Identify plays based upon video footage

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***Abstract*—This document is the Project Deliverable D1.1 for the Practical Machine Learning and Deep Learning course. Our project aims to detect football (soccer) passes, including throw-ins and crosses.**

I. Data Understanding

In this section, we explore and pre-process the data retrieved from Kaggle's competition DFL - Bundesliga Data Shootout, which contains train and test data serving the same purpose as our project.

A. Data description

In the dataset, there are three folders: *train*, *test*, and *clips*. Each of which contains mp4 videos. *train* is a folder containing videos to be used as training data, comprising video recordings from eight games. Both halves are included for four of the games, while only one half is included for the other four games. *test* is a folder containing videos to be used as test data. The test data for the public leaderboard of the competition comprises video recordings from one full game and four half-games, the other half of each game being in the training set. This folder is only used for testing and evaluation purposes as the annotations are not provided. *clips* folder includes short clips from ten games, provided without event annotations. The purpose of these clips is to help models generalize to environments not represented in the training data. Lastly, we have the file *train.csv*. The file is event annotations for videos in the *train* folder. Below is the description of each of the columns.

- video_id - Identifies which video the event occurred in.
- event - The type of event occurrence, one of challenge, play, or throw-in. Also present are labels start and end indicating the scoring intervals of the video. See the Evaluation page for information about scoring intervals. Scoring intervals are not provided for the test set videos.
- event_attributes - Additional descriptive attributes for the event.
- time - The time, in seconds, the event occurred within the video.

1) Event types and Event Attributes: There are mainly five types of events, and 11 possible event attributes. We briefly describe them in this part. If more details are needed, please refer to the competition Event Descriptions page.

- Plays: A Play describes a player's attempt to switch ball control to another member of his team. A play event may be executed as a Pass or as a Cross. It has the following possible attributes: [Pass, Cross], [Open Play, Corner Kick, Free Kick]
- Throw-Ins. The possible attributes are: Pass and Cross.
- Challenge: A Challenge is a player action during which two players of opposing teams are physically capable of either gaining or receiving ball control and attempt to do so. The possible attributes for Challenge are the following: Opponent rounded, Ball action carried out, Fouled, Opponent dispossessed, Challenge during release of the ball, Possession retained during challenge.
- The event type also includes start and end indicating the scoring intervals of the video. Please refer to the Evaluation page in the competition for more details.

'train.csv' contain 11218 records.

B. Data exploration

In this part, we go further than the generic shape of the data to analyze the data at hand and potentially discover underlying properties and correlations. We will use statistical tools in order to analyze the data and find insights that might be useful for us in the subsequent sections and in the following data mining steps.

1) Exploring the video id: The training set contain 12 videos. The duration of all videos are almost an hour. The frame rate is 25 for all training set videos. Figure 1 shows the total number of events by video. We can see from the figure that the video have fluctuating number of events associated with them. The minimum is 737 while the maximum is 1249. This comes as a result of the different styles teams have. For example, a team may focus more on possession which increases the number of passes.

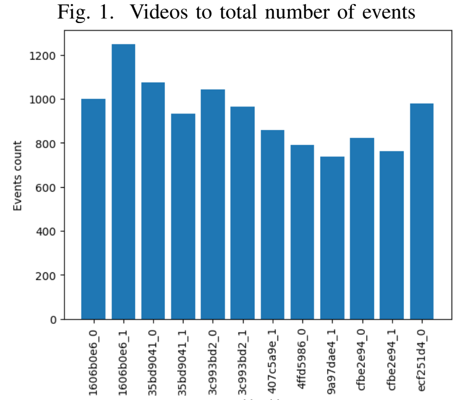
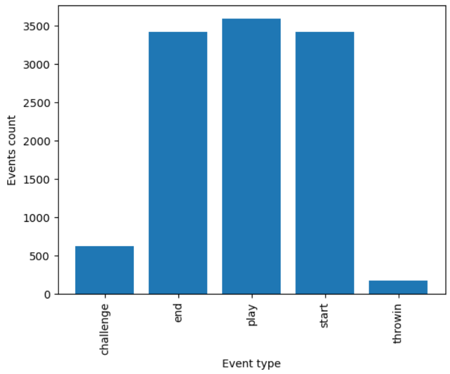


Fig. 1. Videos to total number of events

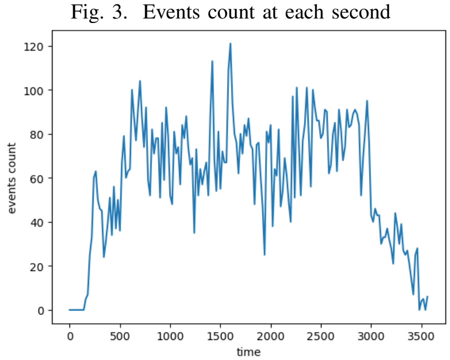
2) Exploring the event type: As we can see in the figure 2, the majority of events is distributed between the events: end, play, and start. The challenges represent only 5% of the events. The throw-ins are even more rare as they cover only 1.5% of the total dataset.

Fig. 2. Events count for each event type



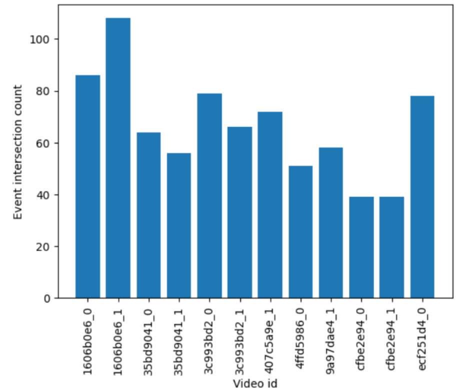
3) Exploring the time: To properly visualize the time-series data, we divided the time into segments, each of 20s duration. This enabled us to plot figure 3 and infer that events reach its peak at the middle of the match half. Please notice that the small values (close to zero) at the beginning and the ending is due to the fact that the half has ended, or has not even started. There are no indicators in the dataset when halves start or end.

Fig. 3. Events count at each second



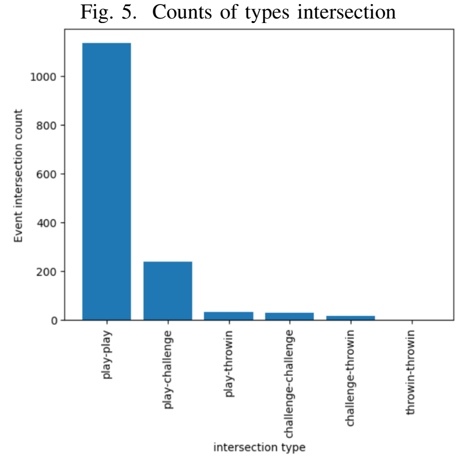
4) Exploring the intersection of events: To understand the cases where more than one event happens at the same time we counted the instances of intersection of events in the training data. More precisely, we looked at the cases where there's more than one event happening between a start and end events. This will allow to understand the likelihood of intersections happening and account for that in our model.

Fig. 4. Intersection of events in every video



5) Exploring intersection types: Understanding intersection doesn't only mean know how much they occur but also which types of events are more likely to occur at the time. As it shows in the figure 5 the majority of cases where an intersection happens it is between a play and a play type of event and we also notice that no two throw events happen at the same time.

Fig. 5. Counts of types intersection

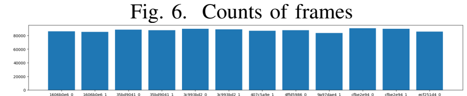


6) Exploring the event attributes: The attributes weren't deeply analyzed because the model is not dependent on them and is not expected to predict them.

II. Data PreProcessing

We started pre-processing our data to make it easier to work with by first chopping the videos into the frames that make them up. The following graph 6 shows how many frames are in each video.

Fig. 6. Counts of frames



III. Work distribution

In this section of the work, Karam worked on getting the data, checking for its cleanness, and understanding and explaining the data to the teammates and preprocessing the data. Mohammad and Mahmood both worked on data exploration and writing the notebook which has the code for the data exploration (present in the git repository). Mahmood did the analysis related to the intersections of events while Mohammad did the rest of the analysis.