The Impact of Segmentation and Overlapping in Feature Extraction for Biometric Human Authentication Systems

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Abstract *— One of the arduous challenges in Machine Learning is how to extract features with enough information that will simplify the learning process of classification models; therefore, leading to better predictions and human interpretations. We investigated the impact of segmentation and overlapping techniques used to extract features from accelerometer data to optimize the performance of Machine Learning models designed for Biometric User Authentication via walking patterns. Results showed that bigger segmentations were beneficial to the individual performance of the features and detrimental for systems fed with a set of features. Also, there was no evidence found supporting the increase in the overall performance of the system by using the method of overlapping. Finally, via a brute-force feature selection algorithm, we achieved a 71% classification accuracy (with 10/34 features) vs. 64% (with 34 features), regardless of the system's configuration meaning that key features hold more weight than mere segmentation and overlapping methods.*

Key Terms *— Acceleration, Biometric Human Authentication, Feature Extraction, Supervised Learning.*

INTRODUCTION

The study of accelerometer data has been latent in the last years, particularly in the analysis of human behavior [1]. Several fields benefit from on-body sensing of accelerometer data as a type of monitoring technology. Some of the applications of the study of accelerometer data are presented by researchers who have been able to: study the effects of age on physical activity over a human's lifespan [2], propose applications of wearable performance devices in sports medicine [3], assess elderly's functional balance and mobility [4-5], recognize personalized patterned behavior from unusual events on mobile users [6], and even estimate the total energy expenditure of daily activities [7].

In the technological realm, accelerometer data collected from devices help in detecting changes in gravitational acceleration. This measurement can support devices such as smartphones, smartwatches, PCs, and game controllers to determine stabilization, vibration, and device orientation for several purposes. In addition, accelerometers are one of the most widely used sensors on embedded devices and the most frequently accessed from applications. These sensors are cheap, low in power consumption and often invisibly embedded into consumer devices. However, the constant and unseen collection of users' accelerometer data could generate threats in terms of privacy. Accelerometer data, by itself, might not generate any insight nor disclose any type of information, yet an analysis of tri-axial accelerometer data can reveal several intel that could be considered invasion of privacy, but also allows researchers to explore other cybersecurity related applications.

According to Matovu & Serwadda [8] and Kröger et al. [9], accelerometers in mobile devices are an open door for invasion of the user's privacy. Researchers claim that even when other sensors such as cameras, microphones, and GPS locators are turned off, accelerometer data can be enough to obtain information from the device's holder. This information or insight can include the holder's location, health condition, age, gender, body features, emotions, and even personality traits. Nonetheless, this is all dependent on some restrictions and limitations such as controlled environments, the location or position of the accelerometer, and even some knowledge of the holder's traits. These limitations open the door to many researchers in the pursuit of real-world applicability of the use of accelerometer data for cybersecurity systems.

Biometric Human Authentication is one of the real-world applicability of accelerometer data that has been under study for quite some time. This field is concerned with authenticating an individual through physical traits such as the fingerprints and the iris. However, there have been other efforts to perform Biometric Human Authentication in an unobtrusive way via accelerometer data. The idea is to collect accelerometer data, in the form of tri-axial signal, of subjects performing an activity such as walking. This signal is later preprocessed so that relevant data values, named features, could be extracted, and then fed to a machine learning classifier to determine the performance of the model whose goal is to authenticate the subjects. During the preprocessing phase segmentation occurs, meaning that the signal is divided into windows of fixed length so that features could be extracted by aggregation. Researchers claim that there's a tradeoff between the systems' performances and the windows size; thus, this idea is the topic under study on this project.

The goal of this project is to use tri-axial accelerometer data for Human Authentication by exploring the effectiveness of overlapping and windowing techniques for feature extraction. The results of this project could help the community into understanding the impact of segmentation and overlapping in feature extraction for Biometric Human Authentication systems and serve as a motivation for future research on cyber systems such as Identification of Friend or Foe (IFF) and Intrusion Detection Systems (IDS) based on accelerometer data.

REVIEW OF LITERATURE

While delving into the sphere of Biometric Human Authentication using patterned human activities recorded by sensors (for example, accelerometers), we encounter the problem of feature extraction of the raw data. Many researchers focus on where the sensor must be placed, the selection of the best supervised learning technique, and/or the improvement of the performance and accuracy of the classification model; commonly ignoring both the method of preprocessing the raw data through segmentation, and the extraction and identification of relevant features for classification purposes.

In terms of the location of the sensor, Davoudi et al. [10] developed a validation study that explored the effect of the placement and number of sensors on Physical Activity Recognition and Energy Expenditure Estimation in older adults. The investigation consisted of 93 participants that completed a total of 32 different activities. Accelerometers were placed on 5 different locations: wrist, hip, ankle, upper arm, and thigh. Even though they found that the performance of their model for Activity Recognition of older adults increased with the placement of additional sensors, they recognized that a single accelerometer had only a minuscule increase in prediction error.

Another similar research was conducted by Cleland et al. [11]; in their study, they tried to determine the optimal placement of accelerometers for detection of everyday activities. They used 6 accelerometers placed in the chest, wrist, lower back, hip, thigh, and foot. They found that there was no significant difference in classification accuracy when using one or more sensors. Furthermore, even when the sensor on the hip resulted in the best classification performance, the data from all the other locations proved to have similar levels of accuracy.

As to methodologies for a higher performing system for user authentication or activity recognition, Casale et al. [12] explored a novel technique for user authentication and verification based on a two-step pipeline. The first step was to personalize a classification model by feeding it with a small sample of the subject's activities measured by an accelerometer; the second stage of the pipeline was to determine whether the subject was classified as authorized or not. Features extracted included the difference between pairs of consecutive peaks in the signal, the difference between the value of consecutive upper-side and lower-side peaks and the mean value of the raw data and the derivative of the acceleration, also known as the Jerk. To achieve the creation of said features, a sliding windowing technique of 2 seconds was used. For the second stage, the researchers used a four-layer architecture built around the concept of a convex hull and found an improvement in user verification compared with state-of-the-art techniques.

McConville et al. [13] explored another method for person identification via supervised machine learning techniques and introduced an unsupervised method for the discovery of individuals via accelerometer data. The researchers created their model thru the technique of segmentation with window sizes of 1 second and extracted features such as the mean, min, max and standard deviation. By using Principal Component Analysis to obtain a two-dimensional visualization, they also explored the progression of the separation of the signals as the size of the windows increased; they observed how larger windows resulted in a greater separation of the signals. The authors also compared several machine learning models based on well-known algorithms and concluded that a Random Forest Classifier or a classification based on a Logarithmic Regression resulted in the highest accuracy of classification per subject, 67% and 68% of accuracy respectively.

Singha et al. [14] explored the problem of obtaining an unobtrusive layer of security from smartphones based on accelerometer data. The goal of this research was to construct a classification model based on a Random Forest ensemble for classification and compare it to other classifiers namely Logistic Regression, Support Vector Machine and Decision Trees. The researchers created their own dataset by using an application on a smartphone placed on the user's pocket to record tri-axial acceleration. To extract the features from the raw data, the researchers used the segmentation technique with window sizes of 100 seconds with a 50 percentage of overlapping. The features extracted were the mean, median, magnitude, cross-correlation, peak count, distance between peaks and the spectral centroid. Their results showed that the best resultant model was a Random Forest Ensemble with a classification accuracy of 96.79%.

Kröger et al. [9] explored a different aspect of accelerometers on mobile and other devices. The researchers expressed their sentiment towards the latent privacy implications of third-party applications accessing accelerometer data without requiring any security permission. According to their findings, via an extensive review of literature, accelerometer data by itself can be enough to obtain information about a device holder including their location, activities, health condition, body features, gender, age, personality, and even emotional traits. In other words, acceleration alone can be used to identify a person based on biometric movement patterns; these patterns can even be used to reconstruct text that is input into the device such as passwords and credentials. The researchers understand that these claims by other investigations have some limitations since the results were obtained under controlled environments, with some context on the user's traits, and by controlling the number of sensors and their respective locations.

However, the focus of these related work lies on developing high performing models for the classification or identification of the individuals overlooking the process of smart feature extraction and the fine tuning of the windowing techniques or the overlapping percentage. Research that investigates the quality and level of information for classification provided by features extracted was conducted by Quiroz et al. [15]. In their research, they focused on the identification of key subsets of features; they used the HARUS dataset, which contains 561 time-domain and frequency-domain features collected from a smartphone. The data was collected from 30 users that were performing staged activities. The dataset was divided into 21 subjects for training and 9 subjects for testing and the features were extracted by using a windowing technique of 2.56 seconds with a 50 percent of overlapping. For the analysis, the researchers created several groups of features and concluded that the gravity signals provided higher classification accuracy, especially for the static activities of sitting, standing, and lying down. They also concluded that features from angular velocity were not as helpful as those from body acceleration, yet some of them considerably improved the accuracy of the feature set on body acceleration.

In a different matter, Banos et al. [16] claims that segmentation may have an influence on a system's performance, meaning that there exists a tradeoff between window size and accuracy that should be investigated. The researchers explored segmentation in three groups: activity-defined windows (partitions based on the detection of activity changes), event-defined windows (partitions based on the location of specific events), and sliding windows, also known as windowing (partitions are created over a fixed size). This extensive study showed that reduced windows of 2 seconds or less proved to have the most accurate activity detection performance.

This project tries to provide a more specific and granular analysis on the features extracted for authentication of individuals using accelerometer data and segmentation. The main goal is to explore which window size is more effective in the authentication of subjects walking and to analyze whether the technique of window overlapping contributes to a better classification accuracy of the models designed for Biometric Human Authentication.

METHODOLOGY

The methodology followed in this investigation can be divided into the following sections:

- Dataset Selection
- Model Design Overview
- Individual Feature Performance
- Collective Feature Performance
- Collective Feature Performance after Feature Selection

Dataset Selection

The dataset used in this research is named User Identification from Walking Activity Dataset and it's publicly available in the UC Irvine Machine Learning Repository [17]. The accelerometer data collected comes from an Android smartphone positioned in the chest pocket of 22 different subjects walking over a predefined path; this makes the dataset univariate, sequential, and a tri-axial time-series. The dataset was developed for research purposes such as activity recognition and authentication and/or identification of humans using motion patterns. In terms of the attributes, the data is separated by participant and each file contains the following information: time_step, x acceleration, y acceleration and z acceleration. Three subjects were eliminated from the dataset since their time-series were repetitive and incomplete (subject number 17, 18 and 19) leaving the dataset under study with only 19 participants.

In this dataset there's a moderate class imbalance between the number of samples per subject as shown in Figure 1; this is equivalent to the data imbalance that there is between the time for which they perform the walking motion activity. The ratio between the largest number of samples versus the smallest number of samples is approximately 1:15. However, in nowadays real-life classification problems we deal with problems with imbalance ratios ranging from 1:1000 and up, thus we decided to move forward with this dataset after removing null values.

For the visualization of the signal in Figure 2, we considered a subset of 400 samples, this is equivalent to about 13 seconds of activity. In this sample, the signal shows a periodic behavior for the walking activity and the goal is to be able to feature extract the most information out of windows of certain length. Since research has shown that smaller values result in the best system performance [16] we will explore the windowing technique from 2 seconds to 10 seconds in length and see how this affect the classification performance of the model created.

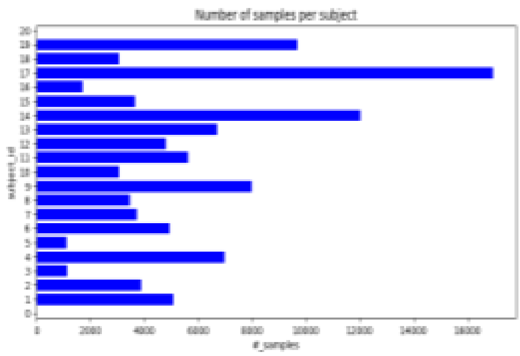

Figure 1
Data Imbalance in Dataset

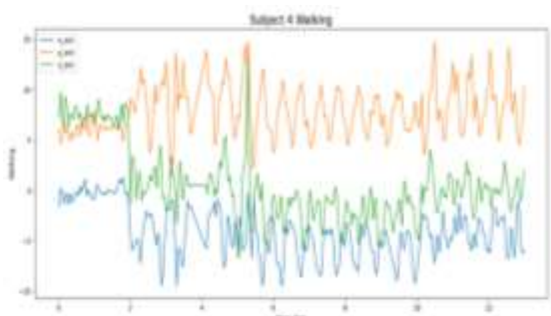

Figure 2
Tri-axial Signal Visualization of a Subject Walking

Model Design Overview

The analysis performed on this study is centered on the performance of machine learning models used for authenticating subjects based on their walking patterns. This is accomplished by training the models with a K-Neighbors Classifier (KNC) and 70% of the subjects' accelerometer data, then using the other 30% of the samples to make predictions. The performance of the models was measured by accuracy, which is defined as the number of correct predictions divided by the total number of predictions.

The construction of the classification models followed in this project can be divided into the following components visualized in Figure 3.

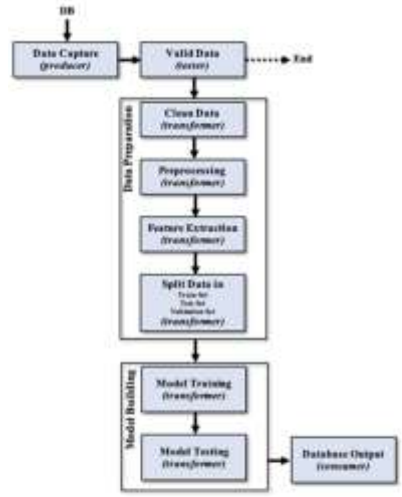

Figure 3
Model Architecture

- Data Capture (producer): was the starting point of the process; here the accelerometer data from csv files was loaded into a Python DataFrame by the following columns: subject_id, time_step, x_acc, y_acc, z_acc.
- Valid Data (tester): here the raw data was assessed over several criteria or thresholds for validation purposes. This validation step verified if the data had no jumps, gaps, or other corruption in the time-series. In addition, it checked whether the individual time-series of a subject was unique. Subjects with invalid data were eliminated from the dataset.
- Clean data (transformer): null values from the dataset were removed.
- Preprocessing (transformer): first, the time-series for the magnitude of the acceleration was calculated. Then, the signals for the x, y and z acceleration and the magnitude were segmented. These segmentations formed a new dataset stored on a new DataFrame. The process of segmentation, also known as windowing, consists of partitioning the raw accelerometer data into windows of *n* seconds; this allows us to generate features by aggregating the sample values contained withing each window. The overlapping technique consists of taking overlapped windows by a specific percentage rather than using discrete windows for the

feature extraction. Both processes can be visualized on Figure 4.

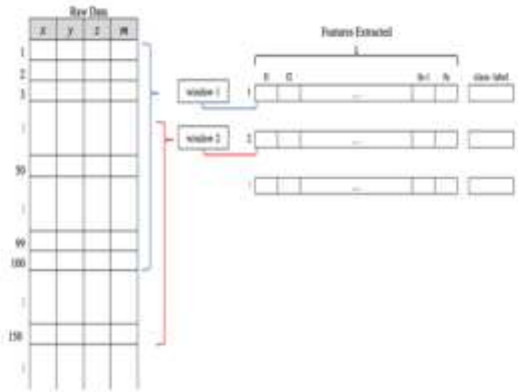

Figure 4
Sample Windowing Technique with Window size of 100 seconds and 50% of Overlapping

- Feature extraction (transformer): After the data was segmented, the following features were extracted by the aggregation of values in the windows created from the xyz time-series, and the magnitude signal as well: max, mean, median, min, negative count, peak count, positive count, standard deviation, and variance for a total of 34 features; the positive and negative value count were not extracted from the magnitude signal.
- Split Data (transformer): here the data was separated into training and testing sets. 70% of the windows of each subject was selected for training, the other 30% of the windows was used for testing. This allowed the model to learn the walking patterns of the subjects before trying to make predictions.
- Model Training and Testing (transformer): a GridSearch was implemented over a K-Neighbors Classifier (KNC) to obtain a model with the highest test accuracy by fine tuning the number of neighbors. In some cases, feature selection was implemented during this phase.
- Database Output: Finally, the following results were stored on csv files for further analysis: feature name, overlapping percentage, window size, train accuracy percentage, test accuracy percentage and best number of neighbors.

Individual Feature Performance

For the individual feature performance, the features were ranked by their individual ability to authenticate the subjects. This was accomplished by creating several classification models, fed with the individual features on different segmentations and overlapping configurations, and storing their predictive accuracy when trying to authenticate the subjects.

Collective Feature Performance

The collective feature performance was measured by using the set of the 34 features extracted to create models with different segmentation and overlapping configurations and storing their predictive accuracy when trying to authenticate the subjects.

Collective Feature Performance after Feature Selection

Finally, we performed feature selection on the set of 34 features to analyze the value of the selection of key features versus the creation of variations in the system's configurations (segmentation and overlapping). For this, we investigated the brute force approach proposed in [18] for feature selection. In sum, this brute force approach starts out with a list of the features extracted ranked by their individual ability to classify the data via K-Neighbors Classifier (KNC). Starting with the first feature, the algorithm will generate models by adding the consequent features from the ordered list, one by one, if and only if the performance of the model increases with the new addition.

INSTRUMENTATION

The primary tools used on this research were the User Identification from Walking Activity Dataset taken from the UCI Irvine Machine Learning Repository, the PyCharm IDE and the Python Programming Language. The libraries used for the development of the code included NumPy, Pandas and Sci-kit Learn – which is a free software machine learning library. Other libraries used for visualizations were Matplotlib and Seaborn.

RESULTS AND DISCUSSION

First, we explored the individual performance of the features extracted with different configurations; the goal was to explore the impact of segmentation and overlapping on individual features. Figure 5 shows how there's not a clear benefit or pattern from overlapping choices or window sizes over the x axis signal, the same happened for the other axis and the magnitude signal. This makes us wonder if the extra computations of overlapping, resulting in some cases in the doubling of the number of partitions or windows, are necessary or even beneficial. What's clear from the plots is the list of features that performed better individually.

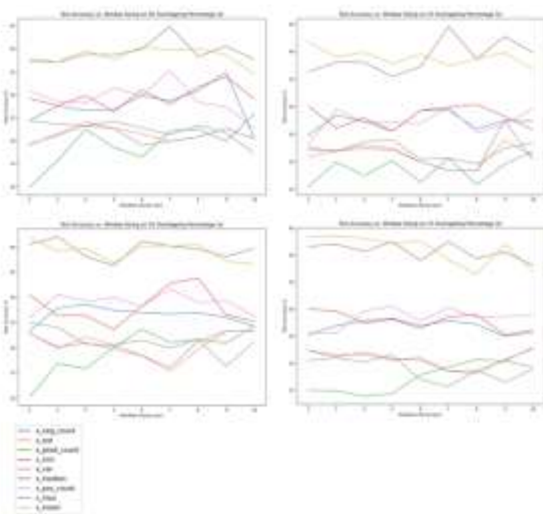

Figure 5
Individual Performance of features extracted from the X acceleration signal over various Overlapping percentages

An analysis of the top 10 ranked features (from all the combinations of window sizes and overlapping percentages) showed how the higher-ranking features were extracted from the x and the z axis. In addition, the following features ranked in the top 10 for all choices of window sizes and overlapping percentages: x_mean, x_median, y_mean, z_mean, and z_median followed by: z_pos_count, z_neg_count, x_pos_count, x_min, x_neg_count and z_min. According to the results, the mean, and the median of the acceleration contains more information about the user's walking pattern than any other of the features extracted. More specifically, the average acceleration of the subjects, and the median of the acceleration are enough to authenticate the subjects with approximately 40% of accuracy but are not enough by themselves to fully authenticate them with a satisfactory accuracy rate.

Figure 6 shows the average individual performance of the features when trying to authenticate the subjects using a K-Neighbors Classifier (KNC). In terms of the individual performance, as the size of the windows increased the average accuracy performance of the features increased as well; meaning that the features saw more representative information of the walking patterns as the size of the windows increased. Yet, for individual features, a 0% overlapping resulted in a better individual performance of the features. In sum, for individual features, it is more efficient to use bigger window sizes with a 0% overlapping for the authentication of users via their walking patterns.

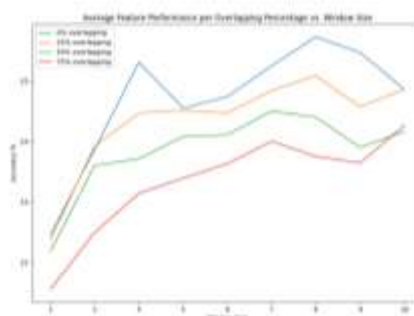

Figure 6
Comparison of average feature performance per window size

Now, Figure 7 shows the performance of different classification models using K-Neighbors Classifier (KNC), and the set of all the features extracted (total of 34 features). Contrary to the results obtained from individual features, the set of all features performed better with windows of smaller sizes. From the overlapping, we see that there's not a considerable benefit from choosing a particular overlapping percentage; thus, when developing models for Biometric Human

Authentication, smaller window sizes impact positively the performance of the model regardless of whether we choose to overlap the windows or not.

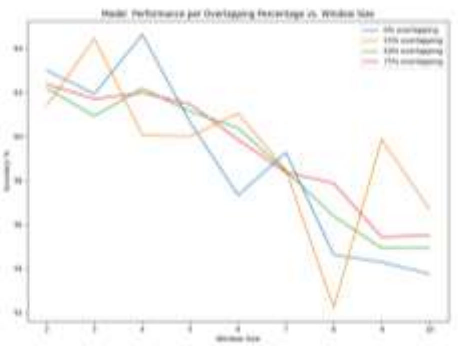

Figure 7
Comparison of model performance with all the features per window size

Figure 8 contains the results of the models' performances after the feature selection method proposed in [18]. We can see how the different overlapping percentages performed similarly except for the 25% whose plot behaves erratically meaning that it should not be considered as a design option. In terms of the window size, with a reduced number of features there's not much change in the accuracy of classification of the models, implying that there's more weight in the quality of the features extracted than in the segmentation and overlapping configuration selected. Lastly, after features were selected, we were able to improve the classification accuracy of the models from approximately 64% of accuracy (with 34 features) to approximately 71% of accuracy (with 10 features).

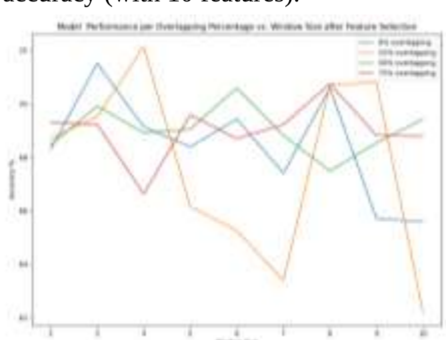

Figure 8
Comparison of model performance after feature selection

LIMITATIONS

The limitations of this research parallel those limitations found by similar investigations on Biometric Human Authentication. First, the dataset obtained from the UC Irving Machine Learning Repository contained uncleaned data, data imbalance and only 22 subjects; this resulted in the elimination of the samples from 3 subjects and a final dataset of only 19 participants with an unequal number of samples per individual. In addition, with this type of research, the walking activities were staged; meaning that the participant could have known the goal of the investigation and may have tried to tamper with their walking pattern to change the outcome of the accelerometer. Lastly, it is mentioned that the accelerometer is placed in the chest pocket, but no further detail is provided. Thus, one can only assume which axis of acceleration is represented by the forward/backward, upper/downward, and left/right motions. Another limitation was the processing power of the machine and the code developed to create the models that didn't allow for the segmentation of the raw data in window sizes smaller than 2 seconds.

CONCLUSIONS

In this project, we explored the tradeoff between segmentation/overlapping, and the performance of Biometric Human Authentication systems based on accelerometer data. The results showed how segmentation with bigger sizes resulted in a better performance of individual features, yet this behavior is opposite when using the set of the 34 features extracted. In terms of overlapping, a 25% overlapping should never be selected, however, there's not enough evidence to support the extra computation for the overlapping of windows. Finally, results showed how key features have more value in the classification performance than segmentation and overlapping, this was determined by a brute-force feature selection based on the individual classification performance of the features. With these results, we hope to help characterize the tradeoff that exists in Biometric Human Authentication systems and to support future systems designers by providing some basis and support to their design choices.

FUTURE WORK

The characterization of the tradeoff between segmentation/overlapping and performance accuracy is not yet completely covered; thus, research on the topic is still needed. Future research can focus their efforts into investigating the impact of segmentation in windows smaller than 2 seconds and in other fields or applications such as Activity Recognition, developing cleaner datasets with higher sample frequencies and more transparent positioning of the accelerometer, comparing the results of this project with other classification algorithms, extracting features in the frequency domain and exploring the impact of segmentation/overlapping on a different set of features.

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