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A MULTIMODAL SEMANTIC MODEL FOR EVENT IDENTIFICATION ON SPORTS MEDIA CONTENT

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ABSTRACT

This paper presents a multimodal semantic event identification model of occurring events in sports games. Sport broadcasting programs and TV shows form a demanding media case, as journalists, experts and analysts tend to examine in detail their gameplay aspects and elements, trying to offer thorough analysis and deep insights to their large audience. Basketball serves as an exemplary case for developing an event identification model in sports media content, since it is full of small or bigger activities that take place throughout the game. In this work, a basketball event is defined as a series of player actions during a team possession in the game. The proposed method leverages and combines the information of various game sources as play-by-play and text reports. Given the current state of research, the current paper proposes multilevel event classification taxonomies that could be used in multimodal semantic processing and conceptualization approaches.

Keywords: event identification, sports media analysis, linked data, data journalism, data mining.

INTRODUCTION

State of the art in the topic and event identification research field focuses mainly on news topics, or historical events and, in general, on happenings that seem to have an impact on a large group of people.

In the general context of news, the detection of the subject can be seen as the identification of an event that groups stories and each such group represents a particular subject (Chen et al., 2007). Such activities have specific properties such as duration (beginning, peak, and end), participating entities (individuals, organizations), a location where it is occurring, and a subject to which it relates (Vavliakis et al., 2013).

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In sports, beside this kind of events, e.g. the final game of a competition, there are also other types of activities that could be defined and identified, occurring not in the competition season lifetime, but during a single game.

This more detailed viewpoint of the event concept may stand for actions or series of actions of players and teams during a game and could help identify key aspects of their plays and tactics, as well. Thus, this model does not take into account how many people in social media or articles in a text corpus are talking about them in a specific time period. Instead, leverages resources such as statistics and game reports to identify the actions that form the gameplay events in sports, applying similar techniques to approaches of different context.

A major task in event identification procedure is the detection of key terms within the content and the evaluation of the importance of each term and the relations between them. This task applies Natural Language Processing (NLP) techniques in a variety of contexts, such as spot words removal, or stemming (taking just the root of the word) of the terms, based on the Porter (Porter, 2008), or KSTEM algorithms (Krovetz, 1993). Besides the traditional uses of stop words and stemming removal (Sayadi et al., 2009), the NLP task can be appropriately configured, depending on the research needs. For example, there are cases where only the English terms are examined (Papadopoulos et al., 2014), or the non-English terms having no less than four letters (Weng et al., 2011). In addition, even short sentences with fewer than three words, or low frequency words can be also excluded (Yin et al., 2013). As for the export of entities, this can be done using, either dictionary (gazetteers) and regular expressions, or hand-crafted rules (Vavliakis et al., 2013).

A gameplay event in sports could be defined in a broader or narrower level. In basketball, for example, it could be even a single player action (e.g. a scoring shot), or a game interval with specific characteristics (e.g. a scoring streak by a team). Previous works considers single actions as game events. The current model considers basketball Possession Events (PE), containing a series of actions that occur from the moment a team gains the ball possession, to the moment that, even instantly, they lose it. For instance, if a player of team missed a shot, took the offensive rebound and made the next shot, the model identifies two events, as the player team regained the ball possession.

A basketball PE, as a normal event, has a start, a peak and an end, where

- the start refers to the action that gives the ball possession to the team
- the end refers to the action that takes off the ball possession from the team and
- the peak refers to the action with which the team offense is running and ends, provoking also the change or the claiming of the ball possession.

It is evident that a basketball game can be sliced into a series of consecutive PEs, where the end of one event indicates the start of its subsequent.

STATE OF RESEARCH

Event detection methods have been used in sports recently, considering an event as any activity that takes places during the game. They are based mainly on the videos of the sports games, as they aim to exploit their low-level, mid-level or high-level attributes (Nepal et al., 2001; Xu et al., 2004; Huang et al., 2006; Liu et al., 2011). These methods are able to identify some of the important actions during the game, but it seems that they cannot go into more detail only with image and video processing algorithms, at least at basketball, where a lot of instant activities may take place simultaneously by ten players in a small area.

Newer works exploit the webcast text of games that include the actions that occur in the and try to align it with the video, in order to provide more identified events and in greater accuracy. The mixture of resources increases the detection potential. However, in most cases, webcast text operates just complementary to the main video detection methods limiting the possibilities of identifying events based on a more granular level. Xu and Chan (2004) combine many sources and external sources, as webcast text to identify important actions in soccer videos and define their boundaries. Xu et al. (2006) analyse both well-structured and "freestyle" text of soccer webcast text to detect some major events and align them with the video.

In Xu et al (2008), a probabilistic latent semantic analysis (pLSA) is used in descriptions of webcast text, in order to cluster them into categories and the identified events occur from a single keyword of each category. This approach, however, while it is generic for both basketball and soccer, it is limited to a few only events.

A more recent work (Chen and Chen, 2014), makes a deeper analysis on webcast text of basketball and soccer, with unsupervised learning on the included descriptions. The method recognizes the useful terms (keywords and names) from the descriptions, constructs terms trees to detect a lot more events than previous methods, 44, and clusters them into groups of similar meaning, based on experts' opinion. There is a term hierarchy, which leads to events, but that is not an hierarchy which classifies the sports events from broader to narrower.

Current work aims to take some steps further, considering a different meaning of a basketball event, as a team possession with one or more actions, rather than single activities that occur during the game. While previous methods on webcast text apply unsupervised learning algorithms, the proposed model incorporates basic sport knowledge for the identification process, as basketball has a finite number of actions, while extracting the keywords from the webcast text. It also extends the respective keyword list, developing a semantic vocabulary of actions terms that are used in different basketball competitions. The semantic vocabulary contains synonyms of the same action which are classified on an event hierarchy. In this way, the model learns to detect events not only in webcast text, but also in game reports, identifying the key entities that might also be included in the vocabulary as well.

METHODOLOGICAL APPROACH

Multiple Data Resources Retrieval

Basketball is one of the most popular sports in the world and there is a plethora of resources about games information, statistics, reports and others on the Web, which are easily accessible. The model aims at leveraging as many sources as possible, such as the official statistics of the games, their basic information (i.e. schedules, results, rounds, datetimes) and their webcasts, namely play-by-plays (PBP), which are log-like files containing all the stat-measurable actions during the game (a small segment is shown in Figure 1), reports with game analysis and recap, quotes of the players and the coaches, as well as videos, social media photos, tags, interactions and others. The PBP and the reports articles, however, are the ones that form, the backbone of the model, while the additional sources could also contribute significantly to the event identification procedure.

Min		Score	
09:27		**60 - 52**	TIMMA, JANIS Three Pointer (1/1 - 3 pt)
09:25		60 - 52	SHENGELIA, TORNIKE Assist (3)
09:08	MCLEAN, JAMEL Turnover (1)	60 - 52	
09:07		60 - 52	TIMMA, JANIS Steal (3)
08:54	MANTZARIS, VANGELIS Foul (3)	60 - 52	
08:54		60 - 52	HUERTAS, MARCELINHO Foul Drawn (5)
08:43		**60 - 54**	SHENGELIA, TORNIKE Two Pointer (5/8 - 13 pt)

Figure 1. A PBP segment

Using multiple resources, the model should be able to retrieve efficiently and in an automated way their data. The most valuable start point web source is the official website of a competition (e.g. Euroleague[5] in basketball) which usually contains all the relevant information, that is, the PBP, statistics, results, reports and quotes. There are many web scraping tools for basic operations, nevertheless, operating this task in multidimensional statistical data might be too complicated.

The model uses scripts written in the Python[6] programming language, exploiting libraries like Beautiful Soup[7] for searching, extracting and retrieving data from various sources such as competition and media websites. A different, customizable script has been created for each resource, to retrieve all the useful information from statistics, PBPs, reports and others.

During and after this task, the retrieved data are cleaned and modified properly in order to include just the information needed from the model, in an appropriate format. For example, different paragraphs of the same game report are joined together in a single text, or play-by-play actions are splitted into pieces, containing separately the player, the statistic and the action itself.

Then, the distinct actions of all PBPs (fouls, turnovers, free throws etc.) form the initial version of the basketball actions vocabulary (BAV), which contains the terms used in the PBP to describe the actions. The BAV will be enriched in many ways and will serve as a key device for the model to identify events in articles, in later stages.

Finally, all the data are stored into corresponding tables in a MySQL[8] database, along with their game metadata, such as the game id and the round (week) of the competition in which they refer to, or they took place. In this way, each element in the database could be used as standalone data or grouped together with data with a similar metadata dimension value, facilitating the tasks under the event identification process.

Event Identification and Components Extraction from Play-by-Plays

Event identification in the PBP of a basketball game is not a trivial or easy task, although the PEs have been defined based on actions contained in the PBP. It requires domain-expert knowledge in order to group together the actions that fit only to some of the events components (start, peak, end). Based on the previous definitions of these components, the event identification algorithm in PBP clusters actions of the BAV that operate or are more frequent as a specific component and then examine the next or previous actions to identify completely the event.

The peak actions group consists of

- the field goals; these are the two-points and three-points shots of a player, either made or missed, where the following end actions should be a rebound, in case of a missed shot, or a change of the game score, in case of a made shot.

- the turnovers, where the ball possession automatically changes from the one team to the other
- the free throws, a special case where the following end action depends on the PBP context (e.g. a made free throw can lead to a change of possession or a new free throw)
- the fouls, which can also lead to a new possession, or free throws

The algorithm (Figure. 2) detects first the peak actions in the game PBP, as well as the respective player that made the action and the moment (minute and second in the quarter) that the action occurred, data already included in the PBP, and later in the database. Then, the algorithm examines the next or even the previous actions, if needed, in order to detect one of the possible ends of the occurring event. As an end of an event indicates the start of the next, it is more effective to search only for the ending actions, because there are specific game actions patterns, as already mentioned. On the contrary, there is no specific rule for the start of an event, as it could be defined just as a new or change of possession.

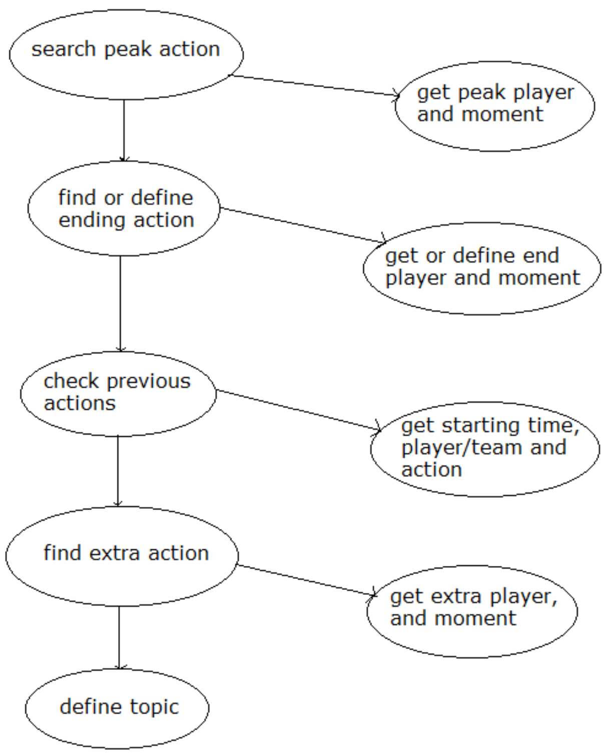

Figure 2. PBP Event Identification Flow

Thus, there is a common group of starting/ending actions that the algorithm searches for and these are mainly the offensive and defensive rebounds of a missed shot. No detection is needed in case of a made shot, as a score change is assumed as the ending action and a new possession of the opposite team starts the next event, while the change of ball possession ends a turnover peak action. The algorithm detects the respective moment (minute and second) and player of the action as well, while it assumes the "home team", or "visitor team" in case where there is not a corresponding player associated with that ending action.

Beside these main groups of actions, there are additional groups of actions that enlighten the identification process. These "extra" actions include

- the assist, which may have led to a basket,
- the steal, which leads to a turnover,
- the block, which leads to a missed shot

and others. These actions are complementary to the peak actions, as they may or may not have been occurred along with them. Finally, the "intermediate actions" refer to timeouts and substitutions. These might be valuable for a greater level of analysis, but they are not used for the PE identification in terms of detecting an action, but only as a starting point (minute and second) of a new offense. An example of a possession event and its components is shown in figure 3.

Applying the algorithm to a PBP of a 40-minute Euroleague game detects about 130 events during the game, that consist of their starts, peaks, ends, "extras", their respective players and moments and a basic topic attribute, such as a successful offense.

The domain specific notion of the algorithm does not exclude its adjustment to other sports as well, as it defines a procedure that leverages key terms of the sport. An equivalent algorithm that uses the corresponding terms of a different sport, clusters them and tries to find patterns as series of actions (terms) that might form an event could be exploited to other sports as well.

Figure 3. Event components in a PBP

Semantic Representation and Alignment of Vocabulary Terms

The event identification process in text such as games reports, includes, beside NLP tasks, the mapping of the identified key terms to the terms of the PBP, that is the actions included in the BAV. Thus, a crucial point to this end is to enrich the BAV with additional terms, either new, or synonyms to the already included terms. This will facilitate the detection and extraction of the interesting concepts in text and, in turn, the event identification in game reports.

Thus, while BAV has been developed by terms of a specific competition PBP (i.e. Euroleague Basketball), it can also include similar terms from other competitions terminology as well. While Euroleague PBPs ended up with 33 distinct actions, there are competitions with richer terminology, such as the FIBA competitions with 53 terms, the Spanish League (ACB) with 71 terms, the Greek League (BasketLeague) with 80 terms and the National Basketball Association of USA (NBA) with 345! These vocabularies include hierarchies of terms, describing in detail the action that takes place (e.g. the way of shooting; lay-up, dunk, tip in and others for a two-point shot). Combining all these vocabularies extends the BAV vocabulary to 367 distinct terms, that is eleven times more from its initial version.

Besides that, the BAV is then transformed and represented also semantically in RDF[9], using SKOS[10], the most appropriate RDF Vocabulary for describing hierarchical classifications and taxonomies. The semantic representation of basketball data has been proposed for better data handling and analysis possibilities (Filippidis et al., 2015). Using properties such as *skos:prefLabel, skos:broader, skos:narrower*, among others, the initial semantic BAV is created with the 367 terms as a hierarchical code list. Each of the above competitions vocabulary is transformed into RDF as well, in a similar way.

Then, using the Alignment[11] tool (Karampatakis et al., 2017), mappings between BAV and the leagues vocabularies are created, in order to connect the synonyms of the vocabularies with each other. Alignment is able to achieve this semi-automatically, enriching the semantic representation with properties as *skos:exactMatch*, pointing out to the semantic entity of the similar basketball concept of another semantic vocabulary. In this way, semantic BAV includes all the knowledge from the above vocabularies, the concepts, the terms used, the hierarchies and all the synonyms from each competition. It may contain also synonyms in different languages, as, for example, the ACB vocabulary include terms in Spanish, thus, facilitating the event identification even in texts of a different language. An example with a common term is shown in figure 4.

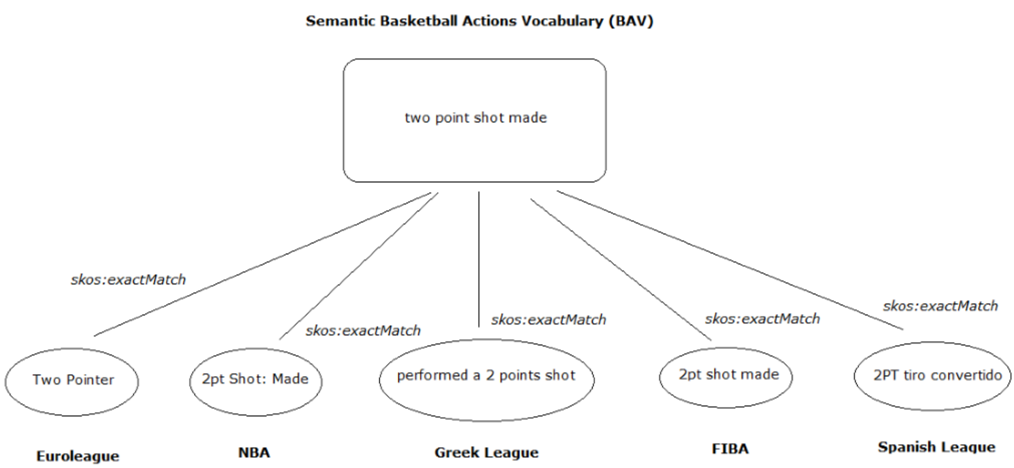

Figure 4. Synonyms of a BAV term from various leagues taxonomies

EVENT IDENTIFICATION IN TEXT

Event Identification through Entities Matching and Vocabulary Enrichment

After the creation and enrichment of the semantic vocabulary basketball actions terms, the event identification task in game reports could become easier and more efficient. This kind of articles usually contain the recap of the game, the leading players and a text timeline of the most important moments during the game. The latter is the most valuable part for the model, as it contains key moments of the game.

The model applies main NLP tasks as sentence breaking, word segmentation, stemming and part-of-speech tagging to the retrieved game reports to detect terms that could form an event. The main task, however, is Named Entity Recognition (NER) for key entities within the text, that could match with terms already found in the game PBP. These terms include

- players
- scores
- actions
- minute of action

where the whole process is supported by the identified events in the PBP and the semantic BAV as well. Thus, a new algorithm aims to find similarities between the report entities and the semantic BAV and PBP events terms, as seen in Figure 5.

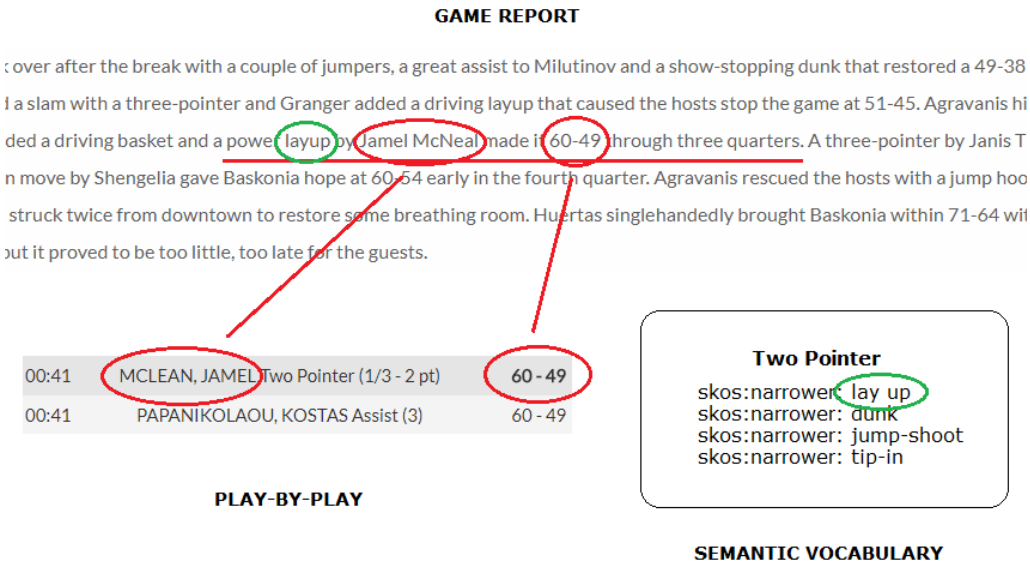

Figure 5. Similarities between game report entities and PBP and BAV terms

As scoring remains the most important, or popular part in sports and basketball contains many scoring actions, it is expected that game reports will include mainly this kind of events. Detecting a score could potentially lead directly to a single identification, as it points out the ending action of an already identified PBP event (where the peak action is a made shot). Then, the algorithm tries to match additional terms, as players, or actions, while a temporal reference could indicate a time interval where it should search in PBP events.

While exploiting scores is a crucial start point for the identification process in game reports, the task is a lot more difficult to be accomplished when a scoring entity is missing from a sentence, using only the PBP events that have been previously identified. The semantic BAV however, allows for the identification even in these cases, as it contains synonyms for many actions that could be referred within the text. Then, the start point for the identification task is not a score, but the action that took place, while participating players matching also contribute, as well as any temporal reference indicating a group of PBP events that occurred in it. If there is not any time indication within the respective sentence, then timestamps from previous or next events could also point out a time interval within PBP. This alternative path to the identification process indicates the importance of developing a semantic vocabulary with terms used in the sport and its utility becomes even greater in later steps, as it potentially grows when examining more articles.

The further enrichment of the vocabulary is accomplished mainly by the event identification task in game reports, when a scoring entity (game score) occurs in text. As mentioned, the scoring detection is the first main step of the algorithm and can easily lead to many identifications. As the algorithm recognizes that a specific sentence corresponds to an event, then the sport action which goes with it might be or might be not included in the current version of the BAV. In the second scenario, the word or words that indicate the player action are imported as a new term in the vocabulary, as a synonym to a broad term that matches with it (i.e. a dunk could match with a two-point shot).

Thus, performing the event identification task in a corpus of game reports strengthens the algorithm, which is trained to identify more terms and entities, based on the vocabulary enrichment. As the algorithm is applied in each text separately, iterations of the procedure allow for the re-examining of game reports with the newly-added terms, facilitating the action-based identification task as well. Additional tasks of verifying the new terms and placing them to the appropriate hierarchy level in the vocabulary are needed in order to integrate completely the new findings into the BAV.

Event Identification in unknown sports articles

After the vocabulary enrichment from specific, known sources, the model becomes more capable of identifying basketball events even in unknown sources, such in sports news media articles from various authors and publishers. This requires, first, another kind of identification, that is the matching of a sports article to the respective game. Additional NLP techniques are evolving to this end, leveraging the same principles and key entities as above, along with the publishing date within the prospective articles. This task takes place in a new, larger text corpus of web articles from various sports websites, which might have additional useful attributes such as tags, keywords, feed categories and others, whilst their title and short description might have a big impact as well.

Having identified the matching articles, if any, the model applies the event identification algorithm in them, as described above, while potentially enriching further the vocabulary used. Through this circular process, combining iterations on both known and unknown text resources, the model is becoming more effective to identify events in any text report. Moreover, the combination of various articles for the same game builds a bigger mosaic of the respective game important or less important activities. Finally, the model should be able to detect all included events in any of the aforementioned sources, as well as be flexible enough to combine even more sources, such as social media, or video. Then, it will be able to build upon them methods for clustering of events, as many PEs may form a generic interval event with a specific topic (e.g. a scoring streak by a team), widening the game analysis possibilities as well.

RESULTS AND CONCLUSIONS

The current event identification model on sports media content can benefit sports journalists in multiple ways, as they become able to obtain additional knowledge on what is happening during sports games, based on the identified events from various resources. The model focuses on basketball, a sport full of activities that take place through its playing, so it is far than difficult for any expert, journalist or analyst to recall all the key moments and details of action. As a basketball game is partially, or fully sliced into a series of events, sport journalists acquire the possibility of searching any kind of events, their sequences, the star players of them and further insights about what has happened during the game, improving spectacularly their analysis possibilities, in a narrow or a broader level.

Thus, they become able to enrich their common analysis, highlight the key points and build data journalism stories on a game, team, player, or season level. Similar possibilities could be also exploited by any other sport stakeholder, such as coaches, experts, or even fans, widening the model scope. This could be evident, as knowledge that comes off the model can be used either as is, or be the source for deeper tasks, such as machine learning for most valuable players highlighting, identification of interval events within the game and events forecasting.

The integration of additional sources such as social media content, or video content at a later stage will increase remarkably the event identification possibilities of the model, while the mixture of all these resources could also benefit other sports-related analysis tasks.

The basketball specialization of the model does not exclude its adjustment to other sports as well, as it develops and uses methods and algorithms that could be customized in different terminology and key concepts. As the key device to the model operations is the semantic vocabulary of basketball actions, a similar process could be also developed for other sports, based on their own key concepts. Thus, apart for developing a basketball-oriented event identification model, the current work proposes a generic approach for event identification on any sports media content, based on classification taxonomies that can be built upon the concepts of the sport.

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