Soccer Commentary Mining
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Abstract

Sports popularity is constantly growing throughout the world. Hence, it is no surprise that the most popular sport, which is soccer, with 3.5 billion estimated fans, brings the attention of scientists from various fields. In this work, we aim to analyze soccer matches from broadcasters' perspective to check how events on the field affect their emotions and, inherently, viewers' emotions as entertainment of the commentary is critical to good transmission. We will perform unsupervised sentiment analysis on transcriptions of the soccer match broadcasts. For that purpose, we will use established methods like lexicon-based VADER, which has already been proven successful in analyzing soccer data, and pre-trained state-of-the-art model flair. Obtained results will be later statistically compared with the on-field events like goals, cards, free kicks, etc., to asses whether occurrence or time between consecutive events significantly affects broadcaster sentiment. We will also use state-of-the-art models for deriving emotions directly from the recording and compare them with results acquired using transcriptions. The analysis will be based on the public SoccerNet databases consisting of hundreds of videos of soccer matches and collect transcriptions using the Whipser OpenAI tool. Overall, the work presents a novel approach to sentiment analysis in soccer by attempting analysis of data that has never been addressed before, which are broadcast's transcription, and comparing them with on-field events and audio characteristics.

1 Introduction

Sports is one of the most prominent people's entertainment worldwide, mainly due to the variety of channels through which we can experience multiple sports events. Among these, the most popular one is undoubtedly soccer, with an estimated 3.5 billion fans worldwide. That figure shows how important soccer is in today's global culture. Such a fact did not slip through the radars of scientists worldwide, who approach soccer from multiple directions, starting with physiotherapy, through pharmaceutics, and ending with statistics and artificial intelligence.

One of the most significant areas in the soccer industry is live broadcast, where experts comment on live events on the field. These experts' duties are not only to describe events happening during the game but also to bring valuable insights and, most important of all, to keep the audience entertained. The ability to engage people is naturally embedded deeply in the commentator's job description, and they are trained to voice their opinions in a matter accessible to the audience. Still, even these professionals can become overwhelmed by the events on the field. That's precisely the place where the motivation for this project comes from. We aim to assess whether and by how much events on the field affect what emotions resonate from broadcasters' words. For that purpose, we will perform a sentiment analysis of the transcripted soccer match commentaries and statically compare the obtained results with the state of the matches at a given moment.

2 Related work

Nowadays, with the progressing globalization and constantly growing usage of various types of Internet media, we are nearly overwhelmed with data. People voice their opinions about almost everything through X (former Twitter) posts, service reviews, and journalistic articles. As underlined by the (Hamborg and Donnay, 2021) the fact that these forms encourage explicit opinion form of opinion, they were a perfect source of data for researchers exploring Sentiment Analysis in these areas for many years now (Pontiki et al., 2015), (Nakov et al., 2016), (Yin et al., 2020), (Sun et al., 2019), (Baccianella et al., 2010). Recently, (Ramnarine, 2023) used unsupervised sentiment analysis to derive whether social media posts about plastic surgeries are positive, neutral, or negative. Although the article has not yet been published, it certainly shows diverse appliances of sentiment analysis that span even medical care. As seen, the subject of Sentiment Analysis exploration is deeply embedded in the scientific community, so there is little surprise that there have been. Considering that, it is not a surprise that there were attempts to implement the same methods in the soccer world.

(Jai-Andaloussi et al., 2015) in their work used Twitter data to analyze sentiment associated with users interacting with each other about the games to predict who they are rooting for and possibly events on the field. Such analysis allowed authors to summarize soccer events efficiently. Similar work was done by (Patel and Passi, 2020), where a team of researchers analyzed historical data about the FIFA World Cup 2014 held in Brazil. The authors used sentiment analysis to detect emotions associated with particular messages covering the matches. It is worth pointing out that, among others, they used lexicon-based methods, which brought pretty successful results. While exploring the past research that has been done in sports sentiment analysis, we could not find anyone trying to analyze broadcasters' sentiments. Hence, we believe our approach to be novel.

Due to the nature of the data, which are transcripts of matches' broadcasts, we do not possess any labels associated with the sentiment. That means the task we aim to solve is unsupervised sentiment analysis. (Birjali et al., 2021) has prepared a profound and exciting survey on sentiment analysis and its applications in different tasks. Their comprehensive summary provided not only an exhaustive study of methods that had never before been gathered in one place but also provided some guidelines and heuristics on which method should be used, supplied with detailed comparison. The proposed general division of sentiment analysis task types was machine learning, lexicon-based, hybrid, and other techniques. In his work (Punetha and Jain, 2023) gave a similar division firmly based on the previous work. They are supervised methods, among which authors explicitly mention one of the oldest approaches, which are machine learning classifiers like SVM (Joachims, 1998) but also some novel approaches that use deep learning (Basiri et al., 2021). The next category consists of semi-supervised methods that use co-training and graph-related methods for imputing labels and improving the model without access to the proper response. Such an approach was shown by (Lin et al., 2011), where they used Latent Dirichlet Allocation (LDA) (Blei et al., 2003) for simultaneous detection of both topi and sentiment from text. Last but not least, there are unsupervised methods where there is no access to the actual labels at all. The authors mention the computational limitations of clustering big datasets, also pointed out by (Vashishtha and Susan, 2019). Among many different methods of unsupervised sentiment analysis, the authors of the article mention lexicon-based methods, which have already been shown in the past to get along well with soccer nomenclature.

The sentiment lexicons methods (Kannan et al., 2016) enable the predictions typically based on the manually created lexicons for which every world is associated with the sentiment. The aspect of manual creation influences two main areas. Firstly, the set of words chosen for the analysis; secondly, the scores, which are the results of an expert decision. That makes the interpretability of the prediction very easy and intuitive. Typically, these methods are tight with a specific language, and the transformation of the dictionary would be needed to apply it to the language differently than designed after the translation of the entries.

We differentiate between two types of lexicons - semantic orientation (polarity-based) lexicons and sentiment intensity (valence-based) lexicons.

The former group has a set of identified categories that might be wider than positive, negative, and optionally neutral. However, for the sake of the sentiment analysis, only the mentioned 2 or 3 are used. Each word from a selected sequence, e.g., a sentence or a paragraph, gets assigned a constant score, e.g., one and minus one for each occurrence that can be identified. Then, the score is typically normalized to be compared to other inputs of varying lengths.

The latter group, intensity lexicons, besides the classification to a category, also assigns a numeric significance of the word such that, e.g., the word excellent has a higher score than good.

Regardless of the scoring, both methods still do not encompass the information about modifiers, e.g., the negation "not." Therefore, they are often surrounded by some additional rule-based approach that can be modified, e.g., by multiplication, the score directly obtained from the dictionary. We call this method context aware because a single word does not determine the score, but the score is dependent on the larger context.

Vader (Hutto and Gilbert, 2014) is an example of a lexicon-based method encompassing the additional. This method was also created with not only concise messages and Twitter posts in mind but to work well also on longer text forms to ensure that the already available intensity lexicon scores were modified. Additional improvements involve context-based rules.

However, that is the only way of approaching this problem. As reviews of the state-of-the-art methods done by (Mathew and Bindu, 2020) and (Birjali et al., 2021) show, one can use a supervised pre-trained model to address the issue of analyzing datasets without labels.

Flair is a popular and robust framework for natural language processing that enables the creation and deployment of cutting-edge models for various text analysis tasks. One of the main features of Flair is its ability to combine different types of word embeddings, such as GloVe (Pennington et al., 2014), FastText (Bojanowski et al., 2016), ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019), and Flair's contextual string embeddings (Akbik et al., 2019a).

The last ones are vital innovations that have improved the performance of many NLP tasks. These embeddings are vector representations that capture the meaning of words based on their surrounding context rather than relying on fixed or static terms. Flair uses these embeddings as the basis for all its models, allowing for more accurate and robust text analysis.

Flair has been used and evaluated in many research papers, demonstrating its effectiveness and versatility. Some examples are (Akbik et al., 2018) and (Akbik et al., 2019b), which show how Flair's embeddings enhance sequence labeling and named entity recognition.

In audio, sentiment analysis is typically called (speech) emotion recognition and might involve more classes than NLP methods. The depend on dataset annotation and might include anger, disgust, fear, happiness, pleasant surprise, sadness, and neutral (Pichora-Fuller and Dupuis, 2020) or anger, happiness, sadness, neutral, excitement, frustration, fear, surprise, and other (Busso et al., 2008), or calm, happy, sad, angry, fearful, surprise, and disgust (Livingstone and Russo, 2018). The typical models used for this task are convolutional neural networks and recurrent neural networks due to the interpretation of the time series. A notable mention is the LSTM network (Purwins et al., 2019). The input to those models can differ from raw audio to feature creation like MFCCs, spectrograms, or embedding (Purwins et al., 2019). An interesting source of the embedding is output from self-supervised wav2vec2.0 (Baevski et al., 2020). The state of the solution that uses the described methodology is (Pepino et al., 2021). This solution still requires training on supervised datasets, yet it can transform the audio into more meaningful embeddings.

3 Datasets

The project is based on the publicly available dataset SoccerNet and its updated version, SoccerNet-v2. The SoccerNet (S. Giancola and Ghanem, 2018) emerged as a benchmark dataset for action spotting in soccer. The dataset is composed of 500 match broadcasts from the UEFA Champions League as well as the top five European leagues: English Premier League, Spanish

La Liga, German Bundesliga, Italian Serie A, and French Ligue 1 (each .mpv file with a recording comprises one half of a particular match). It covers three seasons from 2014 to 2017 and a total duration of 764 hours. Additionally, the dataset contains the annotations of three main classes of events: goal, yellow/red card, and substitution. As the data represents the leagues of multiple countries, the match commentaries are in different languages. The dominant languages are English, Spanish, Russian, German, and French (representing more than 97% of the observations). The dataset contains a few commentaries in Italian, Turkish, and Norwegian, as well as a recording of one-half of a match with Polish commentary.

The SoccerNet-v2 (A. Deliège and Droogenbroeck, 2021) is the expanded version of SoccerNet with significantly more manually specified action annotations, with over 110,000 of them in this version - an average of 221 per match, compared to 13 returned in the previous version of the dataset. Annotation types have been enriched by including events such as ball out of play, corner, direct/indirect free kick, or the penalty (total extension to 17 classes). With this update, a more in-depth analysis of the commentary is possible, depending on the actual events of the match.

Another version of the SoccerNet, SoccerNet-v3 (A. Cioppa and Droogenbroeck, 2022), has also been released. It was built upon the corpus of annotations provided in SoccerNet-v2, enriching them with associated frames from the replay clips. New action-specific data has also been coded, such as the soccer field line (straight or curved) within a given frame, bounding boxes for the players/the referees as well as the objects, including the ball, flag, or yellow/red card, the multi-view player correspondences and jersey numbers. Nevertheless, these additions were introduced with the view to providing a rich environment for the investigation of computer vision tasks related to football. They do not bring new insights into the project's problem of analyzing comments' sentiments. Therefore, previous versions of SoccerNet remain the primary source of the data for the project.

VisAudSoccer (X. Gao and Liu, 2020) is a similar dataset proposed as a benchmark for three different tasks that can be jointly used to produce highlights automatically, i.e., play-back detection, soccer event recognition, and commentator emotion classification. It contains broadcasts from 460 soccer games, 300 of which have been downloaded from the SoccerNet (S. Giancola and Ghanem, 2018) dataset. Audio data is available for 160 games with commentator voices categorized as "excited" and "not-excited." However, the dataset is not publicly available, so it will not be used in the project.

The project's scope includes analysis of both audio data and the transcriptions of broadcast commentaries. The latter data will be gathered using the open-source Whisper model (A. Radford and Sutskever, 2023). It is a deep learning-based automatic speech recognition (ASR) system developed by OpenAI, designed to convert spoken language into written text. It was trained on the 680,000 hours of multilingual and multitask supervised data collected from the web, which has increased its robustness compared to the previous similar models trained on significantly smaller labelled data or unsupervised learning models. Approximately one-third of the audio dataset is non-English and alternately tasked with transcription in the original language or translation into English. Therefore, the Whisper model can handle a wide range of tasks, including transcription for general speech, specific domain applications, and multilingual scenarios. The core architecture of the Whisper model is a simple end-to-end approach based on a transformer encoder-decoder framework. Input audio is split into 30-second chunks of data. Then, it is converted into a log-Mel spectrogram and processed by the encoder. The decoder is trained to capture the corresponding text, mixed with unique tokens, which direct the model to perform language identification, phrase-level timestamps, multilingual speech transcription, and translation to English.

Analyses of voice commentary transcriptions or written live commentaries can be found in many articles. Huang et al. (Huang et al., 2020) conducted an analysis of football match commentary using transcriptions of matches from seven different leagues: Bundesliga, CSL, Europa, La Liga, Ligue 1, PL, Series A, UCL) from Sina Sports Live. The aim of the analysis was to create sports news reports that summarise the match based on its commentaries. Zhang et al. (Zhang et al., 2016) identified common features that have been widely used for general document summarisation and novel task-specific features aimed to generate sports news from live comments properly.

This analysis was conducted based on downloaded commentary scripts from 150 football matches on Sina Sports Live.

4 Project approach

In the upcoming stages of our project, our initial objective is to separate audio tracks from video recordings to isolate the football commentary for thorough scrutiny. We will then proceed to utilize the sophisticated capabilities of the Whisper model to transcribe the audio into text effectively. This critical stage will ensure that the fundamental characteristics of the original commentary are retained for comprehensive linguistic analysis.

Having obtained textual transcriptions, we intend to begin translating the commentary into English while maintaining the original languages to enable a thorough, multilingual investigation.

Afterward, we will proceed to data mining the audio content, which includes examining acoustic features like decibel levels and emotional inflections, referred to as audio sentiment. The aim is to capture the energy and emotions commentators convey during matches.

This study will perform an exploratory analysis focusing on the language complexity used in the commentary. We will examine whether the comment utilizes an uncomplicated, accessible vocabulary or if it features a more intricate diction that could appeal more to passionate football enthusiasts.

The study will include a thorough sentiment analysis using the VADER tool for English content and Flair for English and other language data. This analytical method aims to identify the emotional subtleties within the commentary during different stages of the matches.

Our ultimate goal is to establish a correlation between the emotional tone of the commentary and significant moments in football, including goal-scoring events and red card issuance. We aim to clarify the impact of these moments on the commentary style, thus enhancing our comprehension of the emotional storyline in football broadcasting.

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