# Closing Down Spaces

**Extending Pitch Control to NFL Tracking Data** 

**Andrew Kang** 



#### **Abstract**

This study introduces a novel method to <u>quantify and visualize NFL defense</u> by adapting the concept of <u>pitch control from soccer</u> to American football.

In soccer, pitch control measures each player's potential zone of ball possession. We extend this concept to NFL defense to create <u>tackle zone control</u>.

Tackle zone control quantifies each defender's zone <u>where a tackle is most likely</u>. This is calculated using a <u>monotonic neural network</u> that considers features such as relative velocity, acceleration, and position of the defender, runner.

This approach offers a new way to analyze and visualize NFL defensive strategies and player effectiveness.



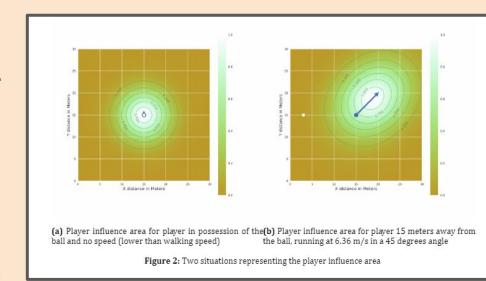
# The Baseline Model

What is *Pitch Control* in soccer?



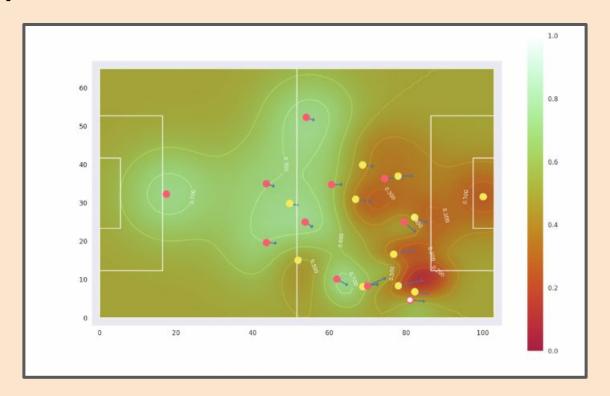
#### "Wide Open Spaces" by Javier Fernandez & Luke Bornn, MIT SSAC 2018

- Soccer is a game where players are without the ball 97% of the time, making <u>off-ball events</u> crucial for understanding the game's complexity.
- The Pitch Control Model: Incorporates motion information, relative distance to the ball, and player position to provide a smooth <u>normal distribution</u> of potential <u>ball control</u>.
- Rewards players based on their controlled space's <u>relative value</u>, using the position of the ball.





### **Exemplary Pitch Control Visualization for Soccer**





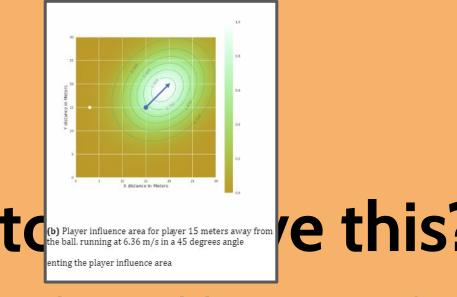
### To adapt this to American football...

- Dataset: Tracking Data of Weeks 1-9 from the NFL in 2022 (Kaggle)
- What does each defender try to control on the pitch?

Soccer	American Football
At each moment in time, how much valuable space are players off the ball occupying?	At the <u>moment before catch/rush</u> , how much space are defenders <u>closing down</u> ?







Which part of the baseline model is most specific to soccer?



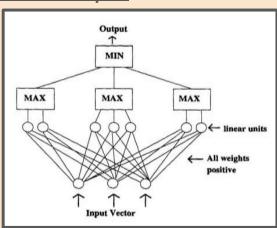
## **Monotonic Neural Networks**

Joseph Sill, NeurIPS 1997



### "Monotonic Networks" by Joseph Sill, NeurIPS 1997

- Enforces a monotonic relationship between input features and output.
  - Improved interpretability compared to traditional neural networks.
  - Predictable decision-making process with monotonic constraints.
  - Suitable for any application requiring transparent decision-making.
- Advantages:
  - Balances <u>accuracy with explainability</u>.
  - Facilitates understanding of how input changes affect predictions.
- Impact:
  - Opens new research avenues for interpretable models.
  - Addresses the "black box" problem of conventional neural networks.





### MNNs for the Tackle Zone Control problem

- Lack of data
- Imbalanced dataset (Only the tackler is labeled, for the last second before tackle)
- ⇒ To utilize a neural network, we need <u>hard-coded features</u> with guidelines (like the monotonicity <u>constraint</u>)
  - 'distance', 'rel\_speed', 'defender\_speed', 'carrier\_speed'
  - 'relative\_x', 'relative\_y', 'cosine\_similarity (of velocity vector)'



## Monotonic NN videos







#### **Future Work**

- Train more! (more data, more epochs, smaller cross-entropy loss)
- Player-specific neural networks to personalize tackle zones
- Defender Rankings:
  - Who outperforms the MNN-predicted tackle success probabilities across a season?
  - Who is always in a good position to tackle on average?
- Team Rankings:
  - Which defending teams cover the most possible receivers?
  - Which defending teams have the largest cumulative tackle control of the receiver on average?
- "Catch Zone Control" to extend concept to catches, swats, and interceptions.



# Thank you.

