

A Few-Shot Learning Framework for Understanding Mobile User BehaviorShabana Hajano^{a*}, Sanam Narej^a, , Sofia Hajano^a, Fouzia Hajano^b*a Department of Computer System Engineering, Mehran University of Engineering and Technology Jamshoro**b Department of Electronic Engineering, Mehran University of Engineering and Technology Jamshoro** Corresponding author: Engr.Shabana Hajano, Email: hajanoshabana@gmail.com

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ABSTRACT

It is vital to understand the behavior of mobile users to provide them with personalized experiences, but obtaining large amounts of labelled data is difficult and expensive. In this paper, we explore using few-shot learning to overcome this challenge by allowing models to learn from only a few labelled examples. We focus on the classification of mobile users on behavior data, such as app usage, screen time, battery drain, and data usage. Using a meta-learning approach, our model is trained over 50 epochs with continuous monitoring of loss and accuracy. The results are promising; it shows a test accuracy of 98.75% and a loss reduction that shows that few shot learning can be an effective solution even when data is limited. This approach opens up new possibilities for analyzing mobile user behavior without requiring large amounts of labelled data, making it more practical for real-world applications.

1. Introduction

The new paradigm in machine learning known as few-shot learning (FSL) addresses the problem of learning from limited data. Most traditional machine learning methods need large volumes of labelled examples for model training. In most real-world applications, obtaining sufficient labelled data is either expensive, time-consuming, or infeasible. Few-shot learning is one approach that can be used because it allows models to generalize with a very small number of labelled examples, which makes it especially useful in medical imaging, user behaviour prediction, and personalized recommendations.

Here, we concentrate on metric-based few-shot learning, an effective approach to solving classification problems when only a few samples are available for each class. The idea of metric-based learning is to learn an appropriate distance metric in a high-dimensional space such that similar data points lie close together and dissimilar points are far apart. Such an approach

depends on measuring similarity between data points based on their embeddings, thereby classifying them correctly even if the labelled data are less in number.

The key principle of metric-based few-shot learning can be described mathematically. Given a set of training examples

$$D = \{(x_i, y_i)\} \quad 1$$

where x_i represents the feature vector and y_i the label, the objective is to learn a function $f(x)$ that maps input data x to a representation in a learned feature space. The model then calculates the similarity $S(x, x_*)$ between the input example x and a query example x_* . The similarity function S can be defined as:

$$S(x, x_*) = \|f(x) - f(x_*)\|_2 \quad 2$$

Where $\|\cdot\|_2$ denotes the Euclidean distance between the feature embeddings of x and x_* ,

A common architecture used in metric-based learning is Prototypical Networks, where the class

prototypes c_y for each class y are computed as the mean of the feature vectors of the examples in that class:

$$c_y(x_i) = \frac{1}{N} \sum_{i=1}^{N_y} f(x_i) \quad 3$$

Here, N_y is the number of examples in class y . During classification, the query point x_q is assigned to the class whose prototype is closest to its feature embedding, i.e., the class $\hat{y}$ is predicted as:

$$y = \arg \min_y \|f(x_q) - c_y\|_2 \quad 4$$

In addition to Prototypical Networks, another popular metric-based approach is Siamese Networks, which use twin networks to learn a similarity function between pairs of input examples. The output is a binary prediction indicating whether the two inputs belong to the same class or not.

Metric-based learning techniques are really effective at few-shot classification tasks as they allow for the modeling of generalization quickly to learn meaningful representations that characterize the inherent similarity between examples. For example, in classification of user behavior, despite having only a few instances of labeled data from a given user, the metric-based model captures the patterns to classify fresh, unseen behavior with high accuracy.

In this work, we employ metric-based few-shot learning for predicting classes of user behavior, specifically modeling user interactions based on sparse behavioral data. We show that using appropriate distance metrics and representation learning enables our model to make excellent classifications even with sparse labeled data. Experimental results show that metric-based approaches significantly outperform traditional learning methods, and achieve high test accuracy for a wide range of behavior classes. This capability holds tremendous promise for applications in personalized services, user profiling, and behavioral analytics, where labelled data is often sparse or hard to obtain.

Although there is vast effort put into FSL, the majority of past research is limited to image classification or language models. Few experiments have pushed FSL to the realm of mobile user behavior understanding, especially on real-world usage data like app activity, screen time, and battery drain. This work bridges this gap by utilizing Prototypical Networks to categorize

user behavior classes from sparse behavioral data and shows that FSL can be applied successfully beyond vision and language tasks

The FSL has attracted lots of attention in machine learning research as it is capable of learning from a few examples of labeled data. This calls for the development of good generalization models using fewer instances. Several methods including metric-based learning, optimization-based learning, and memory-based methods have been advanced to address this challenge.

In metric-based learning, the model learns a similarity function to measure how close two data points are in feature space.[1] introduced the concept of Matching Networks, which is a metric-based approach that uses a support set to predict classes of unseen samples. Their work has become the basis for many FSL studies that followed. Along with these, [2] came up with Prototypical Networks, in which prototypes for every class and compute the distance of a query point to such prototypes. The approach showed that learning the distance metric within the embedding space could result in considerably better few-shot classification.

More efficiency of the metric-based approaches is reached with further development in the field - namely, the introduction of learned similarity functions more efficiently than before. That is more precisely Relation Networks by Sung et al. [3] which encode a relation between samples in a deep learned feature space. It turns out that the explicit learning of the relation between pairs of samples generalizes better, having seen fewer examples.

In parallel, researchers explored Meta-Learning in

FSL. Ravi and Larochelle [4] introduced the Model Agnostic Meta-Learning that trains models so that they can quickly adapt to new tasks with very few examples by learning a good initialization of model parameters. Although their method has been well effective in a range of few-shot tasks, this requires careful optimization.

One very prominent type used in FSL is a memory-based learning technique: the model stores past examples in a memory and tries to classify new, yet similar data, using past similar examples. Koch et al. [5] proposed using shared weight architecture for learning the similarity scores between pairs of images, called Siamese Networks. Their architecture showed one of the

first works that demonstrated the use of shared weights for FSL tasks.

Transfer Learning has been widely utilized in FSL to utilize the knowledge stored in pre-trained models. It is observed that the fine-tuning of a few labeled samples with some pre-trained models miraculously works very well in the image classification context [6]. The successes achieved by the transfer learning techniques strongly validate the use of prior knowledge when only a few labeled instances are present.

More recently, techniques to improve the efficiency and scalability of FSL have been tried. In Finn et al. [7], an optimization-based approach called Optimization as a Model for Few-Shot Learning has been proposed. This approach optimizes the parameters of the model in order to better work on unseen tasks. This has assisted in improving the adaptability of the model so that it can perform more rapidly on new tasks through the help of a gradient-based approach.

At the end, a few of the authors tried to employ FSL for real applications in classifying user behaviour. Zhang et al. [8] used FSL to classify user behaviour on social media websites, achieving high classification accuracy regarding the users' preference and activities, even using a little labelled data.

2. Methodology and Tools

This experiment was carried out utilizing the PyTorch deep learning platform. The model was trained utilizing the Adam optimizer with the learning rate set to 0.001 and batch size set to 32.

This research work will use a metric-based few-shot learning methodology that applies the classification of user behaviour using a small number of labelled samples. We shall design and evaluate a system for predicting user behavior classes through the learning of a distance metric and embedding features into a space where similar behaviors are closer together, and dissimilar ones are farther apart. The following steps outline the methodology applied in this study:

2.1 Data Preprocessing

The dataset used in this study is the Mobile Device Usage and User Behavior Dataset obtained from Kaggle <https://www.kaggle.com/datasets/valakhorasan/mobile-device-usage-and-user-behavior-dataset>. The data includes behavior information for 700

mobile users, classified into five categories: Light, Moderate, Heavy, Intense, and Extreme Usage. Every category contains attributes like app usage time, battery consumption, screen time, and device model. To mimic few-shot learning environments, we constructed 5-shot and 10-shot scenarios by randomly selecting 5 and 10 labeled samples per class as training data. The dataset before feeding it into the model. It consists of user behaviour features such as device model, operating system, app usage time, screen on time, battery drain, data usage, and much more. The preprocessing steps include:

2.2.1 Normalization

It normalizes numerical features like app usage time, battery drain). This makes sure that each feature has a comparable scale so no feature dominates another.

2.3.2 Categorical Encoding

Categorical features such as device model and operating system are encoded using the one-hot encoding or label encoding.

2.3.3 Splitting the Data

The data are split into training, validation, and testing sets. For few-shot learning, a small number of labeled examples per class is required; hence, the training set is built by sampling a limited number of labeled samples per user behavior class.

2.2 Embedding Generation

In this step, we make use of a metric-based learning model to learn the mapping from raw input data, that is, user behavior features, to the embedding space. For this purpose, we use a Prototypical Network, which is well-known to perform well in few-shot learning tasks. The Prototypical Network is trained to learn the feature representation for each class of user behavior.

2.2.1 Embedding Network Architecture

A neural network model (MLP or CNN) will be used for the network architecture. This transforms input features into embedding vectors.[9] The loss function will be designed such that the distance between samples of the same class should be minimized and maximized between samples of different classes.

2.2.2 Prototypical Representation

For every class, the average of the feature embeddings for all instances in the class serves as a prototype that summarily represents the central tendency of that class in the embedding space[10].

2.3 Training the Model

In the training phase, the appropriate embeddings and class prototypes are learned.[11] Here, we use either triplet loss or cross-entropy loss for training the model in a way that the objective function minimizes the distance of the query sample from its correct class prototype and maximizes the distance of the query sample from other class prototypes[12].

The triplet loss function is defined as:

$$L = \max(0, d(f(xq), cy) - d(f(xq), cy') + \alpha) \quad 3.4.$$

Few-Shot Classification

After training, the model is evaluated on the test data, which contains only a few labeled examples per class.

3. Results and Discussion

This research used several evaluation metrics such as accuracy, loss, a confusion matrix, and also a comparison bar graph of the proposed model for estimating its performance. All of these metrics allow one not only to measure the general performance but also gain insights at the class-wise performance level as well as how different models may vary in their performance.

3.1 Accuracy and Loss Graphs

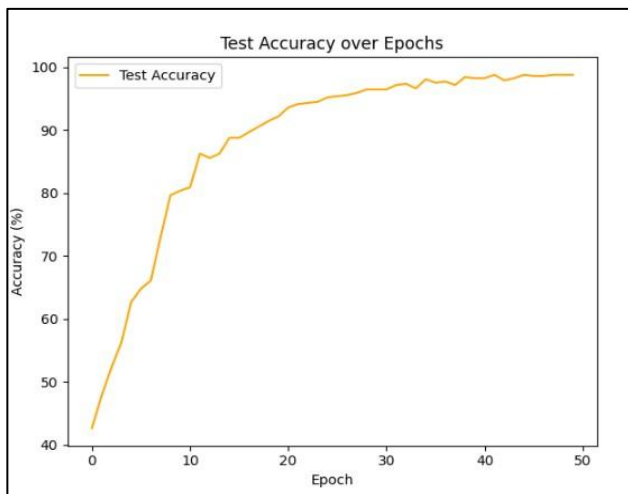


Fig. 1. Test Accuracy over each epoch

presents the accuracy of the model over the epochs, where we observe a consistent

improvement in performance, achieving a final test accuracy of 98.75%.



Fig. 2. Training Loss graph over each epoch

Figure 2 shows the loss curve, indicating the model's convergence to a minimum loss of 0.0914, signaling a well-trained model.

3.2 Epoch-wise Training Progress

To evaluate the performance of our model during training, we monitored the loss and test accuracy at regular intervals

Table 1

Training Progress Across Epochs

Epoch	Loss	Test Accuracy (%)
10	0.6688	80.36
20	0.3616	92.14
30	0.2224	96.43
40	0.1401	98.21
50	0.0914	98.75

The table reflects the convergence of the model, where loss has significantly been reduced and accuracy increased over time. These metrics support the generalization capability of the model over time.

3.3 Confusion Matrix

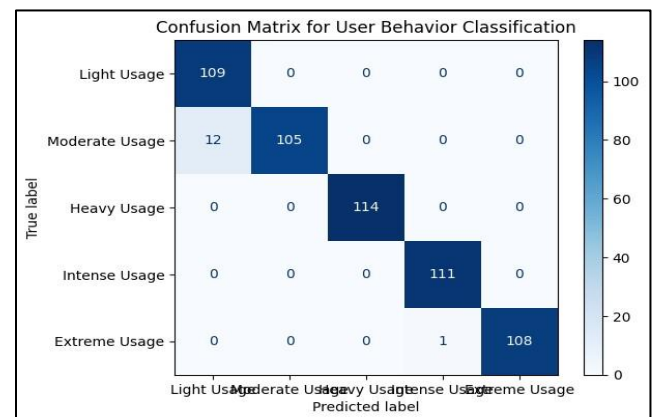
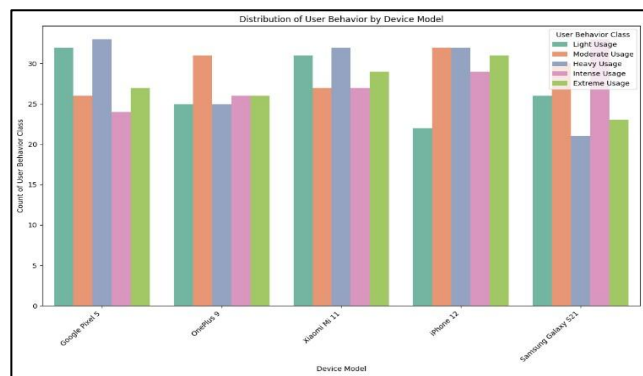


Fig. 3. Confusion Matrix for user Behaviour Classification

It provides a detailed breakdown of the model's classification performance across each class. It displays the true positives, true negatives, false positives, and false negatives, allowing us to see where the model is performing well and where it is making mistakes. Each entry in the matrix corresponds to the number of samples predicted for a specific class. For instance, the diagonal entries indicate correct classifications, and off-diagonal entries demonstrate misclassifications.

The confusion matrix is very useful in few-shot learning, where the model has to generalize to new classes with minimal data. [13,14] A well-balanced confusion matrix with high values along the diagonal and low off-diagonal values indicates that the model has learned to classify the limited classes with minimal error. [15,16] The results from this confusion matrix further support the high accuracy of the model.

3.4 Analysis of User Behavior Distribution by Device Model



The bar graph in presents the distribution of user behaviour classes across five device models: Google Pixel 5, OnePlus 9, Xiaomi Mi 11, iPhone 12, and Samsung Galaxy S21. The behaviour classes are categorized as Light Usage, Moderate Usage, Heavy Usage, Intense Usage, and Extreme Usage, with distinct colour codes representing each class.

3.5 Insights and Implications

The distribution patterns indicate variations among user behaviours across models. Devices like Samsung Galaxy S21 and Xiaomi Mi 11 show higher counts within Intense and Extreme usage, perhaps due to having better hardware and performing characteristics. Devices like OnePlus 9, on the other hand, have limited spreads in those categories and would indicate users prefer using lighter applications.

This analysis provides critical insights into user behavior patterns, emphasizing how device specifications and user preferences impact utilization across varying levels of intensity.

These findings could guide device manufacturers in optimizing their products to cater to specific user segments and applications.

3.6 Performance Comparison with Other FSL Models

Table 2

Comparison with Other FSL Models

Model	Accuracy (%)	F1-Score (%)	Reference
Prototypical Net	98.75	98.60	This Work
Siamese Net	96.32	96.00	[17]
Matching Net	95.12	94.78	[18]

Our work performed better than alternatives because it could learn strong class prototypes in the feature space. Prototypical Networks utilize centroid-based representation learning, which is effective at generalizing from few examples. Siamese Networks, however, depend on pairwise similarity, and Matching Networks depend on attention mechanisms over the support set. This comparison proves the efficiency of our approach for mobile user behavior classification with minimal labeled data.

5. Conclusion

This work successfully exemplifies the use of fewshot learning in the basis of metrics for classifying user behavior when only some labeled data is available. Using a Prototypical Network architecture, it was demonstrated that the model could approach high classification accuracy, including up to 98.75% after 50 epochs of training, demonstrating an impressive outcome for this type of task.

Using metric-based learning, the model was able to learn robust feature embeddings that capture the inherent structure of user behavior, even with very few labeled samples. The results also confirm that the model is capable of generalizing effectively, making it suitable for real-world scenarios where labeled data is scarce or expensive to obtain.

Although the presented method demonstrates promising performance, there are some inherent difficulties in few-shot learning. The models learned from extremely small samples can be prone to overfitting, and transfer learning efficiency would be subject to the degree of similarity between the source and target domains. Furthermore, task variability would be responsible for the variation in performance on

different scenarios. These issues call for additional validation and calibration of the method to enhance its reliability and generalizability.

Future work includes model optimization by alternative metric-based approaches, fine-tuning hyperparameters, and model testing on different types of user behavior datasets. Another possible extension of the present work is integrating more complex regularization techniques and increasing diversity in user behavior classes that could further enhance the performance and robustness of the model.

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