

# Using Contextual Player Movement and Spatial Control To Analyse Player Passing Trends in Football

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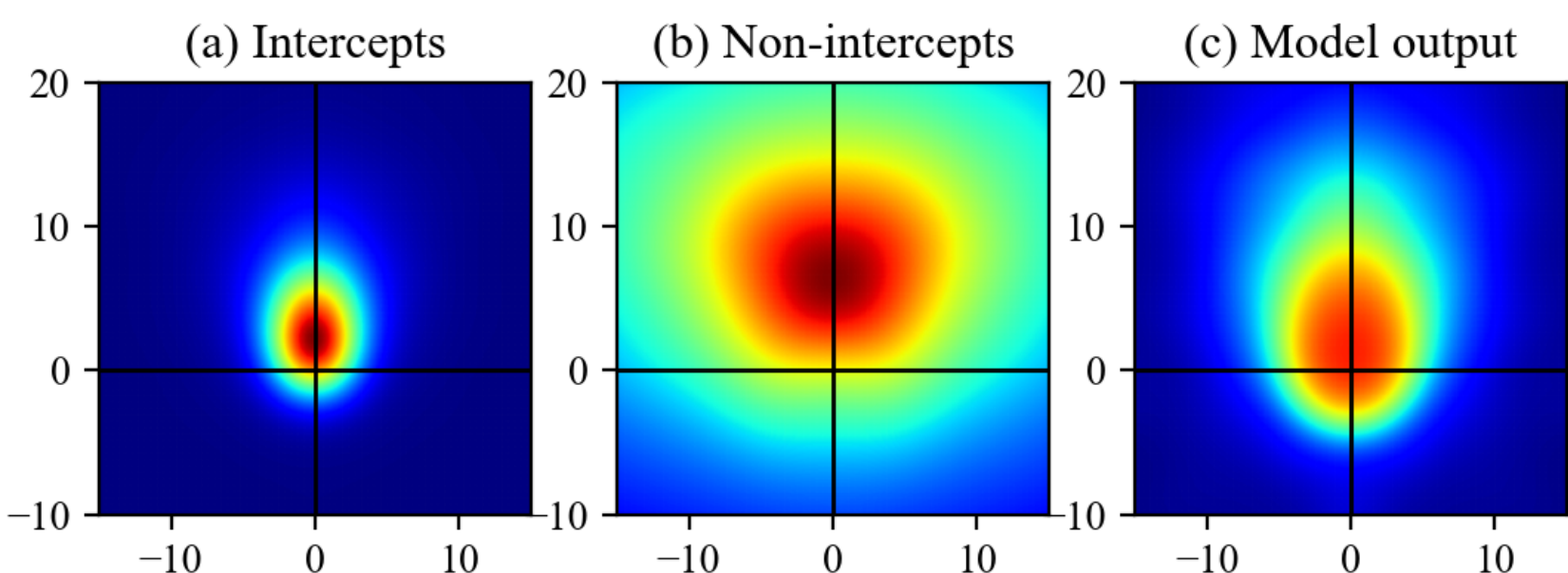
## Introduction & Background

Probabilistic player motion (or movement) models describe the likelihood of future movements, given a player’s current velocity and orientation. Representations of player movement have been used as inputs into spatial control models in football (e.g., [1, 2]).

A limitation of common implementations of motion models is a lack of movement context. Player movement is dependent on multiple factors including the location of the ball. We produce player motion models that incorporate contextual movement information and use these to measure the spatial control of attacking teams in the MLS. From control, we estimate passing risk to analyse passes between teammates.

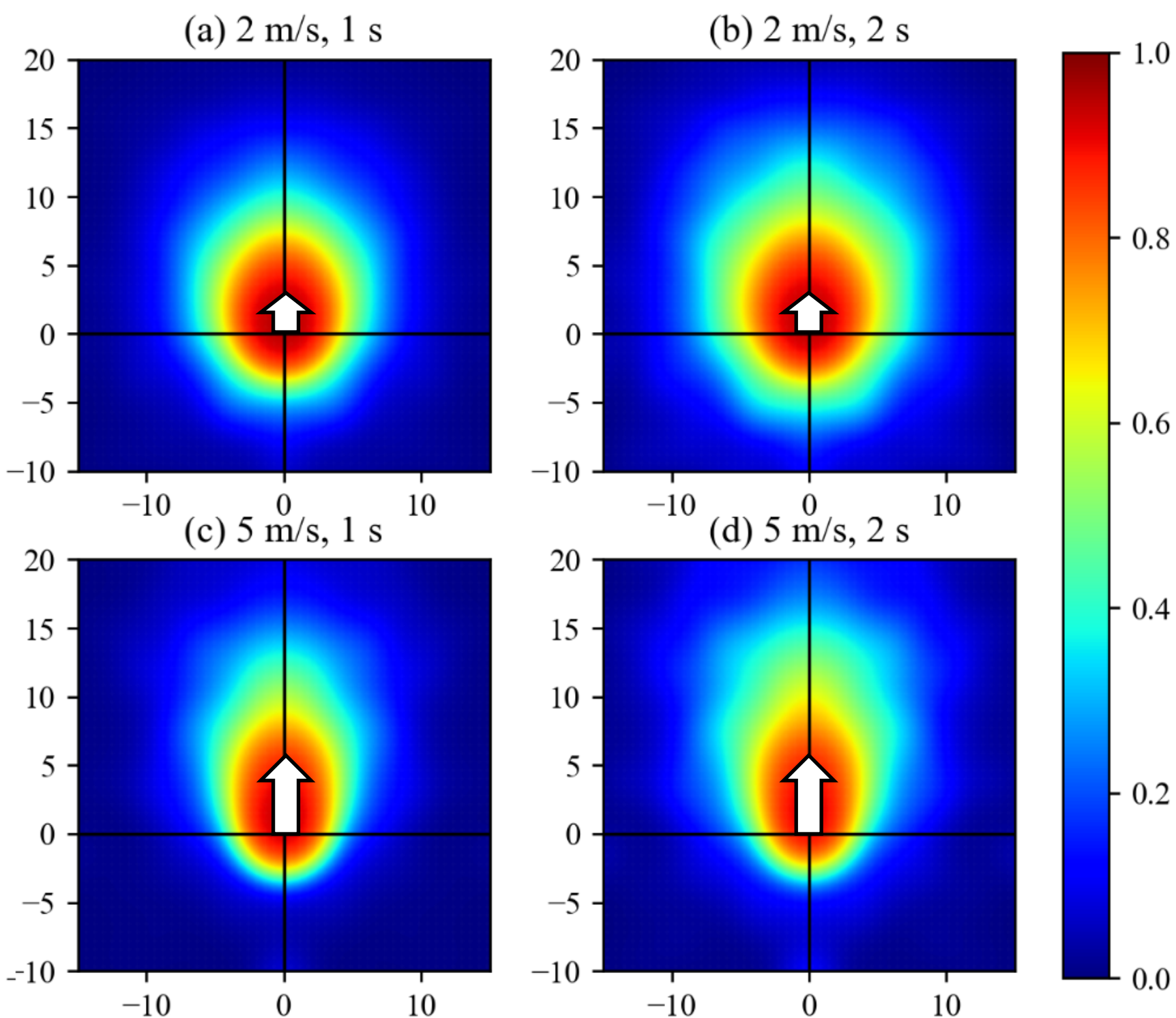
### Modelling Player Motion

- High-effort movements are those requiring acceleration, deceleration, or reorientation. Models fit on player displacements sampled without context underestimate a player’s ability to perform these movements.
- Commitment**-based motion models sample player movement during a specified match context (e.g., interception). Specifics of this process are outlined in [3].

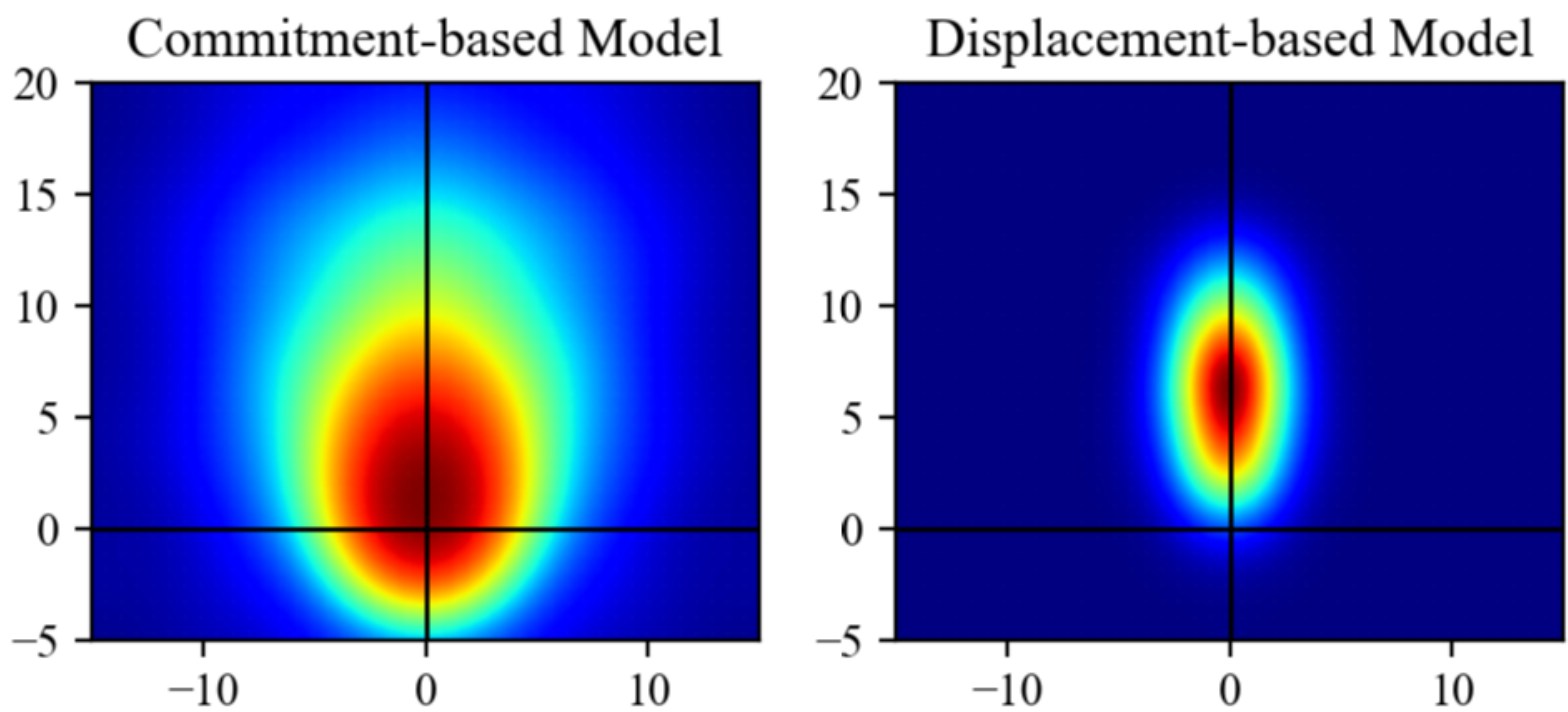


**Fig. 1.** Commitment-modelling process. The relative locations of passes that were (a) intercepted, and (b) not intercepted are combined to quantify the (c) likelihood of interception within a player’s vicinity, for given *velocity* and *time*.

- Areas of space are those in which the attacking team could occupy without opposition interception, hence commitment-models in this study were fit on player movements that resulted in a turnover (**Fig. 1**). Resultant models (**Fig. 2**) are visually different to displacement-based methods (**Fig. 3**).



**Fig. 2.** Resultant commitment-models ( $p_i$ ) for players moving at (a, b) 2m/s and (c, d) 5m/s over different time intervals.



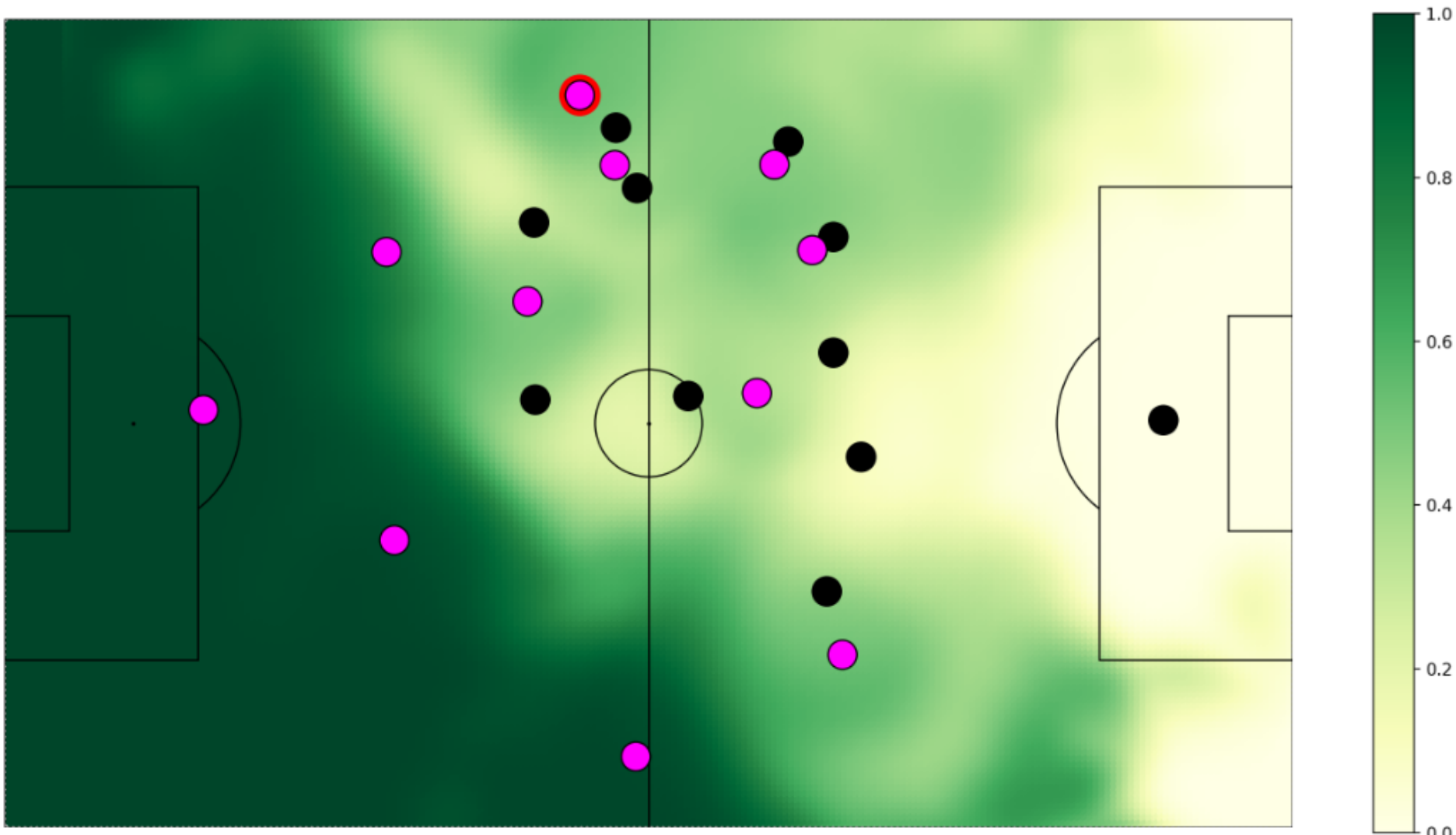
**Fig. 3.** Comparison of commitment- and displacement-based motion models for a fixed velocity and time interval.

### Measuring Space

- Spatial control (SC) is measured from player movement probabilities ( $p_i$ ):

$$SC(X) = \frac{\sum_i p_i(X)}{\sum_i p_i(X) + \sum_j p_j(X)}$$

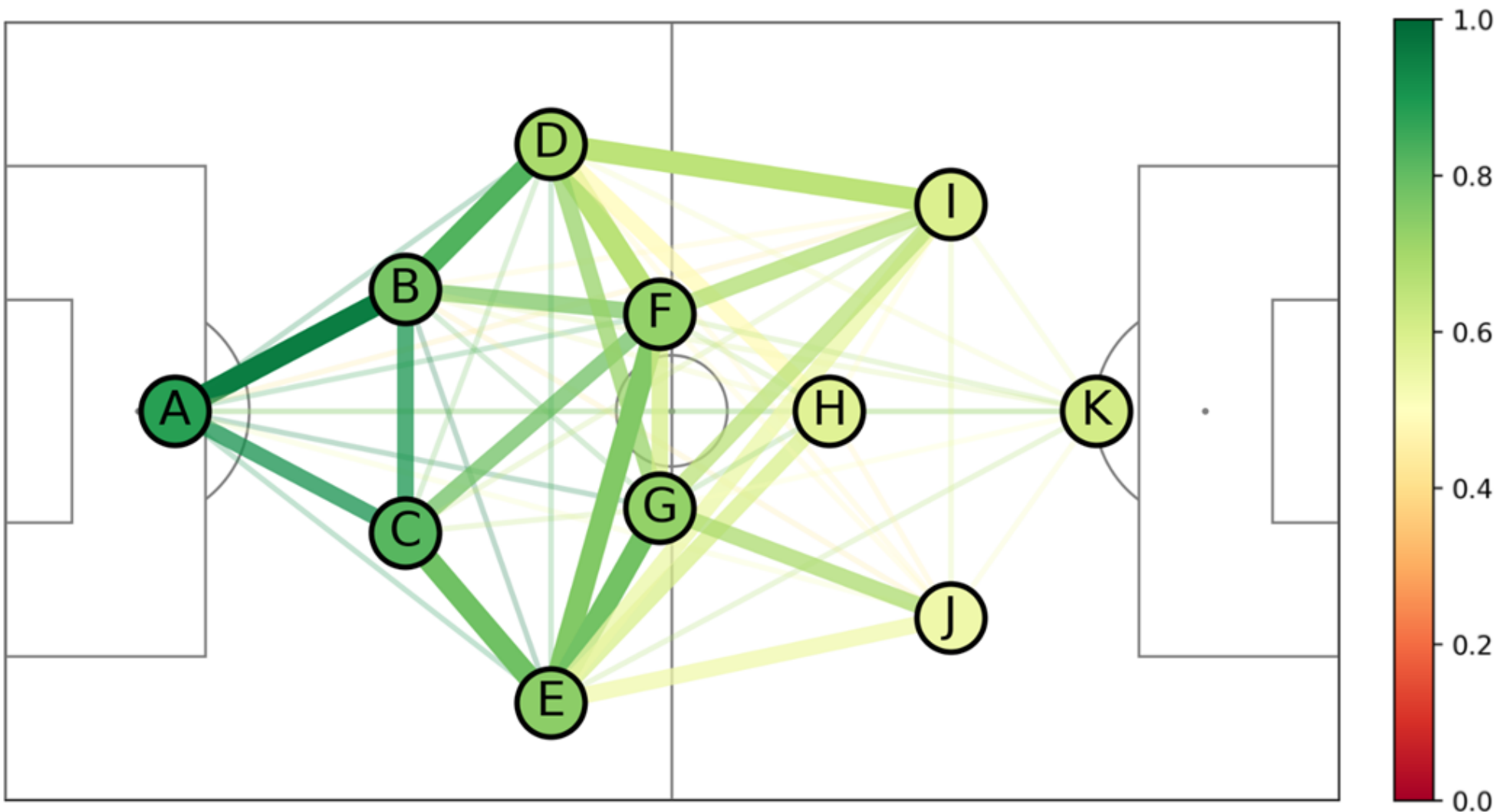
- SC is produced in the range [0, 1] where  $SC(X) > 0.5$  signifies a spatial advantage to the attacking team ( $i$ ) over their opponent ( $j$ ).



**Fig. 4.** An example of SC for the attacking team (magenta) relative to their opponent (black). Ball possession is denoted in red.

### Spatial Control of Passes

- SC is used as a proxy for passing risk (a pass to a region of low control is said to be high risk compared to a pass to a region of high control).
- The SC of passes between players pairs were analysed (see **Fig. 5** for the results of a single team).
- Player  $J$  (a designated player who scored the most goals/xG in the team for the season) was the passer and receiver of the highest risk passes. The ability to identify  $J$  from passing risk has interesting tactical applications.



**Fig. 5.** Player passing network diagram for a single team. Player ( $x, y$ ) location corresponds to playing position. Width and colour of link correspond to frequency and mean SC respectively.

### References

[1] Fernandez, J., & Bornn, L. (2018). Wide Open Spaces: A statistical technique for measuring space creation in professional soccer. In *Sloan Sports Analytics Conference* (Vol. 2018).  
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[3] Spencer, B., Jackson, K., & Robertson, S. (2019). Fitting motion models to contextual player behavior. *arXiv preprint arXiv:1907.10762*.