What Do Developers Ask About ML Libraries? A Large-scale Study Using Stack Overflow

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Keywords
Machine learning, Q&A forums, API misuses

Disciplines
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What Do Developers Ask About ML Libraries? A Large-scale Study Using Stack Overflow

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Abstract—Modern software systems are increasingly including machine learning (ML) as an integral component. However, we do not yet understand the difficulties faced by software developers when learning about ML libraries and using them within their systems. To that end, this work reports on a detailed (manual) examination of 3,243 highly-rated Q&A posts related to ten ML libraries, namely Tensorflow, Keras, scikit-learn, Weka, Caffe, Theano, MLlib, Torch, Mahout, and H2O, on Stack Overflow, a popular online technical Q&A forum. We classify these questions into seven typical stages of an ML pipeline to understand the correlation between the library and the stage. Then we study the questions and perform statistical analysis to explore the answer to four research objectives (finding the most difficult stage, understanding the nature of problems, nature of libraries and studying whether the difficulties stayed consistent over time). Our findings reveal the urgent need for software engineering (SE) research in this area. Both static and dynamic analyses are mostly absent and badly needed to help developers find errors earlier. While there has been some early research on debugging, much more work is needed. API misuses are prevalent and API design improvements are sorely needed. Last and somewhat surprisingly, a tug of war between providing higher levels of abstractions and the need to understand the behavior of the trained model is prevalent.

Index Terms—Machine learning, Q&A forums, API misuses

1 INTRODUCTION

Machine learning (ML) is becoming an essential computational tool in a software developer’s toolbox for solving problems that defy traditional algorithmic approach. Software developers are fulfilling this need by development and refinement of a number of new ML libraries [1]. Recently it has also been suggested that ML can introduce unique software development problems [2], [3], [4]. However, we do not yet know about the problems that users of ML libraries face and those that they choose to ask about publicly.

Prior work has shown that studying question and answer (Q&A) forums such as Stack Overflow can give significant insights into software developer’s concerns about a technology [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], but has not focused on ML libraries. More details of related work are discussed in Section 8.

This work presents a study of the problems faced by developers while using popular ML libraries. Our study also leverages the posts on Stack Overflow. Since 2015, there has been growing interest and significant increase in ML related questions and distinct users making Stack Overflow a representative source of dataset for our study. We selected 10 ML libraries to study, identified by a survey [1] and confirmed by counting the number of posts on Stack Overflow related to those libraries. These libraries are Caffe [20], H2O [21], Keras [22], Mahout [23], MLlib [24], scikit-learn [25], Tensorflow [26], Theano [27], Torch [28] and Weka [29].

Caffe [20] is a deep learning library for Python and C++. H2O [21] is a deep learning library for Java, R, Python or Scala and its key feature is to provide a workflow-like system for building ML models. Keras [22] is a deep learning library for Python whose key feature is to provide higher-level abstractions to make creating neural networks easier. Keras also uses Tensorflow or Theano as the backend. Mahout [23] is aimed at providing scalable ML facilities for Hadoop clusters. MLlib [24] is aimed at providing scalable ML facilities for Spark clusters. scikit-learn [25] is a Python library that uses Tensorflow or Theano as the backend. This library provides a rich set of abstract APIs to hide complexity of ML from the user in an effort to make ML features widely accessible. Tensorflow [26] provides facilities to represent a ML model as data flow graphs. Theano [27] and Torch [28] are aimed at scaling ML algorithms using GPU computing. A novelty of Theano is that it provides some self-verification and unit testing to diagnose some runtime errors. Weka [29] is a ML library for Java. It provides API support for data preparation, classification, regression, clustering and association rules mining tasks and a GUI for making models easier.

All in all, this set is both representative and provides variety. We selected a total of 3,243 highly-rated Stack Overflow posts for this study. A team of three Ph.D. students, with experience in coursework on AI and ML, and using ML libraries, independently read and labeled each of the
TABLE 1: Numbers of posts having different score (S) about ML libraries. The bold column represents selected posts.

<table>
<thead>
<tr>
<th>Library</th>
<th>S ≥ 0</th>
<th>S ≥ 1</th>
<th>S ≥ 2</th>
<th>S ≥ 3</th>
<th>S ≥ 4</th>
<th>S ≥ 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caffe</td>
<td>2,339</td>
<td>1,320</td>
<td>620</td>
<td>318</td>
<td>192</td>
<td>132</td>
</tr>
<tr>
<td>H2O</td>
<td>771</td>
<td>452</td>
<td>167</td>
<td>73</td>
<td>34</td>
<td>17</td>
</tr>
<tr>
<td>Keras</td>
<td>5,708</td>
<td>3,323</td>
<td>1,751</td>
<td>953</td>
<td>568</td>
<td>367</td>
</tr>
<tr>
<td>Mahout</td>
<td>1,186</td>
<td>610</td>
<td>293</td>
<td>160</td>
<td>103</td>
<td>48</td>
</tr>
<tr>
<td>MLlib</td>
<td>1,688</td>
<td>929</td>
<td>498</td>
<td>272</td>
<td>173</td>
<td>119</td>
</tr>
<tr>
<td>scikit-learn</td>
<td>9,246</td>
<td>5,302</td>
<td>2,898</td>
<td>1,759</td>
<td>1,188</td>
<td>856</td>
</tr>
<tr>
<td>Tensorflow</td>
<td>21,115</td>
<td>10,109</td>
<td>4,962</td>
<td>2,769</td>
<td>1,627</td>
<td>1,334</td>
</tr>
<tr>
<td>Theano</td>
<td>2,332</td>
<td>1,341</td>
<td>711</td>
<td>421</td>
<td>265</td>
<td>192</td>
</tr>
<tr>
<td>Torch</td>
<td>1,226</td>
<td>640</td>
<td>312</td>
<td>161</td>
<td>91</td>
<td>61</td>
</tr>
<tr>
<td>Weka</td>
<td>2,512</td>
<td>1,216</td>
<td>568</td>
<td>293</td>
<td>181</td>
<td>117</td>
</tr>
<tr>
<td>Total</td>
<td>48,123</td>
<td>25,242</td>
<td>12,780</td>
<td>7,179</td>
<td>4,622</td>
<td>3,243</td>
</tr>
</tbody>
</table>

posts producing 9,849 labels that were then compared for consistency producing 177 conflicting labels on 177 different posts. All of these conflicts were resolved using mediated, face-to-face conflict resolution meetings between all three participants. We then performed a statistical analysis and a study of the data to answer the following research questions:

**RQ1: Difficult stage** Which stages are more difficult in a ML pipeline? Fig. 1 shows stages in a typical ML pipeline.

**RQ2: Nature of problems** Which problems are more specific to library and which are inherent to ML?

**RQ3: Nature of libraries** Which libraries face problems in specific stages and which ones face difficulties in all stages?

**RQ4: Consistency** Did the problems stay consistent over the time?

The remainder of this work describes our study and results and makes the following contributions: (1) a labeled and verified, dataset of 3,243 ML library-related Q&A on Stack Overflow, (2) a classification scheme for ML-related Q&A, (3) an intra-library analysis to identify strengths and weaknesses of ML libraries, and (4) an inter-library analysis to identify relative strengths and weaknesses.

## 2 Methodology

Our study uses Q&A posts on Stack Overflow, a popular platform used by developers. Our first step was to find the total number of questions asked about all the ML libraries highlighted by some recent surveys [1], [31], [32]. Out of these, we selected 10 popular ML libraries for the study as shown in Table 1. We excluded the other five libraries because the numbers of questions about them were too few (less than 20).

On Stack Overflow, each question is rated by the community. The score of a question is computed as $S = |N_U| - |N_D|$ where $|N_U|$ is the number of upvotes and $|N_D|$ is the number of downvotes. The higher score is an indicator of the higher quality of the question, which has been used in prior works [33]. Table 1 shows the entire distribution of the questions for each library based on the score $S$.

We selected questions with the score of 5 or higher (bold column in Table 1) to focus on high-quality questions while keeping the workload of manually labeling each question manageable.

Next, we manually classified each Stack Overflow question into categories to study them further. We first discuss the classification of categories and then our labeling process.

### 2.1 Classification of Questions

We classify the questions in Stack Overflow into several categories. First, we classify the questions into two top-level categories based on whether the question is related to ML or not. Questions related to installation problems, dependency, platform incompatibility, Non-ML APIs, overriding the built-in functionality, adding custom functionality fall into Non-ML category as shown in Fig. 2. We classify the ML-related questions into six categories based on the stages of a typical ML pipeline [34], also reproduced in Fig. 1. Among those seven stages, data collection is out of the scope of this study because ML libraries do not provide this functionality which leaves us with six categories. These six categories are further divided into different sub categories.

To find these sub categories one of the Ph.D. (an author of the paper) students with ML expertise first studied 50% of posts and created the subcategories using open coding scheme adapted from earlier works [35], [36], [37]. Then these subcategories were sent to three ML experts for review. Based on the review of the experts the subcategories were improved and the process continued until agreement with ML experts was reached. The full classification is shown in Figure 2. Next, we describe its categories.

#### 2.1.1 Data Preparation

This top-level category includes questions about converting the raw data into the input data format needed by the ML library.

- **Data adaption.** Questions under this subcategory are about reading raw data into the suitable data format required by the library. Data reader provided by the library usually provides this functionality. Questions about converting data, encoding, etc., also fall under this subcategory.

- **Featureing.** Questions under this subcategory are about feature extraction and selection. Feature extraction is a process to reduce dimensionality of the data where existing features are transformed into a lower dimensional space. Feature selection is another strategy of dimensionality reduction where informative features that have impact on the model are selected.

- **Type mismatch.** Type mismatch happens when the type of data provided by the user doesn’t match the type required by the ML API. For example, if an API needs floating point data as input but the client provides a String then the ML API raises an exception.

- **Shape mismatch.** Shape mismatch occurs when the dimension of the tensor or matrix provided by a layer doesn’t match the dimension needed by the next layer. These kinds of errors are very common in deep learning libraries.

- **Data cleaning.** Data cleaning phase, sometimes also called data wrangling, includes removal of null values, handling missing values, encoding data, etc. Without proper data cleaning the training may throw exceptions, and accuracy may be suboptimal.

#### 2.1.2 Modelling

The subcategories of this category include:

- **Model selection.** This subcategory includes questions related to the choice of the best model and choice of the API version (e.g. whether to chose SVM or decision tree).
Model creation. This subcategory includes questions related to creating the ML model using the APIs.

Model conversion. This subcategory includes questions related to conversion of a model trained using one library and then using the trained model for prediction in an environment using another library. For example, a model trained in Torch can be used for further training or prediction using Theano.

Model load/store. This subcategory contains questions about storing models to disk and loading them to use later.

2.1.3 Training

The subcategories of this category include:

Error/Exception. Questions about errors faced by users in the training phase fall into this subcategory. The errors may appear due to various reasons. If the errors are due to shape mismatch or type mismatch we put them into data preparation category. Otherwise, all errors are placed into this subcategory.

Parameter selection. Some frameworks have optional parameters, and developers have to choose appropriate values for these parameters and also pass relevant values to the required parameters. Questions related to these problems fall into this subcategory.

Loss function. Questions related to choosing and creating loss functions fall into this category, e.g., whether to use cosine distance.

Optimizer. Questions related to the choice of optimizer are placed into this subcategory, e.g., should I pick Adam or AdaGrad?

Performance. In this subcategory, questions related to long training time and/or high memory consumptions are placed.

Accuracy. Questions related to training accuracy and/or convergence are placed into this subcategory.

2.1.4 Evaluation

The subcategories of this category include:

Evaluation method selection. Question related to the problems in the usage of APIs for doing validation fall into this subcategory, e.g., “which of the eight APIs for eight different types of validations in scikit-learn, namely KFold, LeaveOneOut, StratifiedKFold, RepeatedStratifiedKFold, RepeatedKFold, LeaveOneGroupOut, GroupKFold and ShuffleSplit, should be used?”

Visualizing model learning. The developers sometime need to visualize the behavior of the model to get a better understanding of the training process and also to know the effects of evaluation on the change of loss function and accuracy. Those questions are placed in this subcategory.

2.1.5 Hyper-parameter Tuning

Hyperparameter tuning is used to improve the model’s performance. The values of hyperparameters affect model accuracy. For example, a bad learning rate may cause a model to learn poorly and give low accuracy. The subcategories of this category include:

Tuning strategy selection. Questions about choosing among APIs for different tuning methodologies are placed into this subcategory. For example, one poster wondered whether they should use the grid search or randomized search or parameter sampling for parameter tuning in scikit-learn?

Tuning parameter selection. This subcategory covers discussions related to the selection of parameters for tuning. Some parameters may not have an effect on the model accuracy other than increasing the training time while some might have a significant effect on the accuracy. For example, the following code from a post is trying to tune the kernel and C parameter of the ML algorithm to find the best combination from values given at line 4.

```python
from sklearn import svm, datasets
iris = datasets.load_iris()
parameters = {('kernel': ('linear', 'rbf'), 'C': [1, 10])}
svc = svm.SVC()
clf = GridSearchCV(svc, parameters)
```

2.1.6 Prediction

After the model is trained and evaluated, the model is used to predict new input data. Questions in this top-level category are about problems faced by the developers during prediction and include the following subcategories.

Prediction accuracy. Questions related to prediction accuracy, e.g., due to overfitting, are placed into this category.

Model reuse. Developers might have difficulty in reusing existing models with their own datasets for prediction to make use of the state of the art models from well-known providers.

Robustness. Questions in this subcategory are about the stability of the models with slight changes, possibly noise, in the datasets.

2.2 Manual Labeling

Manual labeling of the Q&A dataset was the most important (and time-consuming) step before our analysis. To decrease the bias in manual labeling we recruited three participants. Each participant had coursework in both AI and ML and had experience using ML libraries to solve problems. Each participant labeled all the questions producing 9,840 labels.

Participant Training. Before the labeling, the participants were provided with the classification shown in Fig. 2. Then, a training session was conducted where each (sub)category was discussed and demonstrated using examples.

Labelling Efforts. First, each participant gave each question one of the labels from top-level categories namely Non-ML, Data Preparation, Modelling, Training, Evaluation, Tuning, Prediction. Then, (s)he assigned a subcategory.

We found that, at the steady state, a participant could label around 50-60 questions per hour. For labeling the whole dataset consisting of 3,283 questions, each participant took around 1 week time. In total, 168 person-hours were spent on labeling this dataset.
Fig. 2: Classification used for categorizing ML library-related Stack Overflow questions for further analysis.

<table>
<thead>
<tr>
<th></th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1.00</td>
<td>0.94</td>
<td>0.92</td>
</tr>
<tr>
<td>R2</td>
<td>0.94</td>
<td>1.00</td>
<td>0.91</td>
</tr>
<tr>
<td>R3</td>
<td>0.92</td>
<td>0.91</td>
<td>1.00</td>
</tr>
</tbody>
</table>

(a) Kappa coefficients (κ).

(b) Interpretation of κ value.

Reconciling Results. After collecting labels separately from each participant, a moderator then compared them. If there was an inconsistency between participants for a question, the moderator created an issue in a repository for resolution. Among all 3,243 questions, 177 (5%) needed further discussion.

Then, the three participants had two in-person meetings to discuss those 177 questions. The participants read the questions carefully again and voted individually. If the votes matched we accepted those as resolved, otherwise participants discussed the reasons behind choosing a label and tried to achieve consensus. In most cases, the opinions differed due to the ambiguous nature of the questions. For example, for a question asking about suboptimal accuracy, it was difficult to say from the question without further exploration whether it is talking about accuracy in the prediction stage or accuracy in the training or evaluation stage. We resolved these type of questions by a careful reanalysis of the Q&A text.

We measured the inter-rater agreements using Cohen’s kappa coefficient (κ) as shown in Fig. 3a. It measures the observed level of agreement between raters of a particular set of nominal values and corrects for agreements that would appear by chance. The interpretation of κ’s values is shown in Fig. 3b. From Fig. 3a we see that the kappa coefficient between all the raters involved in the labeling process is more than 0.9 indicating perfect agreements. We also computed the Fleiss coefficient [38] which is widely used for finding IRR between more than 2 raters. The Fleiss coefficient was 90.68% indicating a perfect level of agreement. We computed all the IRR coefficients based on the ratings before the discussion for agreement. After the discussion for reconciling the conflicts in the presence of a moderator, the agreement level was 100%.

2.3 Threats to Validity

Internal Validity In the manual labeling threat can be due to the possibility that labeling could be biased. We mitigate this threat by using 3 raters and resolving the conflicts via in person meetings. The inter rater reliability coefficient shows that there was perfect level of agreement between raters.

The possibility of missing relevant posts can also be a threat. We mitigate this bias by collecting the tags that are relevant to a particular ML library. We then collect all the posts containing those tags using Stack Overflow API.

Classification of questions in the top level categories can also pose threat. To mitigate this threat we use the categorization used and described by practitioners and researchers [24], [34], [39].

Classifying the top level categories into subcategories can have bias and missing subcategories due to open coding scheme. To mitigate this threat one PhD student initially studied a subset of posts and came up with the subcategories. Then, three ML experts were consulted and their opinion on the classification was used for multiple round of revisions and improvements.

The ML expertise of the raters can affect the manual labeling. To mitigate this threat we selected raters who have expertise in ML as well as using the libraries in the study. The raters also study the answers and comments in posts to improve their insights.

External Validity In Stack Overflow threat to validity can be low quality posts [40], and chronological order of posts. To eliminate the quality threat we studied only the posts that have the tag of the relevant library and then only kept the posts that have score ≥ 5. This balanced both the quality and labeling efforts.

Chronological order of the posts can introduce threat as some older posts may be resolved in later version of the libraries. To alleviate this threat we classify questions that may appear only due to the API versions into Non-ML category.

An external threat can be expertise of the programmers asking the questions. If the questions are asked only by newbies then our results aren’t as general. To understand this threat, we measured reputation, a metric used by Stack Overflow to estimate expertise. Stack Overflow users above 50 are considered reputable and are allowed to comment on posts. Table 2 shows that the mean reputation of programmers asking the questions that we have studied is high indicating that the expertise of the programmers asking the questions is not a threat to our study.

3 Analysis and Results

We have proposed four research questions to understand what developers ask about ML. We explore the answers to
these research questions in this study. The research questions cover the following aspects: identifying the difficult stages in the current ML pipeline faced by the developers (RQ1), understanding whether the problems faced by the developers are due to the design of library or there are some problems inherent to ML (RQ2), exploring whether some of the libraries are more difficult in certain stages and are there libraries that shows comparable difficulties in all the stages (RQ3), exploring whether the problems faced by the developers changed over time or they stayed consistent (RQ4). Next, we answer these questions using a statistical analysis summarized in Tables 3 and 4 and present our findings. Our raters have read and agree with these findings.

4 RQ1: DIFFICULT STAGES

If we know the relative difficulty of ML stages for developers, then software engineering R&D and educational efforts can prioritize work on challenging stages. This section explores this question.

4.1 Most difficult stage

As Table 3 shows, and as expected the model creation is the most difficult, but surprisingly data preparation is the next difficult stage which turns out to be more difficult than training stage.

Model creation has the median of 23% across all the libraries which is the highest compared to all other stages in the ML pipeline. Some of the libraries for distributed ML like Mahout, Torch, Caffe, MLlib have abnormally high difficulty in model creation stage. This suggests that machine learning in distributed environment is not developer friendly yet.

Finding 1: Model creation is the most challenging (yet critical) in ML pipeline, especially for libraries supporting distributed ML on clusters like Mahout and MLlib.

Finding 1 provides indication that, tool support in creating models, especially in distributed machine learning is needed. Enhancing tool support to make model creation in distributed environment easier and research on detecting and resolving problems in model creation is needed.

Further analysis showed that libraries that model creation is especially harder for ML libraries that require developers to use multiple configuration languages to configure their models, for example in Caffe. For example in Caffe, questions about using multiple languages are discussed frequently. According to a case study by Amershi et al. [41], Microsoft developers face similar issues in the machine learning pipeline. It says that though Data Availability, Collection, Cleaning, and Management are most challenging for all three groups of the developer but Model Evolution, Evaluation, and Deployment are more significant for all groups according to the frequency. Our results from studying the posts support what was known at a corporate community and have found several new findings.

4.2 Data preparation

This top level category includes questions about adapting the data to the format required by the library, featuring, dealing with type and shape mismatches, and data cleaning. All together, this stage is the next most difficult stage across ML libraries (median 20%).

Finding 2: Data preparation, especially data adaptation, is the second most difficult stage in ML pipeline.

Further analysis showed that ML libraries that use uncommon formats lead to additional difficulties among the developers to understand the format, use the new formats in their software, data wrangling and preprocessing to the format of the data. For example, Weka, MLlib have higher problem in data adaption due to their use of uncommon ARFF and RDD formats of data. For some libraries data preparation turns out to be ever more challenging compared to model creation. For example, H2O, Torch and Weka have 35.29%, 22.95% and 20.51% of posts, respectively, about data adaption.

This finding suggests that the tradeoff in the design of data preparation APIs, e.g. use of custom formats, needs more study. Interestingly, most of the ML textbooks and courses spend little time on data preparation related discussions.

Surprisingly Tuning and Prediction stages of the ML pipeline—topics discussed frequently in the ML research papers—appear infrequently in Stack Overflow questions.

5 RQ2: NATURE OF PROBLEMS

Are some difficulties inherent to ML and thus all ML libraries face them? If so, general solutions could be developed and adapted to all ML libraries. Otherwise, design of the specific library could be improved by utilizing lessons learned in this section.

5.1 Type mismatch

Type mismatch questions have median of 1.61%, SD of 1.02%, and IQR of 1.80%. The smaller IQR indicates that type mismatch appears in most of the ML libraries. scikit-learn, MLlib, Theano and Tensorflow have higher difficulties in type-related problems with 2.92%, 2.52%, 2.08% and 2.02%, respectively. MLlib uses a custom data format called RDD that seems to make type-related problems more frequent for this library. There are also questions about failures due to type mismatch in scikit-learn, Tensorflow and Theano as their APIs have type requirements that are not currently checked.
Finding 3: Type mismatches appear in most ML libraries.

The finding suggests that ML libraries have not focused on type correctness and ML-specific type correctness. A static analysis tool might be able to prevent the majority of these problems. To understand the characteristics of the type mismatch related posts, we randomly select 44 Stack Overflow posts. We found 31 out of 44 problems were caused by the abstraction created by the libraries to create ML types. The other 13 were standard Python type errors. As an example, the following exception is thrown due to an ML type error:

```python
raise ValueError('Invalid shape')
```

Finding 4: Shape mismatch problems appear frequently in deep learning libraries. Keras is an outlier in this subcategory with 5.5% of posts.

```
def CreateModel(shape):
    if not shape:
        raise ValueError('Invalid shape')

    model = Sequential()
    model.add(Dense(1))
    model.add(LSTM(4, input_shape=(31,)))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

Fig. 4: Question 40430186. An example showing dimension or shape mismatch problem in training in ML.

The finding suggests that techniques for verifying shape and dimension compatibility are needed for deep learning libraries. Such techniques could verify if the data conforms to model architecture, and dynamic modification of the network against data shape.

Abstract APIs that hide the details of inner-working of the deep learning networks can further complicate matters. To illustrate consider the following Keras code.
that input\_shape should be (32, 1) instead. The user could not verify statically whether the built model has compatible shape or if there are any unconnected or extra ports while building the model. If we had the tools that could tell the developer that using dimension (32,1) can cause 2 out of 3 ports of the next layer to be unconnected then it would be much easier for the developer to find these errors by themselves. These kind of errors could be detected by program analyses and by providing feedback to the users. In fact, many discussions in these high-scored posts call for richer analysis features. To understand the reason behind the Keras being an outlier in Shape Mismatch subcategory, we have selected 60 random posts from the dataset. We have found that 21 out of 60 shape mismatch problems are from Keras and the shape mismatch in Keras occurs due to the abstraction of APIs used to create layers in the network. The dimension of the layers violate the contracts between the layers without giving any hints to the developer.

5.3 Data Cleaning

As shown in Table 4, data cleaning related questions across the libraries have median of 1.82%, SD of 1.22% and IQR of 1.61%. Most of the libraries have questions about data cleaning stage except for H2O and Torch. This is not surprising since data cleaning is an integral part of any data science pipelines. Libraries scikit-learn, Weka and MLlib have the most questions.

**Finding 5:** Most libraries have problems in data cleaning.

This finding suggests that tool support for data cleaning is needed, but such techniques may need to overcome inherent technical challenges. The abstract APIs in these libraries sometimes make cleaning fail. For example, the \texttt{nan} values in the \texttt{dataframe} needs to be converted first into numpy \texttt{nan} type before they can be cleaned using APIs provided by scikit-learn. Furthermore, these failures do not clearly indicate the root cause making diagnostics difficult.

5.4 Model creation

In model creation subcategory, the most difficult stage according to RQ1, we see problems that are both inherent to ML, and specific to design choices in the library. Inherent difficulty of distributed ML is a major source of questions, e.g. see Fig. 5.

When we study the questions about Caffe we see that Caffe users have problems in model creation due to the dependency of the model on multiple files. To create a model successfully, one needs to make a schema file in protobuf format, create a solver file and write code in C++ or Python to build the model \cite{42}. Having several components complicates matters. In our study, 36 out of 135 questions about Caffe are about model creation problems.

5.5 Error/Exception

Error/Exception subcategory has the median of 5.10%, SD of 1.80% and IQR of 2.71%. All the libraries have issues on runtime error/exception. Surprisingly, though model creation seems problematic in Caffe, runtime failure is very low in Caffe with 0.76%. MLlib, H2O, Keras, Tensorflow and scikit-learn have higher percentage of runtime errors with 5.88% and 5.88%, 5.50%, 5.32% and 4.78%, respectively.

**Finding 6:** Questions on exceptions/errors are prevalent.

This finding suggests that debugging and monitoring facilities for ML needs much improvement to help developers resolve error/exception independently. We dug deeper to determine where debugging and monitoring might be most helpful and found that deep learning and distributed ML libraries have more posts about runtime errors at training time, e.g. when a model is throwing an exception at training time, a model is not converging or learning as the iteration of training goes on, a model is not predicting well, etc. Fortunately, some recent work has started to address these issues \cite{45, 44}, but much more work is needed. Due to the lack of debugging tools to monitor pipelines causes of failure are hard to identify. More abstract deep learning libraries throw more runtime exception during training, e.g. see Figure 6.

![AttributeError:'Tensor' object has no attribute '_keras_history'](image)

**Fig. 6:** Question 45030966. An example question about Keras showing abstraction in deep learning libraries could make identifying root cause of an error/exception difficult.

5.6 Parameter selection

We expected parameter selection to be an inherent ML issue but found some variation between libraries, median of 4.50%, SD of 2.60% and IQR of 2.89%, suggesting key differences among libraries. Caffe and Torch have comparatively more problems with 9.10% and 8.20%, respectively. Libraries like Keras, Weka, H2O, MLlib shows larger percentage of questions on choice of parameters.
Finding 7: Parameter selection can be difficult in all the ML libraries.

For selecting parameters adding support for meta-heuristic strategies in the libraries can be helpful.

5.7 Loss function selection

Loss functions are used to quantify the difference between values predicted by the model and actual values (labels). Our results show that developers have difficulty selecting an appropriate loss function but the extent of difficulties varies across the libraries (median of 2.16%, SD of 1.86% and IQR of 2.62%). All deep learning libraries have comparatively more questions about loss function, for example Caffe, Keras, Tensorflow and Torch have the highest percentages of 6.10%, 4.09%, 3.74% and 3.30%.

Finding 8: Choice of loss function is difficult in deep learning libraries.

This indicates the necessity of further research on the usage of loss function in deep learning libraries, e.g. on loss function recommendation. The selection of the loss function is primarily dependent on the type of the problem. A wrong selection of the loss function can cause a machine learning model to perform poorer (low accuracy) or can decrease the security of a model by decreasing the robustness that can be utilized by attackers to perform adversarial attack [43].

5.8 Training accuracy

We expected training accuracy to be an inherent ML issue impacting all libraries; however, there are few questions about this on Stack Overflow. Caffe and scikit-learn stood out with 3.78% and 3.62% questions about training accuracy. These libraries provide highly abstract APIs and a large number of optional parameters that need to be selected.

Finding 9: Abstract ML libraries have higher percentage of questions about training time accuracy and convergence.

This suggests that the library documentation could be clearer about the impact of optional parameters on training accuracy. Secondly, recommendation system could be developed for parameter recommendation based on dynamic traces.

5.9 Tuning parameter selection

Like accuracy, we considered tuning parameter selection to be an inherent ML issue, impacting those libraries more that have higher number of parameters. Even though not too many libraries have questions about it, scikit-learn and Tensorflow stand out. Tensorflow has higher usage and questions in general, but scikit-learn was as expected due to the large number of optional parameters.

As an example, consider creating AdaBoostClassifier with 5 optional parameters initialized to some default values shown below.

Finding 10: scikit-learn has more difficulty in hyper parameter tuning compared to other libraries.

Overall, our results from this and two previous subsections suggest that parameter recommendation is an urgent need for ML libraries, especially those that have a lot of optional parameters.

5.10 Correlation between libraries

Next, we study whether the pattern of problems exhibited by libraries have similarities. The correlation between libraries based on common pattern of problems is shown in Fig. 8. We have identified two major groups.

Group 1. Weka, H2O, scikit-learn, and MLlib form a strongly correlated group with correlation coefficient greater than 0.84 between the pairs. This suggests that the problems appearing in these libraries have some correlation and the difficulties of one library can be described by the difficulty of other libraries in the group.

Finding 11: Weka, H2O, scikit-learn, MLlib form a strong correlated group with correlation coefficient greater than 0.84 between the pairs indicating that these libraries have similar problem in all the ML stages.

This finding is interesting because other than H2O, other libraries in this category don't support deep learning. We believe that the correlation may be because each of these libraries support many different ML algorithms and allow the user to select an algorithm for their tasks. This design
Fig. 8: Correlation between distributions of percentage of questions over stages of the libraries.

choice is markedly different from the other groups that are specialized for a single ML algorithm.

**Group 2.** Torch, Keras, Theano, and Tensorflow form another group with strong correlation of more than 0.86 between the pairs. These libraries are all specialized for deep learning.

**Finding 12:** Deep learning libraries Torch, Keras, Theano and Tensorflow form another group with strong correlation of more than 0.86 between the pairs indicating these libraries follow similar problem in all the stages.

This finding is interesting because each of these deep learning libraries have adopted different design and philosophies. Tensorflow and Torch are focused on providing low-level general facilities, Keras focuses on high-level abstractions, whereas Theano focuses on efficiency on both CPU and GPU. Our finding suggests that despite different design philosophies followed by each of these ML libraries, the problems are interrelated for the libraries in this category. So, the software engineering research results for one library may generalize to other deep learning libraries.

5.11 API Misuses in All ML Stages

The ML libraries have APIs that are very often misused. To identify the misuses we have studied both the questions asked by some developer and the well accepted answers. If the answers pointed out to incorrect or wrong use of API and provided solution using correct use of APIs, we marked them as posts containing API misuse. API misuse is seen across all the stages of ML pipeline.

For example, see Figure 9 where a user is asking that their training takes much time or longer number of iterations to get a certain training accuracy. When they use one API they are able to achieve the desired accuracy in 5 iterations whereas in the other API they need 60 iterations to reach the same accuracy. The second API works fine, without any error and eventually reaches the same accuracy. But still, the user is puzzled that almost 12 times higher number of iterations are required when using the second API. The answer in Figure 9 suggests that the second API needs the data to be shuffled properly before passing to the API in every iteration. Making that change solves the performance problem. This is an example of API misuse where the precondition of the second API is not satisfied which leads to a performance bottleneck. For another example, let’s consider a problem related to the creation of a NaiveBayes model. Only a part of the code snippet where API misuse occurred is shown below:

```python
from pyspark.mllib.clustering import KMeans

def convert_to_csr_matrix(vectors):
    row = [[i] + len(v) for i, v in enumerate(vectors)]
    row = list(chain(row))
    row = list(chain(row))
    column = list(chain(row))
    csr =csr_matrix((data, (row, column)))
    return csr_matrix((data, (row, column)))
```

The code failed to work successfully giving dimension mismatch error in some parts of the code. The solution to the problem is to properly use the API csr_matrix(). This API needs to have a shape parameter defined explicitly and the correct way to use the API is to explicitly define the shape shown in the code below.

```python
return csr_matrix((data, (row, column)), shape=(len(vectors), dimension))
```

We have observed another kind of API misuse due to API update by the library provider. To illustrate, consider the code below that worked well in Apache Spark MLlib version < 2.0. For Apache Spark version >= 2.0, this API doesn’t work. This is one of the top voted questions on Apache Spark MLlib category.

```python
from pyspark.mllib.clustering import KMeans
spark_df = sqlContext.createDataFrame(pandas_data)
```

**MLib version 2.0 isn’t backward compatible and so the code at Line 3 is outdated and must be replaced by the following**

```python
rd = spark_df.rdd.map(lambda x: Vectors.dense(x[0]))
```

We have found that similar version incompatibility problems are also prevalent in other ML libraries.

Besides, the API misuse scenarios discussed above, many other kinds of API misuse are common in ML libraries, and a more detailed analysis and categorization of errors is needed (much like MUBench). Some common
problems include failure to find important features, improperly preparing the dataset, performance, over-fitting problems, suboptimal prediction performance, etc. A detailed analysis of API misuse is beyond the scope of this work.

6 RQ3: Nature of Libraries

In this section we explore whether some of the libraries are more difficult in certain stages and are there libraries that shows comparable difficulties in all the stages (RQ3). To answer RQ3, we look at three measures. Which libraries have non-zero percentage of questions under the majority of subcategories? Which libraries have above median percentage of questions under the majority of subcategories? Which libraries have outliers?

It turns out that scikit-learn and Tensorflow have questions under all subcategories, and Keras, Weka, MLlib, Caffe, and Theano have questions under the majority of subcategories. On the other hand, H2O, Mahout and Torch have questions concentrated under few subcategories and other subcategories have no questions. We further observed subcategories under which H2O have the majority of questions and found that the majority of the questions are in the initial stages such as how to adapt data to use within H2O, how to create a model, or how to setup to use the library adequately. We also observed similar trends for Mahout except it has proportionally higher percentage of questions about model creation and setup.

Finding 13: Early stages for H2O and Mahout especially setup and model creation have comparatively higher percentage of questions compared to later stages.

This may suggest that getting started is harder with H2O and Mahout. Reflecting further on the nature of H2O and Mahout, there is a key similarity between the two libraries. Both present non-traditional models of computation to the developers. H2O presents a workflow like model, and Mahout is for distributed ML. The absence of questions for later stage subcategories might suggest either that developers who started with H2O and Mahout stopped using the library or that all developers who faced problems getting started with H2O and Mahout continued using the library without any major difficulties, and had no questions. Further research is needed to understand which was the case and we didn’t find any definitive evidence during this study to suggest either way.

Next, we look at libraries that have above median percentage of questions under the majority of subcategories. At the top, >30% subcategories, we have MLlib (13 subcategories), Caffe (12 subcategories), Weka (11 subcategories), Theano (11 subcategories), and Torch (9 subcategories). At the bottom, we have Mahout (6 subcategories) and H2O (8 subcategories). We have previously observed that Mahout and H2O have questions observed under few categories associated with initial stages. Combining with this observation suggests that such difficulties are higher for Mahout and H2O compared to other libraries.

Next, we look at outliers. For shape mismatch Keras is an outlier, for model creation Mahout is an outlier, for model selection scikit-learn is an outlier, for output interpretation H2O and Keras are outliers, for tuning strategy H2O is an outlier, for tuning parameter selection scikit-learn is an outlier, for model reuse Keras and Weka are outliers, and for bug Caffe and scikit-learn are outliers.

Finding 14: scikit-learn is an outlier in several categories suggesting that a deeper look into its API design might be necessary to improve usability of this important library.

scikit-learn provides a lot of optional parameters to be selected in their APIs, whose values are hard to select yet affect accuracy. That could be the reason why its users have more difficulties in selecting parameters. scikit-learn also has an abnormally high percentage of questions about model selection, which is surprisingly because it is one of the few libraries to provide abstract model selection APIs, but the use of these APIs could be simplified. This calls for research on designing better APIs for scikit-learn.

Next, we will look at the error/exception related questions.

Finding 15: Deep learning libraries Caffe, H2O, Keras, Tensorflow, Theano, Torch show more training time difficulties compared to other ML libraries.

While this finding shouldn’t be a surprise, it reinforces a well-established worry in both the AI/ML and SE/PL communities that explaining why a deep learning model has worked or failed at training time or gives unexpectedly low performance remains a hard and open question. We confirm that it is important to solve it to help developers make effective use of deep learning APIs. To ensure that the dataset represents the usage of these libraries in the open source projects, we have calculated the number of occurrences of these libraries in Github open source projects. Table [F] reports the number of occurrences of each library in Github. Furthermore, we performed the Kolmogorov Smirnov [47] test among the distribution of the library usage population and our dataset population. We have found p-value of 0.675 and KS – statistics value as 0.3, which suggest that both samples have been taken from a similar population.

7 RQ4: Time Consistency of Difficulty

In this section we explore the answer to RQ4 to understand whether the problems across different stages stayed consistent over time or are there problems that were prominent
only for a certain period of time and then solved by the library developers. To study this question, we plot the percentage of posts across different stages of all the libraries from the year 2009 to March 2018.

Our major observations from Figure 10 are described below: Model creation related problems are consistent over time. Choice of model problems seem consistent over time indicating model creation problems are not being affected by the evolution of libraries. While these are fundamental problems for ML, deeper involvement of SE engineering researchers is needed to glean and disseminate lessons, patterns, and anti-patterns to help ML practice.

Data preparation related problems slowly decrease after 2013 and show sharp increase after 2017. Weka the library that has most difficulty in data preparation stage started losing popularity and new tensor representation of data gained popularity which explains the slow decline in the data preparation difficulty. The increase in data preparation since 2017 coincides with the increasing interest in deep learning, and popularity of deep learning libraries that provide higher levels of abstraction. Data from a varied set of sources are prepared for deep learning tasks.

Training related problems shows slow increase over time. Due to the popularity of deep learning where training time errors occur more frequently the training related problems are slowly increasing.

Evaluation problems are consistent over time. Evaluation related problems have not been solved by the evolution of ML libraries over the last decade.

8 RELATED WORK

Stack Overflow is the widely used platform to study the software engineering practice from the developer’s perspective. However, existing work has not studied the usage of ML libraries using Stack Overflow. Meldrum et al. [33] studied 266 papers using Stack Overflow platforms to show the growing impact of Stack Overflow on software engineering research. Treude et al. [5] did a manual labeling of 385 questions to manually classify 385 questions into 10 different categories (how-to, discrepancy, environment, error, decision help, conceptual, review, non-functional, novice, and noise) to identify the question types. This study is useful to learn the general categories of questions asked by developers. Kavaler et al. [8] used Stack Overflow data to study the queries on APIs used by Android developers and showed the correlation between APIs used in producing Apps in the market and the questions on APIs asked by developers. Linares-Vásquez et al. [9] studied the effect of the changes in Android API on the developer community. They used the discussions arising on Stack Overflow immediately after the API is changed and behavior of the API is modified to study the impact of the change among the developers. [48] studied machine learning based algorithms, approaches, execution frameworks and presented a brief discussion of some libraries used in machine learning. Barua et al. [11] studied the Stack Overflow posts and used LDA topic modeling to extract topics to study the trend of different topics over time. Rebouças et al. [17] studied the usage pattern of swift programming language among developers using Stack Overflow data. Schenk et al. [15] studied the geographical distribution of usage and knowledge of different skills using Stack Overflow posts and users data. Stanley et al. [16] proposed a technique based on the Bayesian probabilistic model to predict the tags of a Stack Overflow post. McDonnel et al. [17] presented a study of API stability using Stack Overflow data and as a test case they used Android Ecosystem. Baltadzhieva et al. [18] proposed a technique to predict the quality of a new Stack Overflow question. Joorabchi et al. [19] studied the challenges faced by computer science learners in different topics and subjects using the Stack Overflow data. These works are orthogonal to ours.

9 CONCLUSION

This work is motivated by the need to empirically understand the problems with usage of ML libraries. To understand the problems, we retrieved a significant dataset of Q&A from Stack Overflow, classified these questions into categories and subcategories and performed analysis from four viewpoints: finding the most difficult ML stage, understanding the nature of problems, nature of libraries and studying whether the difficulties stayed consistent over time. We found that model creation is the most difficult stage followed by data preparation. We found that type mismatch, data cleaning and parameter selection are difficult across all libraries. We also found that initial stages are harder for H2O and Mahout, and scikit-learn has proportionately higher problems in several subcategories. Lastly, we observed that data preparation and training related problems are showing a sign of increase going forward. These findings are a call to action for SE researchers as engineering of software with ML components is likely to be routine in the next decade.
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