Detecting motor activities from sensor datasets is becoming increasingly common in a wide range of applications with the rapid commoditization of wearable sensors. To detect activities, data scientists iteratively experiment with different classifiers before deciding on a single model. Evaluating, comparing, and reasoning about prediction results of alternative classifiers is a crucial step in the process of iterative model development. However, standard aggregate performance metrics (such as accuracy score) and textual display of individual event sequences have limited granularity and scalability to effectively perform this critical step.

To ameliorate these limitations, we introduce Track Xplorer, an interactive visualization system to query, analyze and compare the classification output of activity detection in multi-sensor data. Track Xplorer visualizes the results of different classifiers as well as the ground truth labels and the video of activities as temporally-aligned linear tracks. Through coordinated track visualizations, Track Xplorer enables users to interactively explore and compare the results of different classifiers, assess their accuracy with respect to the ground truth labels and video. Users can brush arbitrary regions of any classifier track, zoom in and out with ease, and playback the corresponding video segment to contextualize the performance of the classifier within the selected region.

Track Xplorer also contributes an algebra over track representations to filter, compose, and compare classification outputs, enabling users to effectively reason about the performance of classifiers. We demonstrate how our tool helps data scientists debug misclassifications and improve the prediction performance in developing activity classifiers for real-world, multi-sensor data gathered from Parkinson’s patients.

1 INTRODUCTION

The large diffusion of consumer-level wearable devices has opened many possibilities related to activity monitoring. Smart watches and devices such as Fitbit [10] are increasingly used by people to track their daily motor activity, whereas a wide variety of biosensors is starting to play an important role in patient monitoring. The task of detecting motor activities such as walking from sensor data is thus becoming very popular in the fields of data science and machine learning. The development of these prediction models generally relies on validating their performance on a database of labeled sensor data. Numerical metrics such as accuracy score, precision and recall.
are often computed to establish how well a classifier can identify specific activity events. Based on these metrics, data scientists can compare the performance of different prediction models and establish which of them can be deployed. Data scientists may also have to evaluate the combined performance of multiple classifiers, which can be based on the input from different sets of sensors.

While performance metrics try to condense the effectiveness of a model to ready-to-use numerical estimates, they often fall short in conveying insights into why one prediction model seems to perform better than the other. The lack of contextual information prevents data scientists from analyzing classification results at a more granular scale, which in turn makes reasoning about misclassifications difficult. Also, performance metrics often assume the availability or reliability of ground-truth labels, which may not always hold—especially for long streams of sensor data.

We introduce a novel visualization system, Track Xplorer (also referred to as Xplorer for short), to interactively analyze the classification results of sensor-based predictive models. Xplorer enables users to debug and compare multiple classifiers up to the level of granularity of a single prediction, providing different ways to validate the performance of each model. Xplorer facilitates the interpretation of classification results in application context, enabling data scientists to reason about the causes of misclassifications and to improve their predictive models. We note that our system does not aim at gaining insights on the internal behavior of a predictive model, rather it serves the purpose of analyzing its output.

To illustrate the usefulness of our system, we report a use case involving the development of predictive models to detect motor activities used in evaluating the progression of a person’s Parkinson’s disease. We study the usage of Xplorer through a group of fourteen participants, data scientists and business managers, working on the same project. We demonstrate how Xplorer proved to be essential for visually validating and comparing predictive models for reasoning on the causes of mispredictions, and for understanding the trade-offs in the usage of different sensors. We further observe how the system facilitated the discussion among data scientists as well as between data scientists and business managers in general. To ensure patient privacy, we use synthetically-generated data for the figures in this paper.

In the following, we first give a synopsis of prior work, followed by a brief discussion of our system design. We then provide details on Track Explorer’s interactions and visual design along with its track algebra, command line set and classification validation support. Next, we discuss the usage of Track Explorer in the development of classifiers for detecting movement patterns to automatically assess a person’s Parkinson’s disease progression [1]. We conclude the paper by summarizing our contributions.

2 Related Work

Our work is related to earlier research in interactive analysis of classifier performances [4,5,20], sequential and temporal data querying and visualization [3,11,17,19,21,23,26,22], and systems that facilitate visual analysis through algebraic operations (e.g. [8,24,25]). Researchers have introduced interactive tools, e.g. [4,5,20] to help data scientists make sense of their classifier performances. Squares [20] supplements summary performance statistics with instance-level distribution information, uncovering distinct characteristics of classifiers that otherwise show similar aggregate performance behavior. Similarly, ModelTracker [5] and Confusion Wheel [4] adopt a tighter coupling of performance with data instances to enable multiscale analysis. Xplorer complements earlier work on classifier performance analysis by focusing on temporal data classifications, integrating additional “human soft knowledge” (e.g., activity videos and expert labels), and introducing a visual algebra over classifier results and associated data that enables composable and rigorous performance comparison and analysis.

The visual design of Xplorer draws from genomic data browsers (e.g. [11,16,21,23]) and multimedia editors [2,6] in part, using visual encoding along a linear axis (track) of data and metadata sequences as the basic unit of representation. Genomic browsers enable the visualization of molecular sequences from various sources as aligned, linear tracks, which can be added, removed and reordered on demand. They support interactions such as zooming and panning to enable fine-grained exploration of the data, often encoded as horizontal bars of variable length. These features are also common in multimedia editors, where tracks typically represent audio or video sources, and are shared by many other tools, e.g. [12,15,19,26] from the temporal and sequential data visualization literature.

In order to formulate and validate complex hypotheses, earlier work proposes algebraic operations over data and its representations. Polaris [24] introduces a table algebra, drawing from Wilkinson’s grammar of graphics [25]. invis [8] provides an algebraic approach to inspecting RNA sequences, where mutations can be visually aggregated using the logical operators AND, OR, and NOT. Xplorer builds on earlier work and introduces a basic track algebra, facilitating the ability to effectively filter, compose, and compare track representations of classification results. Our visual track algebra over temporal data classification results also complements earlier work on query-based selection of temporal and sequential data [3,11,17,22,27].

3 System Design

Interacting with activity predictions based on sensor data poses a wide set of design challenges related to temporal and computational scalability. Our system tackles these issues through automated precomputation and data compression. As shown in Fig. 2, predictive models are modularized within an analytics pipeline and automatically run on subsets of the sensor data, which is stored in a centralized database together with the classification results. By merging similar predictions close to each other in time, we compress the results and store them in a JSON-based file (.BSX) that can be later opened from the public, web-based Xplorer user interface. This method further allows file versioning and an easier distribution of classification results. We refer readers to our supplemental materials for further implementation details.

4 Xplorer

The interface of Xplorer (Fig. 1) is composed of a main view, where classification results and labels are represented as linear tracks stacked vertically. A track visually corresponds to a set of non-overlapping colored blocks, positioned over a common timeline. We categorize tracks into two types based on the form of the data they visualize; classifier tracks and label tracks (Fig. 3).

In the case of classifier tracks (Fig. 3a), a block corresponds to a single prediction or to a set of consecutive identical predictions, which may result in blocks of variable length. If the output of a classifier is binary, the block is visible only when the activity is detected. If a classifier outputs continuous probability scores, the block is generated
While analyzing each track separately may be sufficient for some wheel and drag actions. By hovering on a block, information about (Fig. 7). Track information can be analyzed at different levels of granularity and easily zoom to specific events contained in the protocol track. While all other temporal data is represented as a linear track, video is shown in a separate undocked window (Fig. 14), which can be dragged across the interface and freely resized by the user. The interface of Xplorer also includes some auxiliary modal windows and a left sidebar, from which users can decide which tracks to visualize through zooming and panning, which are performed with the mouse.

4.1 Interactions

Track information can be analyzed at different levels of granularity through zooming and panning, which are performed with the mouse wheel and drag actions. By hovering on a block, information about the correspondent prediction or label is shown (e.g. author, duration) as a tooltip. For classifier tracks, the tooltip shows classifier-specific details on prediction (e.g. “tremor frequency,” “angular velocity”) (Fig. 7). Each classifier track further includes four buttons, enabling the user to 1) increase its height for better visibility, 2) play consecutively the videos of all detected activities, 3) display information about the underlying predictive model (e.g. sensors, prediction window and threshold used), and 4) switch between two different visualization modes. Fig. 6 explains how a classifier track can be represented also as an area chart, visualizing a continuous probability score over time. This mode is particularly useful for observing how the threshold of a classifier determines which events are positively predicted (and thus generate a block). The threshold can be dynamically changed by the user by moving the red horizontal line shown in Fig. 5 thus avoiding the recomputation of classification results. All tracks can be vertically moved by dragging, enabling users to better compare them visually by placing tracks of interest next to each other.

4.2 Visual Track Algebra

While analyzing each track separately may be sufficient for some applications, in many cases the possibility to combine different tracks could be essential. For instance, a user may want to analyze the output of a tremor classifier only when a different classifier is predicting no walking movement. Similarly, a user may want to consider all moments in which a subject is stationary, thus needing to unify the labels associated to “Sitting” with the labels associated to “Standing”. To enable reasoning beyond the scope of single classifiers and labels, we define a visual algebra that allows to generate new tracks as a combination of existing tracks. Operations such as addition, subtraction, logic conjunction and disjunction can be applied to both classifier and label tracks with a different semantic meaning. Fig. 4 illustrates how the most common operations can be used for classifier validation. If we denote a classifier track by A and a label track used as ground-truth by B, A ∨ B corresponds to the intersection of both tracks, that is to the events that were correctly predicted by the model (true positives). Similarly, we can define difference between track A and track B as a new track where all block instances of B are removed from A. This way, the track A − B will contain all classifications that do not match any ground truth label (false positives), while B − A will conversely represent labeled events that were not identified by the predictive model (false negatives).

The power of the track algebra consists in enabling users to quickly combine tracks to validate complex hypotheses about the classification process. In particular, in presence of ground-truth labels, it makes the identification of misclassified events visually straightforward. In combination with the video functionality, it also enables to play consecutively all false positive and all false negative predictions for a particular classifier. This way, the user can visually validate the performance of his predictive model and reason on the causes of each single misprediction.

4.3 Command Line

Track Xplorer interface features a command line interface for enabling users to quickly perform complex interactions, such as track manipulation through visual algebra. Fig. 6 shows a list of the most common commands that can be executed from the command line. Each command is composed of one operator and one or two operands, which can be track identifiers or numerical values. A track identifier is automatically generated as a combination of the track name, author and version (e.g. the first version of the “Sleeping” classifier created by author “John” will generate the id “SleepingJohn1.0”) and is made available through auto-completion. When a command generates a new track, this one is added to the main view and its name and identifier are automatically defined based on the operation performed.

4.4 Classifier Validation

While observing a classifier track A and a ground-truth label track B next to each other, it is intuitive to understand that the performance of the predictive model depends on how much the blocks of each track are aligned with each other. Optimally, for each block in A there should exist a block in B of equal length, whose start end and points match the ones of A. Misclassifications and other prediction-related errors may however make one of this two blocks absent or misaligned. A straightforward, numerical way to quantify the visual overlap of
two tracks is the Jaccard distance, computed as their intersection over union. By sampling each track into a sequence of prediction values or binary labels, it is possible to compute different performance metrics commonly used in data science, such as accuracy score, precision, recall and F1 score.

Note that the value of all these metrics often depends on the threshold applied to the continuous prediction of a classifier. The choice of the threshold is often critical since it allows to balance the number of true positives and false negatives allowed for a predictive model. For this reason, we include in the Xplorer interface a modal window displaying also a Receiver Operating Characteristic (ROC) curve is also displayed to help the user choose an adequate threshold for the selected classifier.

![Figure 5: Performance metrics. Xplorer features a modal window to display different measures of classification performance.](Image)

| Operator | \( P_1 \) | \( P_2 \) | Description |
|----------|----------|----------|-------------|
| negate   | \( T \)  | \( T \)  | Generates \( ¬T \) |
| add/union| \( T_1 \) | \( T_2 \) | Generates \( T_1 \lor T_2 \) |
| intersection | \( T_1 \) | \( T_2 \) | Generates \( T_1 \land T_2 \) |
| errors   | \( T_1 \) | \( T_2 \) | Generates \( T_1 \oplus T_2 \) |
| subtract | \( T_1 \) | \( T_2 \) | Generates \( T_1 \ominus T_2 \) |
| play     | \( T \)  |           | Plays all events in track \( T \) |
| threshold| \( C \)  | \( \text{Float} \) | Changes \( C \)'s threshold to a fixed value |
| show/hide| \( T \)  |           | Shows/hides track \( T \) |
| jaccard  | \( T_1 \) | \( T_2 \) | Jaccard distance between \( T_1 \) and \( T_2 \) |
| report   | \( C \)  | \( L \)  | Computes ROC curve and AUC score |
| transform| \( C \)  | \( L \)  | Computes precision, recall and F1 score |
| rename   | \( T \)  |           | Renames a track |

![Figure 6: Commands available from the Xplorer command line. \( P_1 \) and \( P_2 \) are the parameters required by each command. \( T \) is a placeholder for a generic track's identifier, whereas \( C \) and \( L \) indicate a classifier and a label track respectively. Track type conversion is automatically handled according to the definition explained in Fig. 5.](Image)

5 Use Case: BlueSky Project

BlueSky project [1] aims at deploying predictive models to automatically assess the symptoms of Parkinson’s disease using wearable sensors. Xplorer was used by a team of fourteen data scientists and business people as a companion tool over most of the project.

A total of six wearable IMU sensors were used, worn by Parkinson’s disease subjects over sessions (visits) of about one hour. The sensors measured accelerometer, gyroscope and magnetometer information at 128Hz and were placed on the wrists, feet, chest and back of the patients [18]. During each visit, all subjects performed the same set of predefined tasks, according to a single clinical protocol. A group of external technicians took care of recording sessions, labeling specific activities and time-stamping the execution of tasks. Sensor data, ground-truth labels and video files were all stored in a single database, that all data scientists could access during the development of their predictive models.

Each time a data scientist produced a new version of a model or algorithm, its classification results were loaded into our visualization system and analyzed by the whole team during group meetings. Xplorer demonstrated in fact to be a great tool for team discussion, enabling even non-technical people to understand classification results. Without knowing the implementation details of each predictive model, it was sufficient to visually check the alignment of tracks and further validate it with the video.

The playback functionality, in combination with the track algebra, proved to be a fundamental feature for quickly identifying mispredictions. For instance, by subtracting the “Walk” label track to the “Walking” classifier track and by playing the resulting track, it was possible to observe all cases in which the classifier wrongly predicted the subject was walking (false positives). By observing the video and the task labels, data scientists realized that, since the model was using the sensor worn on the chest, it was incorrectly detecting movements such as arising from the chair and coat buttoning. Similarly, the “Step detector” classifier track (based on sensors worn on the shoes) showed false positives in correspondence of feet tremor, particularly common when subjects were sitting with their legs crossed. Based on these insights, data scientists decided to re-train their classification models with data from different sensors or by including in the training set the activities that had been misclassified.

Another widely used feature was the possibility to inspect information about each single prediction. After having noticed that the two hand classifiers “Pronation-supination” and “Tremor” were biased by the action of walking, data scientists were able to mouse over mispredicted events and observe the attributes computed by their predictive models. In this case, each prediction held numerical information about hand rotation angle, hand rotation speed, tremor frequency and tremor amplitude. By analyzing these attributes, data scientists were able to filter out the movements happening at specific frequencies associated to walking, thus making their model more robust.

Xplorer was also useful in handling ground-truth labels. The track algebra allowed to quickly combine partial labels (e.g. the tracks “ShortWalk” and “LongWalk” were combined into a single track “Walking”) and to identify mismatches with other reference tracks and the video. In particular, Xplorer opened a discussion on the

![Figure 7: Sample tracks from the BlueSky Project. By observing the pattern of green boxes (label tracks), it is straightforward to observe that the subject is alternating walking to turning movements. While the alignment of the classifier tracks “Walking” and “Turning” with their correspondent ground-truth labels seems satisfactory, we may note that the predictive model “Body Turn” appears to detect events too early. By inspecting sensors usage in the video and the attributes associated to each prediction (shown as a tooltip), data scientists can try to debug their prediction models. The possibility to dynamically change the threshold of a classifier (as shown on the “Turning” track) further aims at a better understanding of predicted motor events.](Image)
quality and reliability of labels, which otherwise would have never been questioned. By observing labels associated to false negatives, data scientists observed an incoherent labeling and an unclear definition of movements such as walking and turning. Should few short steps be considered a walk? Should a larger rotation of the chest be considered a turn? If so, would they be useful to consider for the purpose of the project? Similarly, false positives showed the absence of a large number of labels, which were not annotated by human operators because the subject was out of camera. Data scientists further noticed correct classification results were often misaligned with ground-truth labels: with the help of the video feature, it was demonstrated that human-generated labels generally occurred before a subject started a movement. For instance, a technician would annotate a walk whenever a subject showed the intention to move, without waiting for him to make a first step.

Finally, our visualization system played an essential role in model validation. Increasing the number of true positives without increasing the number of false negatives (i.e., keeping classification recall or sensitivity high) was an important criterion in the project, which required focusing on reducing the uncertainty on positive predictions. The ability to dynamically change the threshold applied to classifier encoding, empowering users with diverse backgrounds to better understand, debug, and improve the performance of classifiers.

We also introduce an extensible visual algebra over track representations, enabling composable and rigorous performance comparison and analysis by data scientists. We demonstrate the usefulness of our tool through its application in a collaborative project for developing classifiers to discern motor activity patterns for scoring the degree of disease progression among Parkinson’s disease patients. Track Xplorer enables the project team members to identify early on possible systemic errors in the model development and debugging experience for multiclass classifiers. Supporting interactive performance analysis for multiclass classifiers. 

6 Conclusion
We introduce Track Xplorer, a system for interactive visual analysis of predictions of classifiers modeled to detect events in temporal sensor data. Our system enables the visual and quantitative comparison and contrast of results from multiple classification models, improving the model development and debugging experience of data scientists. Track Xplorer couples contextual information such as ground truth labels, expert annotations and event videos together with track visualizations of predictions through interaction and visual encoding, empowering users with diverse backgrounds to better interpret, debug, and improve the performance of classifiers.

We also introduce an extensible visual algebra over track representations, enabling composable and rigorous performance comparison and analysis by data scientists.

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