: Deep Learning · Service · Web Service · Service Classification.

1 Introduction

Software reuse is treated as a promising way to reduce the cost of software development [12] since last decades. Web service provides a unified and loosely-coupled integration to reuse the services from the heterogeneous software components [25]. Notwithstanding the advancement of the service and cloud computing in recent years, more and more high efficient and reliable web services are available in the public repositories, which can be regarded as the valuable resources for software reuse. The common repositories include the standard (Universal Description, Discovery, and Integration) UDDI registry [18] and APIs sharing platform (e.g. programmableweb). These repositories require service providers to publish services with their specification, which mainly includes the functionality of service such as service description in natural language, service signature,

* Supported by organization x.
1 http://www.programmableweb.com
query APIs and search keywords (labels or tags). Therefore, the key of software reuse is to search and then find the required services in the repositories to satisfy the requirements based on the service specifications, which is the main concern in service discovery [8].

Two search approaches are widely used in service discovery [9][4]. The first one is the keyword-based method. Service consumers use several keywords to search the candidate services first, and then use the service description to confirm the target one. The second one is semantic search and validation based on the semantic web service [4], such as WDSL-S, OWL-S, WSMO. The target services are matched according to the signatures of the service, i.e., the input and output parameters of the services, and then validated by the contract of the services, i.e., the pre- and post-conditions [17]. Although semantic search has higher accuracy than keyword-based methods, it only works when we provide the semantic information for all the service in the repository as well as in the service query, which is too ideal to be practical in the real-world situation. Moreover, semantic search is less efficient than keyword-based methods. Therefore, keyword-based methods are usually the first choice in most cases of service discovery.

The success of keyword-based searching highly relies on the quality of service keywords, which are manually assigned by service developers. However, the assigned keywords are not always reliable and adequate. This is mainly because the developers may have difficulty to choose the correct keywords from a large candidate pool, and lack the knowledge of all candidates. The limitation of manual keyword assignment creates the need for automated keywords prediction and tags recommendation through machine learning. The work [11][23] compared several machine learning methods such as Naive Bayes [22], Support Vector Machines (SVM) [20], k-Nearest Neighbors (kNN) [1] and C4.5 [16] for service classification in seven categories. They show that SVM has the best accuracy than other machine learning methods. By integrating Latent Dirichlet Allocation (LDA) [5] with SVM for feature extractions, the work [15] shows that LDA-SVM model can reach around 90% accuracy in ten categories. However, when the number of categories is increased to fifteen or even twenty, the work [14][21] shows that only less than 50% accuracy can be achieved. This is still far from the ideal in the practice. E.g., ProgrammableWeb contains at least 400 categories.

There are two challenging problems causing prediction hard. The first one is data imbalance. More than half of the categories from service repository contain less than 10 services. This extreme imbalance problem makes the distribution of test set differ from the training set. We proposed a data splitting algorithm with Kullback-Leibler divergence [10] and one-shot (small group) filter (remaining data still within the 90% confidence interval) to alleviate the imbalance problem in service dataset. The quality of feature engineering is another problem which the conventional machine learning methods heavily rely on. Feature engineering takes advantage of human ingenuity and prior knowledge to compensate for the weakness of inability to extract and organize the discriminative information from the data [3], which is normally both difficult and expensive. To overcome
the problem, deep learning is a promising alternative which can automatically abstract low level representation from raw data to high level features without feature engineering [13]. It has been successfully applied to many fields such as image and text classification even with a large number of categories (e.g., the ImageNet [7] result shows less than 5% Top-5 errors within 1000 categories). In this paper, we present a deep neural network ServeNet, which can reach 88.69% Top-5 accuracy in 50 service categories. By comparing with other deep learning networks such as Convolutional Neural Network (CNN) [2], Long Short-Term Memory (LSTM) [26] networks, and LDA-SVM, the result shows that ServeNet can achieve higher Top-5 accuracy and Top-1 accuracy than other machine learning methods.

The contributions of this paper are summarized as follows:

- We proposed a service splitting algorithm with minimum Kullback-Leibler divergence, category and description filters to alleviate the imbalance problem in service dataset.
- A novel deep neural network ServeNet is proposed and it can automatically abstract low level representations to high level features without feature engineering.
- We demonstrate that ServeNet has higher accuracy than other machine learning methods for service classification even with 50 categories (which largely extends existing work).

The remainder of paper is organized as follows: Section 2 provides the architecture of the proposed deep neural network ServeNet. Section 3 presents the evaluation of ServeNet and the benchmark with other machine learning methods. Section 4 concludes the paper and plans future work.

2 ServeNet

In this section, we first introduce the architecture of the proposed deep neural network ServeNet, and then provide the hyper-parameters of ServeNet.

2.1 ServeNet Architecture

The structure of ServeNet is shown in Figure 1 which contains an embedding layer, feature extraction layers, and tasks layers. ServeNet requires the description of a service as input. Then it outputs the classification of the service. The embedding layer transforms the description of service into vectorization representation. Then the feature layers abstract the low level vector representation of description to high level representation. Finally, the task layers predict service classification based on the extracted high level representation.

Embedding layer Global Vectors for Word Representation (GloVe) [19] is a general technique to map a word to a vector representation in natural language
In this paper, we choose Glove6B as the embedding layer $f_e$, which is a pre-trained neural network on 6 billion words from Wikipedia and Gigaword and can transform a word of description to an n-dimensional vector. By limiting the maximum length $mLen$ of service description, the embedding layer can output a $mLen$ by $n$ description matrix $e$ for the next layer. We assume that $x$ is the description of a service. The embedding layer can be defined as:

$$e = f_e(x)$$

**Feature extraction layers** The output of the embedding layer ($e$) is low level representations of service description. To retrieve high level features, local relation and sequential relation of words are taken into account. Therefore, we introduce two convectional layers $f_{cnn}$ to automatically discover the local relation features between neighbouring words. Then, the sequential relations between words are automatically extracted by a Bi-directional Long Short Term Memory (Bi-LSTM) layer $f_{lstm}$. The output $h$ of feature extraction layers is:

$$h = f_{lstm} \cdot f_{cnn}(e)$$

$f_{cnn}$ is a deep convolutional model, which uses the trained filters to extract local features between adjacent words. After the embedding layer outputs service description $e$ with shape $(mLen, n, 1)$, it will be convoluted with $k$ filters with kernel size $(f, f)$ and zero padding is used to make all service descriptions have the same shape. $f_{cnn}$ contains two convolutional layers with $k_1$ and $k_2$ filter(s) on the respective layer. $k_2$ is set to 1, because the features need to be reshaped to $(mLen, n, 1)$ for the LSTM layer. In short, the convolutional layers output service features as shape of $(mLen, n, 1)$ and $(mLen, n, k_2)$.

$f_{lstm}$ is a deep sequence model, which extract sequential features through time. In our case, each word vector is involved in the computation in each time step, and the relations of words between the time step are stored in the hidden state $a$. Comparing to Recurrent Neural Network (RNN) [24], which computes the hidden state with activation: $a^{(t)} = \text{tanh}(W_{aa}a^{(t-1)} + W_{ax}x^{(t)} + b_a)$, LSTM can learn from the longer pass, because cell state or memory variable $c^{(t)}$ at every
time-step is computed from the cell state $c^{(t-1)}$ and the hidden state $a^{(t-1)}$ in the previous time step:

$$
c^{(t)} = \Gamma_f^{(t)} \cdot c^{(t-1)} + \Gamma_u^{(t)} \cdot \tilde{c}^{(t)}
$$

$$
\tilde{c}^{(t)} = \tanh(W_c[a^{(t-1)}, x^{(t)}] + b_c)
$$

Then the hidden state of current step $a^{(t)}$ is:

$$
a^{(t)} = \Gamma_o^{(t)} \cdot \tanh(c^{(t)})
$$

where $\Gamma_f^{(t)}$, $\Gamma_u^{(t)}$, and $\Gamma_o^{(t)}$ are the forget, update, and output gates of timestep $t$:

$$
\Gamma_f^{(t)} = \sigma(W_f[a^{(t-1)}, x^{(t)}] + b_f)
$$

$$
\Gamma_u^{(t)} = \sigma(W_u[a^{(t-1)}, x^{(t)}] + b_u)
$$

$$
\Gamma_o^{(t)} = \sigma(W_o[a^{(t-1)}, x^{(t)}] + b_o)
$$

$\sigma$ is activation function $\text{sigmoid}$. $W$ is the weight, and $b$ is the bias of the neural network. In ServeNet, the maximum time step $T_x$ is the maximum length of service description $mLen$. $f_{lstm}$ iteratively computes $a^{(t)}$ and $c^{(t)}$ through each time step $t$, and then outputs the hidden state $a^{(mLen)}$ as the high level feature vector to the next layer.

**Task layers** The task layers contain a fully connected feed-forward neural network $f_{fc}$, which inputs high level representation $a$ from feature extraction layers and outputs a service classification $l$:

$$
l = f_{fc}(a)
$$

$f_{fc}$ contains two fully connected layers with activation function $\sigma_1$ and $\sigma_2$. Each layer computes $a_{i+1}$ with the output $a_i$ from the previous layer:

$$
a_{i+1} = \sigma(W \cdot a_i + b)
$$

where $\sigma_1$ is the $\tanh$ function and $\sigma_2$ is the $\text{softmax}$ function computing the probability of a service belonging to each category. In short, the proposed ServeNet takes service description $x$ as input, and outputs service classification $l$ through the embedding layer $f_e$, the feature extraction layers $f_{lstm} \cdot f_{cnn}$, and the task layer $f_{fc}$:

$$
l = f_{fc} \cdot f_{lstm} \cdot f_{cnn} \cdot f_e(x)
$$

### 2.2 Hyper-parameters

The hyper-parameters of ServeNet contains two parts: network and training hyper-parameters.
Network Hyper-parameters: We choose the pre-trained Glove6B200d in the embedding layer, which transforms each word of service description into a 200-dimension vector. The maximum length of description is 110, which is chosen by confidence level of 90% in Fig. 5. ServeNet contains two convolutional layers, which use 3 by 3 kernel with 64, and 1 filters respectively, and connected with one bidirectional LSTM layer. The hidden state of LSTM is a 1024-dimension vector. The task layers contains 200 hidden nodes with an activation function tanh. The output of the task layer contains 50 nodes with an activation function Softmax to compute the probabilities for each category. To avoid over-fitting, we add a dropout layer between each two layers of ServeNet with drop probability 0.5.

Training Hyper-parameters: ServeNet adopts the categorical cross-entropy as the loss function. The Adam optimization algorithm is used with learning rate 0.002, beta1 0.9, beta2 0.999, and learning decay 0.0001. The total epoch number is 50 with batch size 64. The hidden state of LTSM and all bias are initialized to zero. Xavier normal initializer is used to initialize kernel parameters.

3 Evaluation

In this section, we will show the evaluation result of ServeNet. The service dataset is introduced first. Then, we compare ServeNet with other machine learning methods.

3.1 Service Dataset

Service Collection Web services are collected from API directory website\(^2\) in which, service specification includes title, description, end point, home page, primary category, secondary categories, provider, SSL support, and etc. We implemented a web crawler by Python and web browser automation tool Selenium\(^3\) download all service data and store them into a service dataset \textit{WSDataset} in JSON format.

The original \textit{WSDataset} contains 15344 services. We clean the dataset to exclude the services containing empty description or catalog. After this basic cleanup, the dataset remains 15340 services with 401 categories, each service is specified by 20 descriptors. In this paper, we only take descriptors \textit{Description} and \textit{PrimaryCategory} into account. To prevent ambiguity, we define \textit{Description} as service description, \textit{PrimaryCategory} as service classification, and service classification and category is exchangeable in this paper. For example, five services of \textit{WSDataset} are shown in Fig. 2. The third one is a Google video API, the category of this service is Video. The service description is:

\(^2\)\url{programmableweb.com}  
\(^3\)\url{https://www.seleniumhq.org}
It has been split into multiple APIs, including the Twitter Ads API, Twitter Search Tweets API, and Twitter Direct Message API. This profile is maintained for historical, research, and reference purposes only. The Twitter micro-blogging service includes two RESTful APIs. The Twitter REST API methods allow developers to access core Twitter data. This includes update timelines, status data, and user information. The Search API methods give developers methods to interact with Twitter searches by keywords.

Fig. 2. Services Description and Catalog

The Data API allows users to integrate their program with YouTube and allow it to perform many of the operations available on the website. It provides the capability to search for videos, retrieve standard feeds, and see related content. A program can also authenticate as a user to upload videos, modify user playlists, and more. This integration can be used for a variety of uses such as developing a web application allowing users to upload video to YouTube, or a device or desktop application that brings the YouTube experience to a new platform. The Data API gives users programmatic access to the video and user information stored on YouTube. This can be used to personalize a web site or application with the user’s existing information as well as perform actions like commenting on and rating videos. This RESTful API provides responses in XML format.

Fig. 3. Histogram of Service Categories
Service Category Analysis After counting and ranking the number of services in each category, the histogram of those categories is shown in Fig. 3. In these categories, the maximum category *Tools* contains 767 services, while the minimum category are categories with only one service, leading to the one-shot classification problem in machine learning. Moreover, only 41 categories contain the number of services greater than 100, and 217 categories (more than the half of categories) contains the number of services less than 10, which is the extreme imbalance problem. We need to eliminate the one-shot, small groups and keep big groups to make categories more balance. To evaluate the imbalance degree of dataset, we introduce the imbalance rate \( ir \):

\[
ir = \frac{1}{n} \sum_{i=1}^{n} |c_i - c_{max}|
\]  

(1)

where \( n \) is the number of the categories in services dataset, \( c \) is the number of the services in a category, and \( c_{max} \) is maximum value of services among all categories. Before selecting categories, we compute imbalance rate on the original dataset \( ir = 728.83 \). Then we select the services only belonging to the top 50 categories, and the imbalance rate is reduced to \( ir = 547.86 \). To visualize the categories distribution, we draw the top 50 categories in histogram. Fig. 4 shows that the imbalance problem of service dataset is largely mitigated. Now, the

![Fig. 4. Histogram of Top 50 Categories](image-url)
service dataset contains the following categories with the corresponding number of services:

Tools (767), Financial (687), Messaging (511), eCommerce (466), Payments (460), Social (433), Enterprise (412), Mapping (362), Government (304), Telephony (300), Science (298), Email (255), Security (251), Reference (251), Video (251), Search (251), Travel (243), Sports (228), Advertising (224), Transportation (218), Education (215), Games (203), Music (191), Photos (185), Cloud (173), Other (158), Bitcoin (143), Project Management (142), Data (142), Shipping (136), Database (136), Backend (134), Stocks (133), Weather (132), Application Development (123), Analytics (115), Internet of Things (113), Banking (111), Medical (110), Real Estate (108), Events (108), Storage (99), Entertainment (95), File Sharing (86), Domains (84), Images (83), Media (82), Chat (82), News Services (82), Office (81).

Note that the top 50 categories have already included Other category. We do not add the removed services into this category to avoid making dataset imbalance again. At this stage, service dataset contains 10957 services with 50 categories.

**Service Description Analysis**  Since service description is specified by natural language, different companies and developers may use different formats. One outstanding difference is the length of service description. In the dataset, the minimum length of service description is only 3, which is described as Czech mapping API within category Mapping, whereas the maximum length of service description is 334, which is the GroupDocs service under the category File Sharing. To figure out the distribution of description length, we present a histogram in Fig. 5. From this histogram, we can see that the length of service description...
conforms to a normal distribution. After calculating, the average length $\mu$ is 67.3663, and the standard deviation $\delta$ is 26.0072. When the confidence level is 90%, we can get the confidence interval from 24.5882 to 110.1444. We use this confidence interval $(24, 110)$ to exclude those anomaly services of too short or too long description. Finally, we retrieved 10182 services specified by description and category in our service dataset. In short, the status of service dataset from the raw data to the final dataset is shown in Table 1.

Table 1. Pre-processing of Service Dataset

| Process Step               | Services | Categories |
|----------------------------|----------|------------|
| Original Dataset           | 15344    | 401        |
| Balance Categories         | 4387*    | 351*       |
| 90% Confidence Level       | 775*     | 0*         |
| Final Dataset              | 10182    | 50         |

* Those numbers are the services removed from the dataset.

**Dataset Splitting** The training and testing results of deep learning model highly depend on the similarly of training set and test set. It means the training set and test set conform to the same distribution. Random methods are broadly used for splitting dataset when the problem contains big data (e.g., millions of data). However, when facing the imbalance problem in relatively low data, the splitting methods are more important. If we randomly choose 20% data from the dataset as the test set and the remaining data as the training set, the histograms of training and test are shown on left side of Fig. 6. It clearly shows that the training and test sets contain some dissimilarity. But the diagrams do not quantify the dissimilarity between the training and test sets. Kullback-Leibler
Input: Service<sub>ds</sub> - Service dataset
rate - Splitting rate
N - Minimum number of categories
T - Threshold of imbalance rate
M - Number of random selections

Output: trainS - Training Set
testS - Test Set

begin
// Step 1: Category filter to reduce imbalance rate
/* Counting and ranking categories on datasets */
rank<sub>c</sub>, n ← countRankCategories(Service<sub>ds</sub>);
/* Compute imbalance rate ir of all categories */
ir ← computeImbalanceRate(rank<sub>c</sub>);
/* Select top n − 1 categories and compute imbalance rate ir<sub>n−1</sub> */
while n ≥ N and |ir − ir<sub>n−1</sub>| ≥ T do
    n ← n − 1;
    top<sub>n−1</sub> ← selectTopNCategories(rank<sub>c</sub>, n);
    ir<sub>n−1</sub> ← computeImbalanceRate(top<sub>n−1</sub>);
end
Service<sub>cf</sub> ← categoriesFilter(Service<sub>ds</sub>, top<sub>n−1</sub>)

// Step 2: Description filter with 90% length confidence level
dlc ← descriptionLengthCounts(Service<sub>cf</sub>);
Service<sub>dl</sub> ← descriptionLengthFilter(Service<sub>cf</sub>, dlc, 0.9);

// Step 3: Minimum KL Selection
/* Initialize training set and test set */
trainS, testS ← randomSplitDataset(Service<sub>dl</sub>, rate, seed = 1);
kls ← computeKL(trainS, testS);
/* Find training set and test set with minimum KL */
for i ← 2 to M do
    train, test ← randomSplitDataset(Service<sub>dl</sub>, rate, seed = i);
    kl ← computeKL(train, test);
    if kl ≤ kls then
        kls ← kl;
        trainS, testS ← train, test;
    end
end
return trainS, testS;
end

Algorithm 1: Service Splitting Algorithm
(KL) divergence is used for evaluating the similarity of two distributions, which is shown in (2).

\[
D_{KL}(P\|Q) = -\sum_i P(i) \log \frac{Q(i)}{P(i)}
\]  

We randomly split a dataset 10000 times, and compute the KL values between the training and test sets for evaluating the splitting result. The minimum value is 0.0069, and the maximum value is 0.0319. The mean value is 0.0154, and the standard derivation is 0.0032. Finally, we pick the training and test sets with the minimum value of KL, which is shown on the right side of Fig. 6.

We conclude the solution of data spitting in Algorithm 1. This algorithm takes service dataset as input, and outputs split training set and test set for ServeNet training and evaluation. We can set splitting rate rate for the proportion of training and test sets, N and T for thresholds of categories number and imbalance rate, M for the number of random selections. This algorithm includes three steps: Step 1). It uses category filter to reduce imbalance rate first, in which it counts the number of services in each category and then ranks them. Next, it computes the imbalance rate \( ir \) of all categories by (1) as the baseline. Then it iteratively selects top \( n-1 \) categories \( top_{n-1} \) and compute imbalance rate \( ir_{n-1} \) based on those selected categories until the difference value between the computed \( ir_{n-1} \) and \( ir \) is less than the threshold \( T \) or the number of the categories is less than the minimum value \( N \). Step 2). It uses description filter to retain the services with length in 90% confidence level based on counting the length of the service description. Step 3). It repeatedly splits service dataset into training set and test set \( M \) times based on the splitting rate rate and the KL divergence \( kl \) computed by (2). Finally, it returns the training set \( trainS \) and test set \( testS \) which have the minimum KL value.

3.2 Experiment Result and Discussion

Top-N accuracy is generally used to evaluate a classification model. E.g., Top-1 accuracy is usually used to evaluate a binary classification model. A multi-classes classification model (\( classes > 10 \), e.g., ImageNet) requires Top-5 evaluation metrics. Note that Top-5 accuracy means that a prediction is correct when Top-5 predictions contain the target category. We focus on Top-5 accuracy to evaluate our model, but also compare other machine learning models with Top-1 accuracy. Furthermore, several machine learning models are used in the evaluation benchmark. All source codes are available on GitHub\(^4\). All the models are trained and tested on Google Colaboratory\(^5\) with Nvidia K80.

**Experiment Result** Most models are convergent around epoch 20. Therefore, we show top-5 accuracy from epoch 0 to 20 on Fig. 7 and the highest accuracy for

\(^4\) https://github.com/yylonly/ServeNet

\(^5\) https://colab.research.google.com
each model among 20 epochs in Table 2. As can be seen, ServeNet has the highest test accuracy 88.69%, which is higher than other models. The CNN and LDA-SVM models have the similar prediction ability around 50%. Therefore, only considering local neighboring words by CNN and topic features by LDA cannot get a good prediction result for service classification. After adopting the sequence model LSTM to consider the context information from previous words of the service description, we boost the result to around 70%. Keep considering context information not only from the antecedent words but also from the subsequent words of service description, we achieved the accuracy around 85%. It shows that the sequence model works well on the prediction problem based on natural language. Finally, our proposed model takes both the local neighboring information and the context information, which can achieve the highest accuracy of all models.

![Fig. 7. Top-5 Benchmark](image)

Table 2. Top-5 Accuracy on different learning models

| Model                               | Training Set | Test Set |
|------------------------------------|--------------|----------|
| TF-IDF-LDA-Linear-SVM              | 97.50        | 55.89    |
| TF-IDF-LDA-RBF-SVM                 | 94.16        | 53.08    |
| Glove-CNN-FC                       | 93.54        | 59.29    |
| Glove-LTSM-FC                      | 86.77        | 78.65    |
| Glove-BI-LTSM-FC                   | 95.43        | 86.17    |
| Glove-CNN-BI-LTSM-FC (ServeNet)    | 96.95        | 88.69    |
Top-1 benchmark is shown in Fig. 8, which has the similar result with the Top-5 benchmark. ServeNet and bi-directional LSTM models have higher accuracy around 60% than other models around 30%. LSTM and LDA-SVM models have similar Top-1 accuracy but LSTM has higher accuracy in Top-5. It means that the sequence model is more robust than LDA-SVM models. CNN model has not the lowest accuracy in Top-5 but in Top-1, that means the highest probability of prediction is not always the correct category in CNN model. Therefore, CNN model is less robust than other machine learning methods for service classification. In short, our proposed ServeNet has the highest prediction accuracy in both Top-1 and Top-5, which demonstrates the validity and robustness of our proposed deep neural network.

To show the details of prediction result for each category, we present the confusion matrix of ServeNet for 50 service categories in Fig. 9. X-axis and Y-axis are the predicted and actual true categories. Diagonal values show the numbers of correct prediction. For example, the category Project Management totally has 41 services, 34 services of which are correctly classified. In this classification, 7 services belong to other categories such as File Sharing, Events, Photos, Images, and Media.

**Limitation** After analyzing those failures from the confusion matrix, we found that the errors are mostly because those service descriptions not only contains the information about target categories, but also includes the information in other categories. E.g. project management usually contains the process about file sharing, media uploading and the management events. Although experts can easily classify these services, deep learning methods are hard to learn the
difference only based on the limited data of each category (e.g., the Project Management category only contains around 200 services for training). One possible way is to invent a more advanced model to enable the neural network to discover more detail features. But the more efficient way is to collect more high quality data in the practice.

Fig. 9. Confusion Matrix of ServeNet

4 Conclusion and Future Work

In this paper, we introduce a novel deep neural network ServeNet for service classification. This network is trained and tested on the dataset with 10957 services including 50 categories, and achieved 96.95% and 88.69% Top-5 accuracy on training and test set respectively. The benchmark demonstrates that ServeNet is robust and can achieve the best performance than other machine learning methods.

As discussed in the limitation section, although ServeNet has higher prediction accuracy than other machine learning methods, there is still space to improve the prediction accuracy. In future, we will collect more data, especially to balance the categories with low data. Furthermore, more service categories should be applied for more fine-grained classification. In this paper, ServeNet
reuses pre-trained Glove5B neural network in embedding layer. In the natural language processing filed, there are many other successful deep learning models for text classification. Therefore, transfer learning can be adopted to promote ServeNet.

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