**Data-driven detection of counterpressing in professional football**

<https://link.springer.com/article/10.1007/s10618-021-00763-7#Tab3>

**Ideas:**

Key performance indicator (KPI)**—**metrics quantifying certain aspects of the game: pass evaluation metrics were examined (Steiner et al. 2019; Goes et al. 2019), metrics to quantify controlled space were defined (Kim 2004; Fernandez and Bornn 2018; Brefeld et al. 2019) and several studies evaluated shot metrics (Lucey et al. 2014; Rathke 2017; Fairchild et al. 2018; Anzer and Bauer 2021)Footnote 4 and goal scoring opportunities through possession values (Link et al. 2016; Spearman 2018; Fernandez and Bornn 2018; Decroos et al. 2020)

**Goal:**

Automatically identify counterpressing and derive metrics that support coaches with the analysis of transition situations. Additionally, infer objective influence factors for its success and assess the validity of peer-created rules of thumb established in by practitioners.

**Methodologies:**

Counterpressing detection:

* manual tagging procedure for counterpressing
* around 20 features used for counterpressing detection
* XGBoost model for classification
* SHAP values to evaluate features

Success metric for counterpressing:

* Extracted: shots, expected goals, actual goals
* Successful: ball is regained within five seconds and above occurs within the following 20 seconds.

**Results:**

* Cntr Press det: Prec: 0.72; Recall: 0.63 F1: 0.67 AUC: 0.874
* Outcome of counterpressing regarding goals and shots scored or conceded within 20 seconds

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**Improvements:**

* Low inter-labeler reliability (82.1%) using labeling-support methods.
* Consider using continuous features, or even the raw positional data of all players instead of features at discrete time points.
* Comparing their risk-reward structure to counterpressing situations, could lead to crucial insights by evaluating a teams’ decision to counterpress versus falling back objectively

**Connection:**

**Goal!! Event detection in sports video**

/Users/karol/Desktop/Antwerp/dissertation/EI\_2017\_art00004\_Grigorios-Tsagkatakis.pdf

**Ideas:**

**Goal:**

Goal detection in broadcast low quality football videos.

**Methodologies:**

* C3D
* LSTM networks
* Two-stream CNN, two streams raw frames and optical flow which are independently encoded by CNN and fused to SVM classifier (using pre-trained models can have a dramatic impact on training time)
* Combination of C3D and two-streams
* **Final choice:** two-stream CNN:
  + First stream: spatial features extracted using VGG 16 Network.
  + Second stream: temporal features using VGG 16 Network and using VGG 16 Network estimation.
  + Fusion: sparsity regularized Autoencoder
  + Classification: SVM
* Three experiments: Spatial, Temporal, Fused features

**Results:**

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**Improvements:**

* Using stacked encoders
* Different classification tool
* More efficient way to capture features than simple VGG 16 Network

**Connection:**

**Spotting Football Events Using Two-Stream Convolutional Neural Network and Dilated Recurrent Neural Network**

<https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9410263>

**NOTE:** A lot of examples of different works in the event detection field.

**Goal:**

Spotting football events in long videos, which models the long-range and mid-range correlations between frames in addition to the local spatiotemporal features in the neighborhood of each frame.

**Difference from other works:**

* Localization of the significant moments in football videos and classification of the localized moments into pre-defined event categories are the two important challenges in football video analysis.
* We identify that the key shortcoming in prior work is that they do not consider various ranges of dependencies between frames in a unified architecture.

**Ideas from other works:**

* Synchronizing video with text
* Combining RNN with CNN
* Video summarization based on Bayesian Networks for low-level image features used alongside high-level algorithm.
* New loss function specifically designed for event spotting in football videos.

**Data:** <https://www.soccer-net.org/data>

**Methodologies:**

* Two stream convolutional neural network to compute short-range spatiotemporal features using ResNet50 backbone for both. Uses pre-trained model and fine-tune the last layer. For temporal stream uses two consecutive frames to calculate stacked opticalflow channels as input to the stream.
* DilatedRNN with LSTM units to model mid-range and long-range correlation. It has three layers and each of them is 128 dimensional. It consist skip connections

**Results:**

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**A screenshot of a video

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**Improvements:**

* Using stacked encoders
* Different classification tool
* More efficient way to capture features than simple VGG 16 Network

**Connection:**

**Making Offensive Play Predictable - Using a Graph Convolutional Network to Understand Defensive Performance in Soccer**

<https://www.statsperform.com/wp-content/uploads/2021/04/1617733444_PaulPowerOffensivePlaySoccerRPpaper-1.pdf>

**Goal:**

Model defensive behaviour and its effect on attacking behaviour.

**Difference from other works:**

* They use GNNs

**Data:** Positional data from wide range of games from top 5 europe leagus

**Methodologies:**

Graph Convolutional NN which are able to deal with unstructured tracking data. They do that by training 6 models:

* XReceiver: Probability for every player to become the pass receiver
* xThreats: probability of a shot occurring within next 10 seconds if a pass was played to attacker.
* xPass: Predicts how likely a pass would be completed to each attacker off the ball at any moment within a player possession.
* Player Availability: Using the outputs from xReceiver and xPass we infer how available every attacker is off the ball at each frame.
* Defensive Impact: We are able to detect high level defensive concepts such as ball and man orientated defending, defensive position play and off ball runs.
* Disruption Maps: Global visual representations of defending teams’ ability to disrupt the oppositions attacking strategy.

These models allowed to investigate patterns. Depending on the situation on the field the statistics were updated. Therefore, it was possible to find behavior patterns of the team or particular player.

The GNN architecture looked as follows. The data was represented by graph G(V,E,U). To learn relationship between graph input and outputs the spatial GNN was used. It included separate operations (blocks on the edges and nodes). Each block is defined by neural network. Edge blocks take inputs from the edge features, sending node features and receiving node features then provides a new edge embedding as an output. Node blocks takes inputs from the node features, sending edge features and receiving node features and outputs a new node embedding. Each model outputs a prediction for each player from the final node block.

Node features consists player position, speed, acceleration, angle of motion, distance and angle to the attacking goal, distance to the ball carrier, difference in the angle of motion to the ball carrier and a flag that indicates whether the player is the ball carrier. The edge included a flag defining relationship between connected player, distance between two players and the difference in the angle of motion.

**Results:**

Based on the results the **defensive impact** toolbox was created which determines how much the defending team disrupts the opposition’s play. xThreat and xPass models allows to value not just what did happen but what could have happened or more accurately what was prevented.

They also created something called **Disruption Maps** is a weighted 2d distribution that shows where a team, positively or negatively, disrupted the opposition’s off ball options.

**Improvements:**

**Connection:**

**Event Detection in Football using Graph Convolutional Networks**

<https://arxiv.org/pdf/2301.10052.pdf>

**Goal:**

Their goals were listed with these four bullet points:

1) Formulating the pipeline for generating a high-level view of the football field (referred to as a minimap) using ball-player bounding boxes and camera calibration

2) Describing how football tracking data can be modelled using graphs and then processed using Graph Convolutional Networks

3) Formulating event detection as an action spotting task, which involves localizing events to a certain timestamp in a video

4) Experimenting with different pooling methods for modelling the temporal context around each action

**Data:**

* Using video data which was transformed to the 2D tracking data.
* There are also annotations for events: game flow annotations (out, stop, goal), post-out annotations (goal kick, corner kick, throw in), post-stop annotations (offside, foul, yellow and red card) and other (goal chance, shot)

**Methodologies:**

* Transforming videos to 2D tracking data:
  + Merge videos into panorama by calibration.
  + Faster-RCCN with ResNet backbone used to detect players and ball
  + Then features were extracted
  + Hungarian algorithm weas used to associate detections with trajectories based on extracted features, positioning the previous frame and estimation of their current position using Kalman filter.
  + Then positions are projected onto the pith minimap.
* Collecting graph features two for positions and 3 one-hot encodings
* Plug them into GNNs
* Pooling (AVG, MAX, NetVLAD, NetRVLAD)
* Multi-label classifier

**Results:**

* Overcome problems with unclear order players ina sequence and to handle missing objects of the interest.
* Show how the performance of pooling layers in event detection models can be improved by considering the context before and after the action separately

**Improvements:**

* Introduce self-supervising tasks to pretrain graphs.
* Predicting the future motion of teams given the previous positions of its players over the window.

**Connection:**

**VAEP: An Objective Approach to Valuing On-the-Ball Actions in Soccer**

<https://www.ijcai.org/proceedings/2020/0648.pdf>

**Goal:**

- A language for representing player actions; A framework for valuing player actions;

- A model for predicting short-term scoring and conced- ing probabilities at any moment in a game;

- A number of use cases showcasing our most interesting results and insights;

**Data:**

* Data consists the following features: action starts and ends locations, SPADL features like pass, shot, etc. There are also some complex features which combine information within and across consecutive actions. They also included game context features.

**Methodologies:**

* Used VAEP score to represent action values: V(ai) = V(Si) – V(Si-1)
* V(Si) = Pk(Si)scores – Pk(Si)concede
* To estimate probabilities the gradient boosting models were used.

**Results:**

Allowed to select players with highest VAEP scores.

**Improvements:**

* Reinforcement learning to analyze technical performance in a match.
* Multi agent learning to learn the value of teamwork from outcomes of pass interactions between players.

**Deep soccer analytics: learning an action-value function for evaluating soccer players**

<https://sci-hub.wf/10.1007/s10618-020-00705-9>

**Goal:**

Apply Deep Reinforcement Learning (DRL) to learn an action-value Q-function from events in a soccer game. Apply Deep Reinforcement Learning (DRL) to learn an action-value Q-function from events in a soccer game.

**Difference from other works:**

* Expected Scoring Impact metric determined from Markov model
* XThreat model discrete Markov Model

**Data:**

Data consisted of tabular data.

**Methodologies:**

Markov game model:

* Two agents Home and Away
* Action denotes movements of players who control the ball
* Observation is a feature vector specifying a value of the features,
* Reward is the goal value.

Goal Q-function:

* Divide a soccer game into goal-scoring episodes (start at the beginning of the game and terminates on the goal or at the end of the game).

Architecture:

* Two tower design for home and away teams separately. Each tower captures the play history with a stacked LSTM
* Home/Away Team Identifier to select the hidden state from home or away tower according who possess the ball.
* Selected hidden state values are sent to hidden layers whose outputs are normalized by softmax.

Weight training

* Sarsa method and apply a dynamic possession LSTM to control the trace length during training.

**Results:**

**Connection:**