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2021 SIS Analytics Challenge:

General Track - Route Concepts

Main Takeaways

- **Route concepts identified using a Convolution Neural Network model**
- **Identified which route concepts were the most popular and effective**
- **Quantified concept performance against specific coverages**
- **Compared concept performance in MOFO coverages against MOFC coverages**
- **Distinguished which route concepts paired well together**
- **Found that "Novel" route concept variations performed similarly to "Traditional" route concepts**
- **Identified which concepts performed best as an RPO dropback**
- **Characterized route concepts as either "Explosive" or "On-Schedule"**
- **The most effective 2020 NFL passing offenses utilized a blend of Explosive and On-Schedule route concepts**

Data Adjustments

Initial Dataset contained 32,170 plays

Dataset reduced to 16,348 plays of interest

Filtered out:

- non-passing plays
- screen plays,
- plays without defensive coverage assignment
- plays w/ only non-route skill information (e.g., blocking, run fake)

Dataset focused on typical passing plays with quality route information

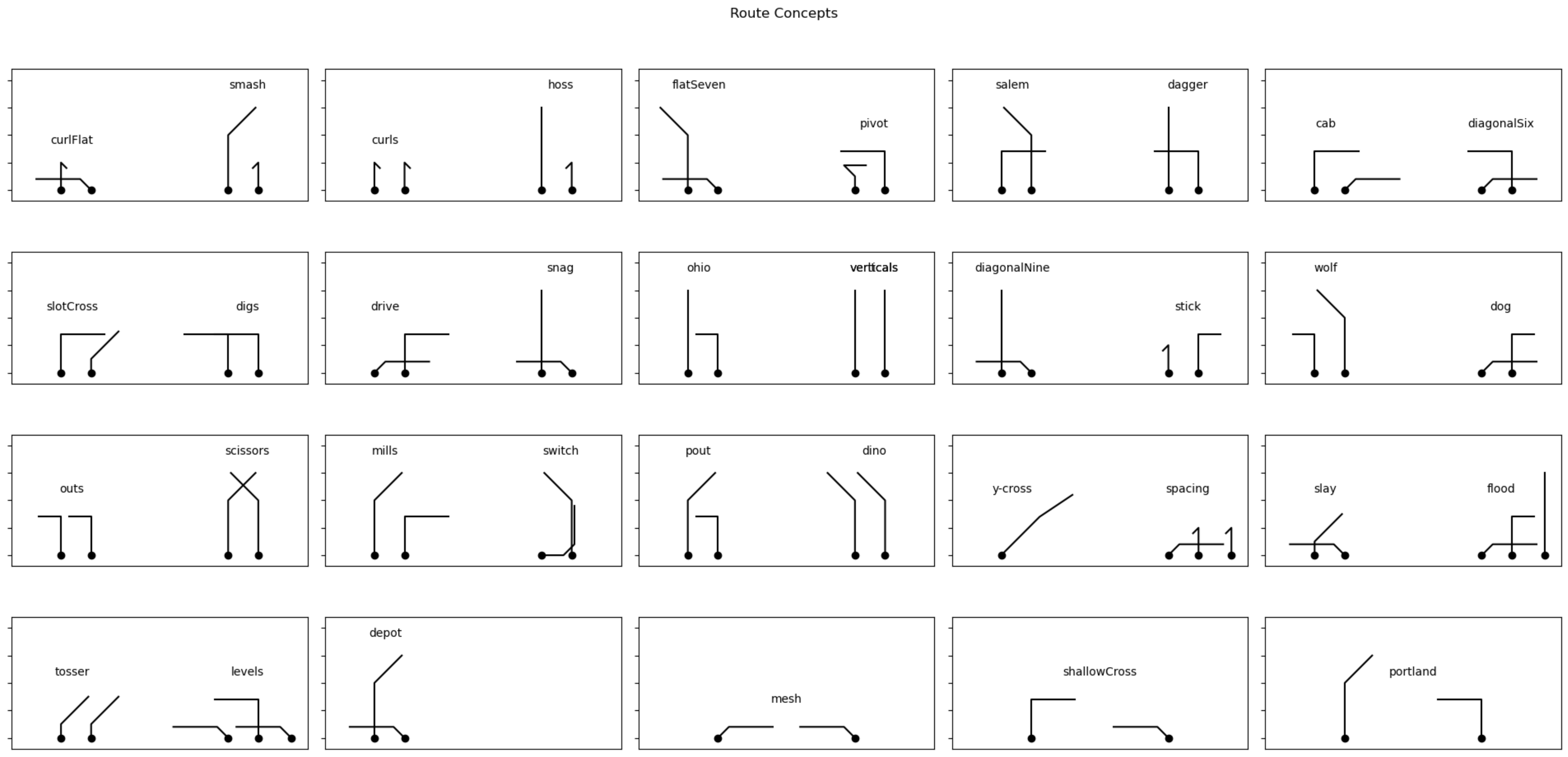
Route Combination Dictionary

A route combination dictionary was developed

- Characterized common route concepts by route ordering, position, and/or combination
- 36 route concepts included
- Vertical routes were grouped such as: “Out & Up”, “Hitch & Go”, “Go/Fly”, “Fade”, “Seam”, “Chip – Seam”, “Fade – Backshoulder”

Route combination dictionary provided a first-pass identification of route concepts for each play

An example of each route concept is shown in the subsequent slide



Route Concept Dictionary

Dictionary Route Concept Attempt

1. The route combination dictionary provided a first attempt at identifying route concepts within the dataset

- Route concepts were identified for 11,580 plays of our dataset

- But for the other ~30% of our dataset (4,768 plays) no route concept was identified

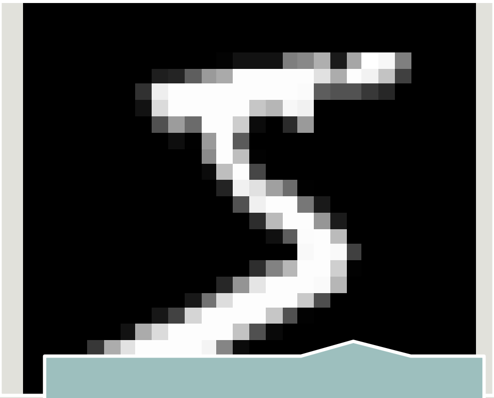
- To overcome this limitation, techniques from computer vision methods were used to visually identify route concepts for every play in the dataset

Convolution Neural Network

Convolution Neural Networks (CNNs) are highly effective tools in computer vision methods

The same mathematical techniques used to identify handwriting samples or bird species can be used to identify NFL route concepts

We've built & utilized a CNN model to identify the route concepts within the SIS dataset



"the number five"

"parrot"

"hoss + ohio + curls"

CNN Route Concept Identification

The routes information for each play was plotted to a .png image

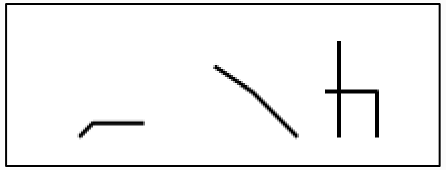
Dictionary-identified route concept labels were associated with 11,580 images

These images & labels were used to train and validate the CNN model

Multi-item classification (i.e., each play could be classified as one or more route concepts)

The CNN model utilized a layer structure similar to the standard Visual Geometry Group

play images



example play image

dictionary labels

- "dagger"
- "y-cross"

CNN Model

- trained/validated on dictionary labeled data
- expanded to identify route concepts on entire dataset

CNN Model Performance

CNN Model achieved ~80% accuracy

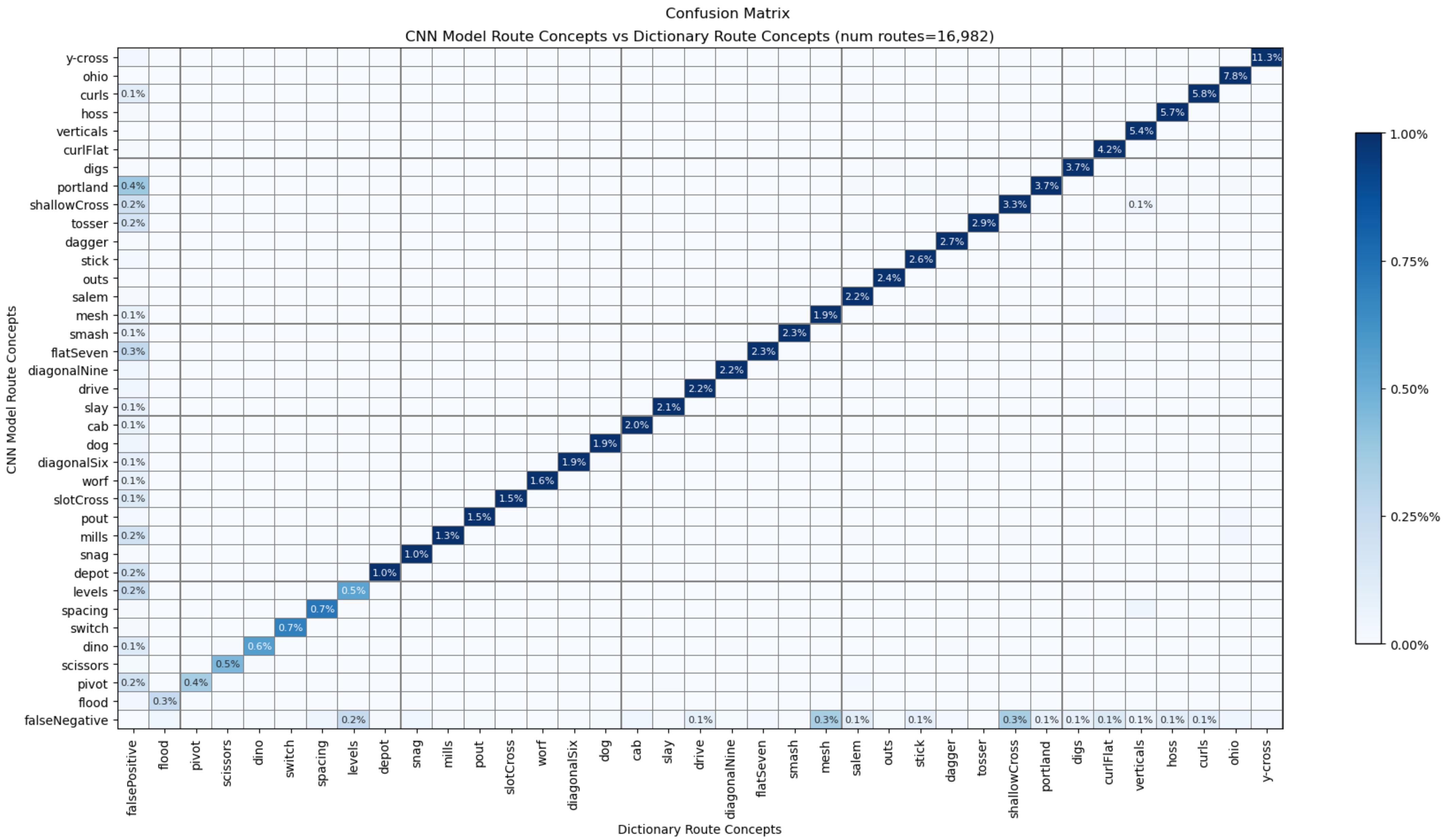
Most errors associated with either

- False Positives: identified a route concept not labeled by the route concept dictionary
- False Negatives: failed to identify the route concept labeled by the dictionary

Model Confusion Matrix (next slide) shows little systematic error

Potential errors that might affect data

- Overestimate of Portland & Flat-Seven route concept frequency
- Underestimate of Mesh & Shallow-Cross route concepts frequency



CNN Confusion Matrix

CNN Model Assessment

The CNN model was used to identify route concepts

- Applied to the entire 16,348 play dataset
- Identified the 1-3 route concepts which best characterized the play

Advantage:

- Larger dataset
- Route concepts identified based on spatial characteristics, not strict dictionary rules
- Captures "Novel" atypical versions of route combination concepts

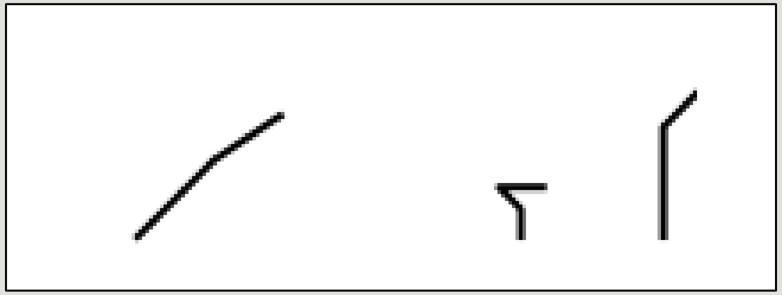
Disadvantage:

- ~20% error rate
- May over/under-estimate frequency of some route concepts

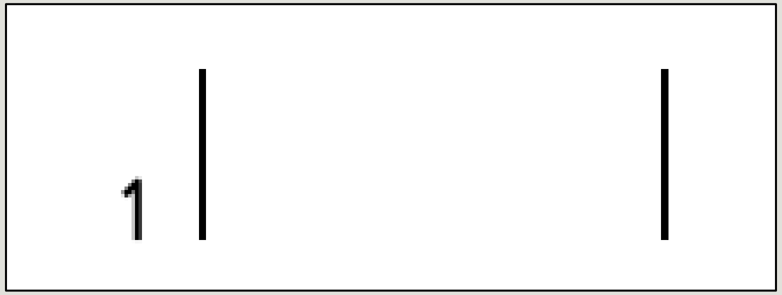
CNN Model Examples

These are plays where the route combination dictionary failed to identify a route concept

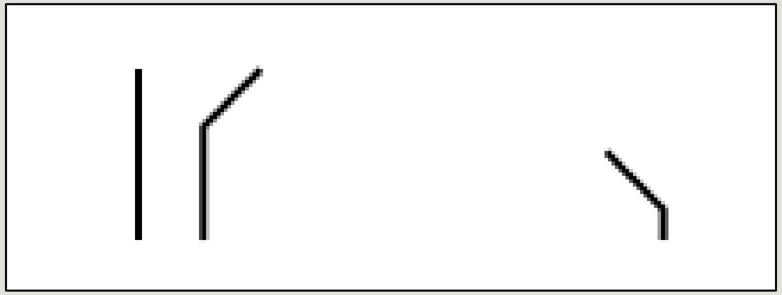
But the CNN model was able to (1) assess at the spatial characteristics of the play and (2) suggest a route concept



CNN ID: flatSeven
- usually a "corner+flat" combination
- here a "corner+whip" combination



CNN ID: hoss
- usually a "curl+go" combination
- here a "comeback+go" combination



CNN ID: portland
- usually a "post+dig" combination
- here a "post+slant" combination

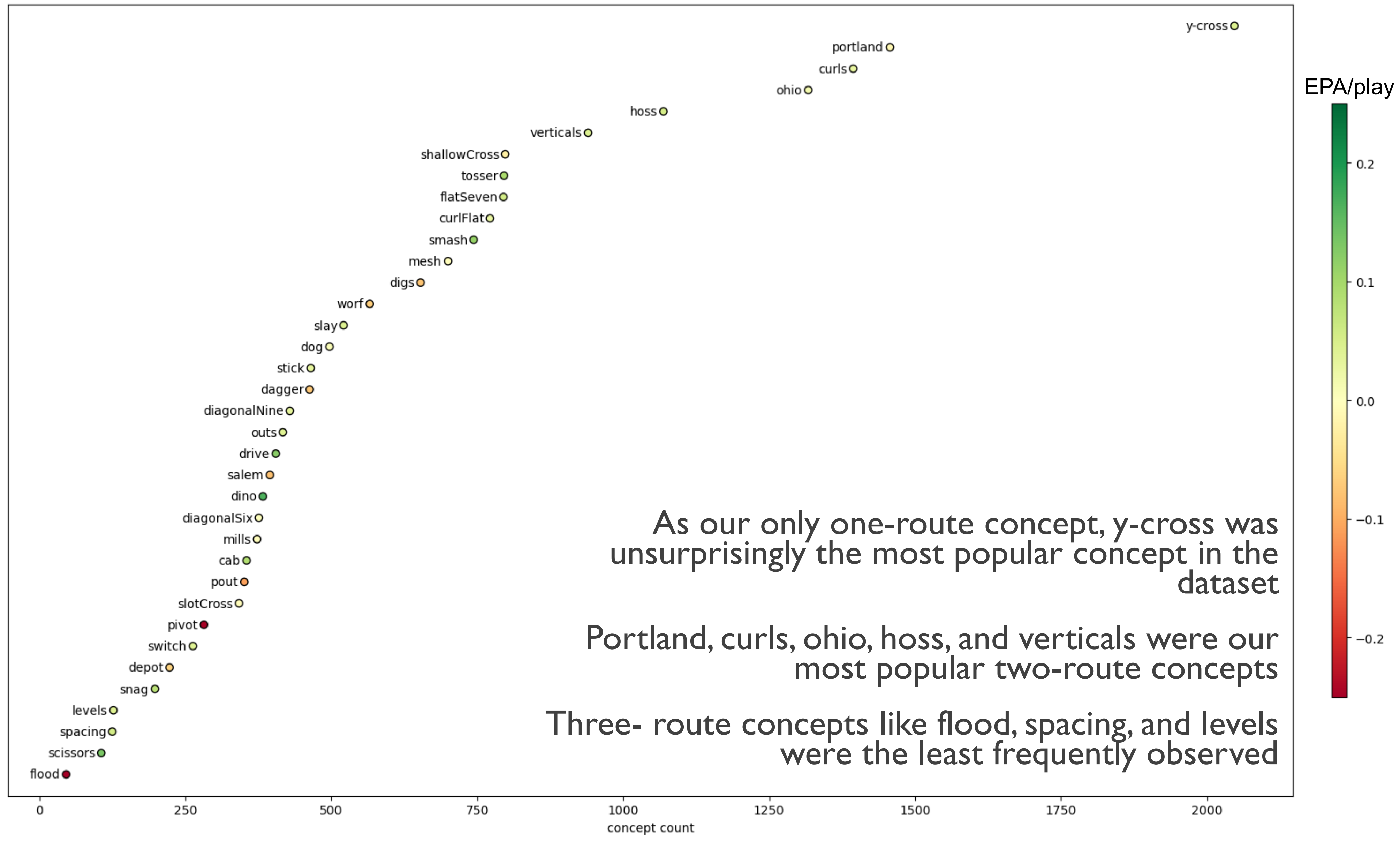
Application: Terminology

In the following section we will look at how our identified route concepts performed in various situations

Terminology that we will use

- EPA/play: average expected points for the grouped concept of interest
- MOFO: Middle Of the Field Open defensive coverage (Cover 0, Cover 2, Cover 4, Cover 6, Tampa 2)
- MOFC: Middle Of the Field Closed defensive coverage (Cover 1, Cover 3)
- Success Rate: The percentage of plays which resulted in positive EPA
- Explosiveness: The average amount of EPA generated by successful plays
- Traditional Route Concepts: route concepts which fit the dictionary definition (e.g., hoss = curl+go)
- Novel Route Concepts: identified route concepts which did not fit the dictionary definition (e.g., hoss = comeback+go)
- Explosive Route Concept: route concept that generates higher-than-average Explosiveness
- On-Schedule Route Concept: route concept that achieves a higher-than-average Success Rate

Route Concept Frequency



As our only one-route concept, y-cross was unsurprisingly the most popular concept in the dataset

Portland, curls, ohio, hoss, and verticals were our most popular two-route concepts

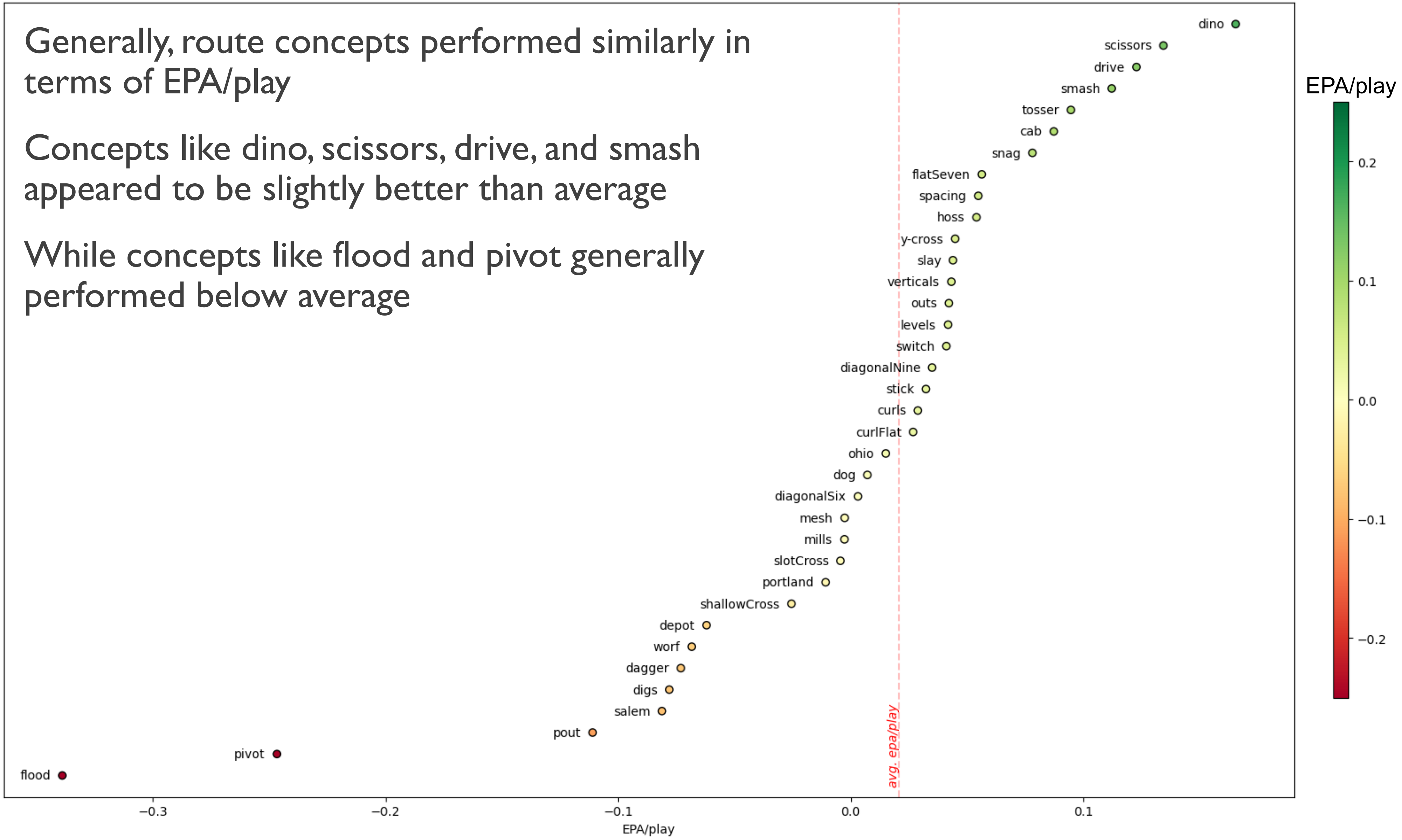
Three- route concepts like flood, spacing, and levels were the least frequently observed

Route Concept Performance

Generally, route concepts performed similarly in terms of EPA/play

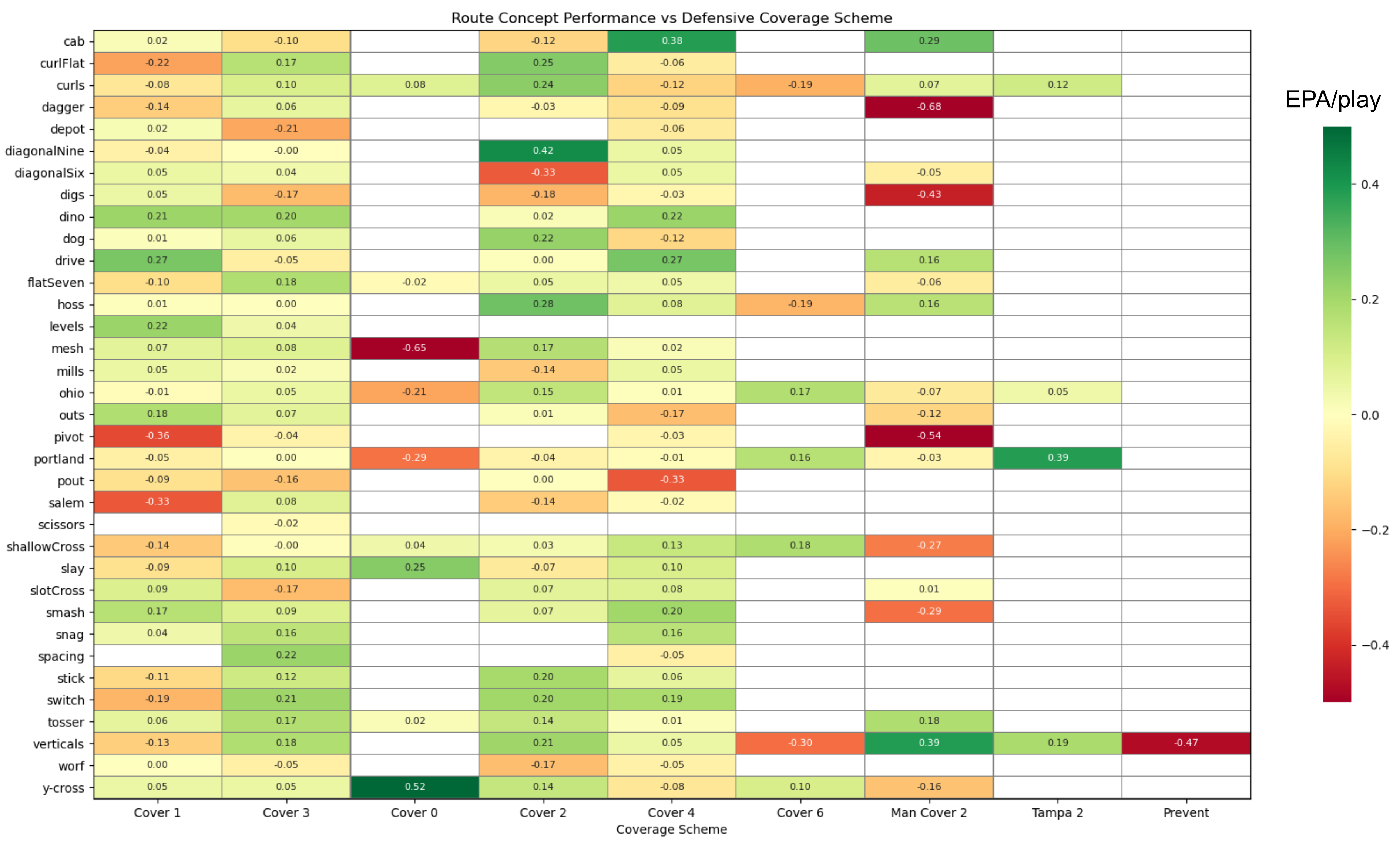
Concepts like dino, scissors, drive, and smash appeared to be slightly better than average

While concepts like flood and pivot generally performed below average

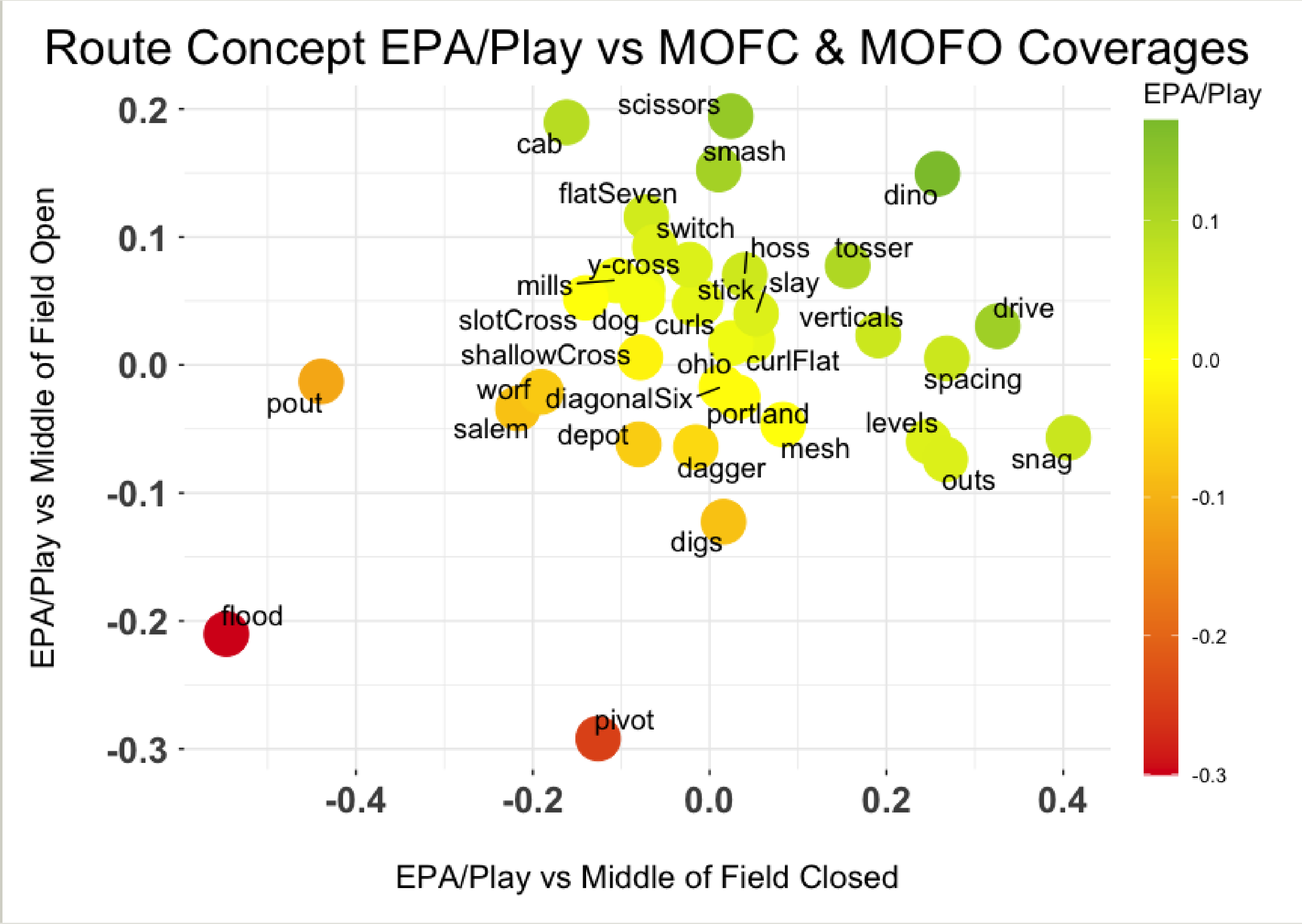


Route Concept vs Coverages

- EPA/play was computed for each route concept and coverage pairing
- Pairings with less than 25 instances were excluded for sample-size issues
- Some route concepts (dino) performed well against most coverages
- Some coverages (Man Cover 2) performed well against most route concepts
- This table can be used as a lookup for which concept performed best against which coverage & vice-versa



	Cover 1	Cover 3	Cover 0	Cover 2	Cover 4	Cover 6	Man Cover 2	Tampa 2	Prevent
cab	0.02	-0.10		-0.12	0.38		0.29		
curlFlat	-0.22	0.17		0.25	-0.06				
curls	-0.08	0.10	0.08	0.24	-0.12	-0.19	0.07	0.12	
dagger	-0.14	0.06		-0.03	-0.09		-0.68		
depot	0.02	-0.21			-0.06				
diagonalNine	-0.04	-0.00		0.42	0.05				
diagonalSix	0.05	0.04		-0.33	0.05		-0.05		
digs	0.05	-0.17		-0.18	-0.03		-0.43		
dino	0.21	0.20		0.02	0.22				
dog	0.01	0.06		0.22	-0.12				
drive	0.27	-0.05		0.00	0.27		0.16		
flatSeven	-0.10	0.18	-0.02	0.05	0.05		-0.06		
hoss	0.01	0.00		0.28	0.08	-0.19	0.16		
levels	0.22	0.04							
mesh	0.07	0.08	-0.65	0.17	0.02				
mills	0.05	0.02		-0.14	0.05				
ohio	-0.01	0.05	-0.21	0.15	0.01	0.17	-0.07	0.05	
outs	0.18	0.07		0.01	-0.17		-0.12		
pivot	-0.36	-0.04			-0.03		-0.54		
portland	-0.05	0.00	-0.29	-0.04	-0.01	0.16	-0.03	0.39	
pout	-0.09	-0.16		0.00	-0.33				
salem	-0.33	0.08		-0.14	-0.02				
scissors		-0.02							
shallowCross	-0.14	-0.00	0.04	0.03	0.13	0.18	-0.27		
slay	-0.09	0.10	0.25	-0.07	0.10				
slotCross	0.09	-0.17		0.07	0.08		0.01		
smash	0.17	0.09		0.07	0.20		-0.29		
snag	0.04	0.16			0.16				
spacing		0.22			-0.05				
stick	-0.11	0.12		0.20	0.06				
switch	-0.19	0.21		0.20	0.19				
tosser	0.06	0.17	0.02	0.14	0.01		0.18		
verticals	-0.13	0.18		0.21	0.05	-0.30	0.39	0.19	-0.47
worf	0.00	-0.05		-0.17	-0.05				
y-cross	0.05	0.05	0.52	0.14	-0.08	0.10	-0.16		



In addition to concept/coverage pairings, we classified coverages as MOFO vs MOFC (Prevent coverage was excluded)

We then computed the EPA/play for each coverage-type

This overcomes many of the sample size issues of specific concept-coverage pairings

Concepts that perform relatively better against MOFC: snag, drive, spacing, levels, outs

Concepts that perform relatively better against MOFO: cab, scissors, smash, flatSeven, switch, y-cross

Route Concept vs Coverages

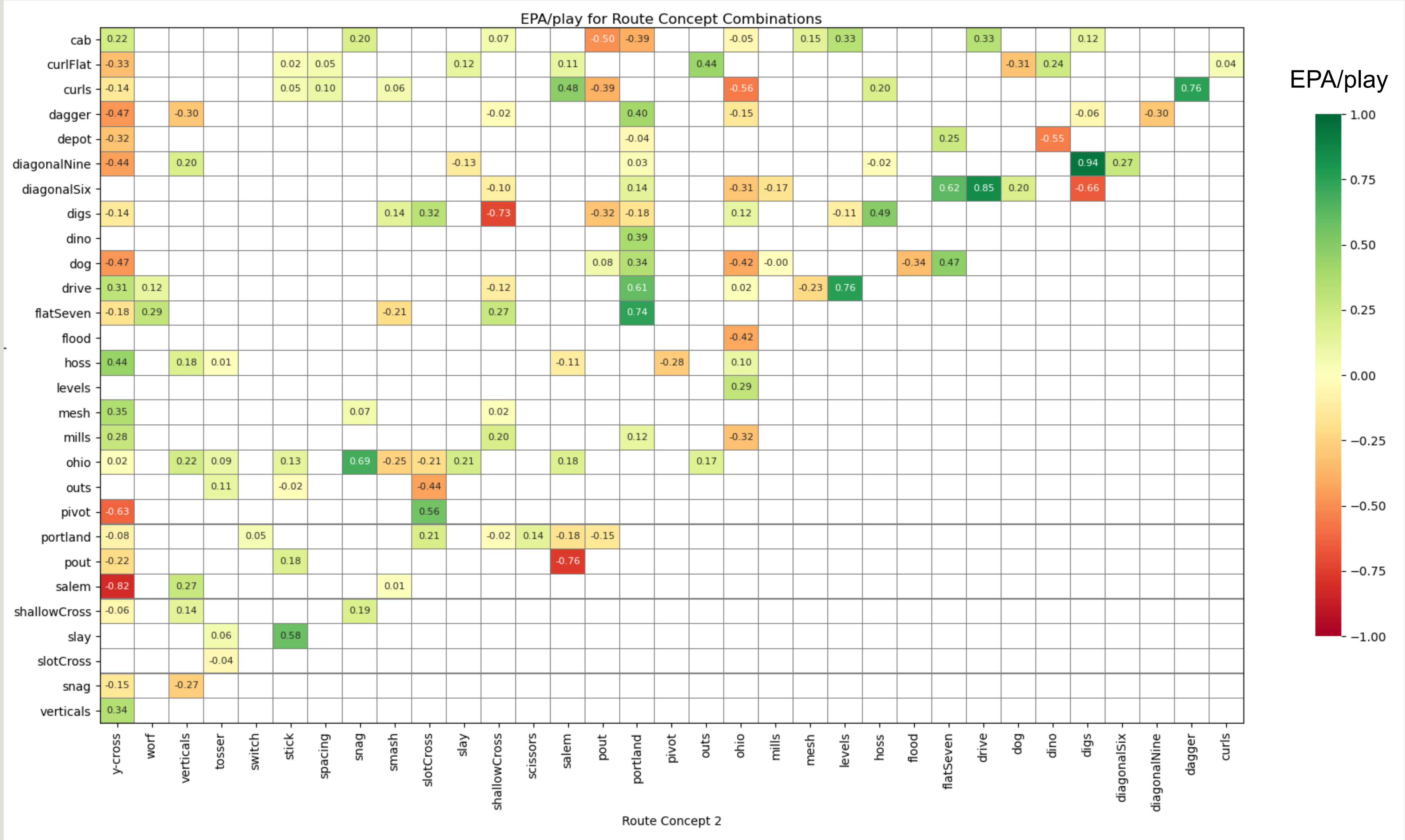
EPA/play was computed for each route concept pairing

Ex., Plays when cab was run in conjunction with y-cross averaged an EPA of 0.22

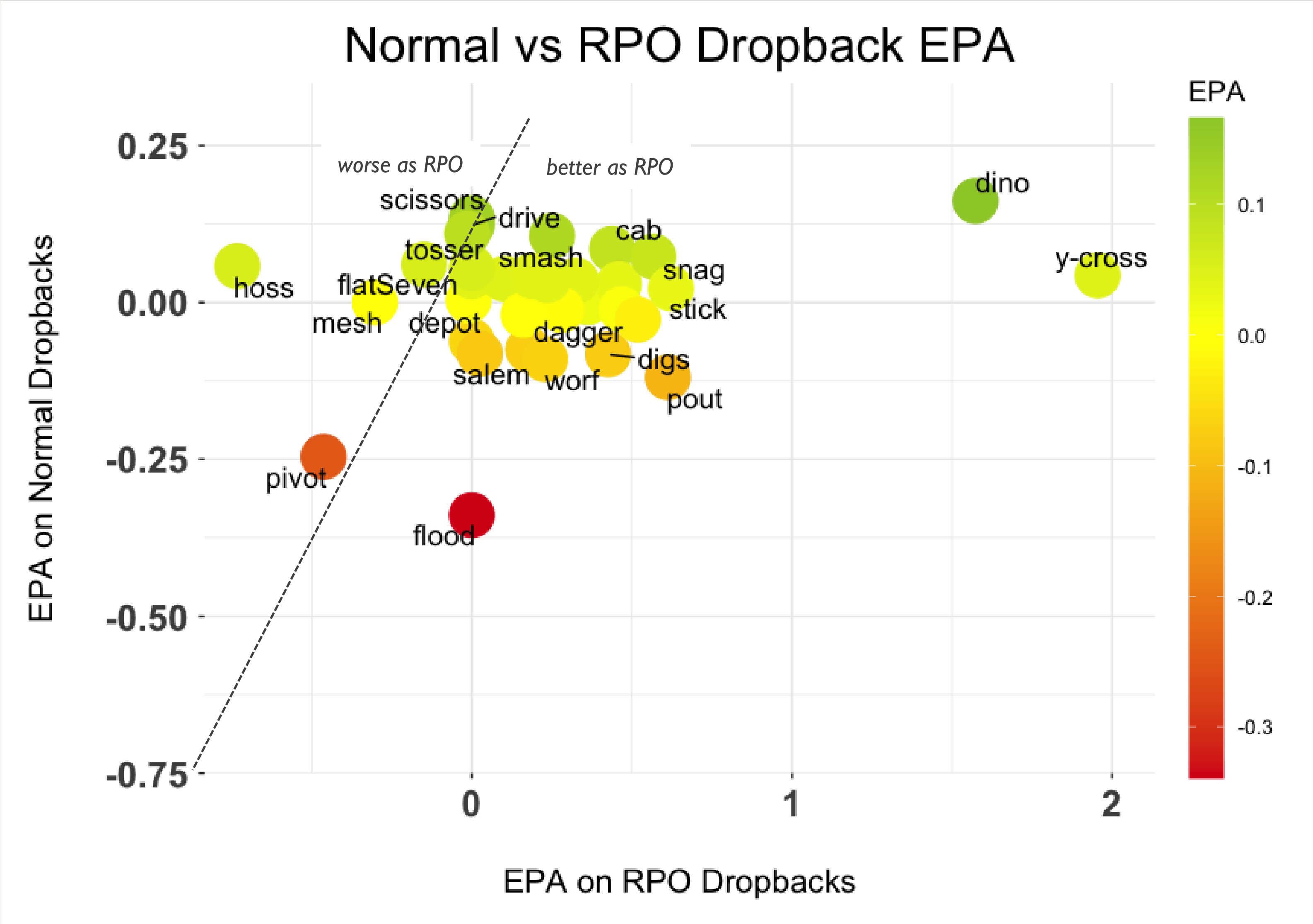
Pairings with less than 10 instances were excluded

Some concepts like portland & ohio seemed amenable to combination with other concepts

Other concepts like dagger and y-cross were much more varied in their pairing success



Route Concept Combinations



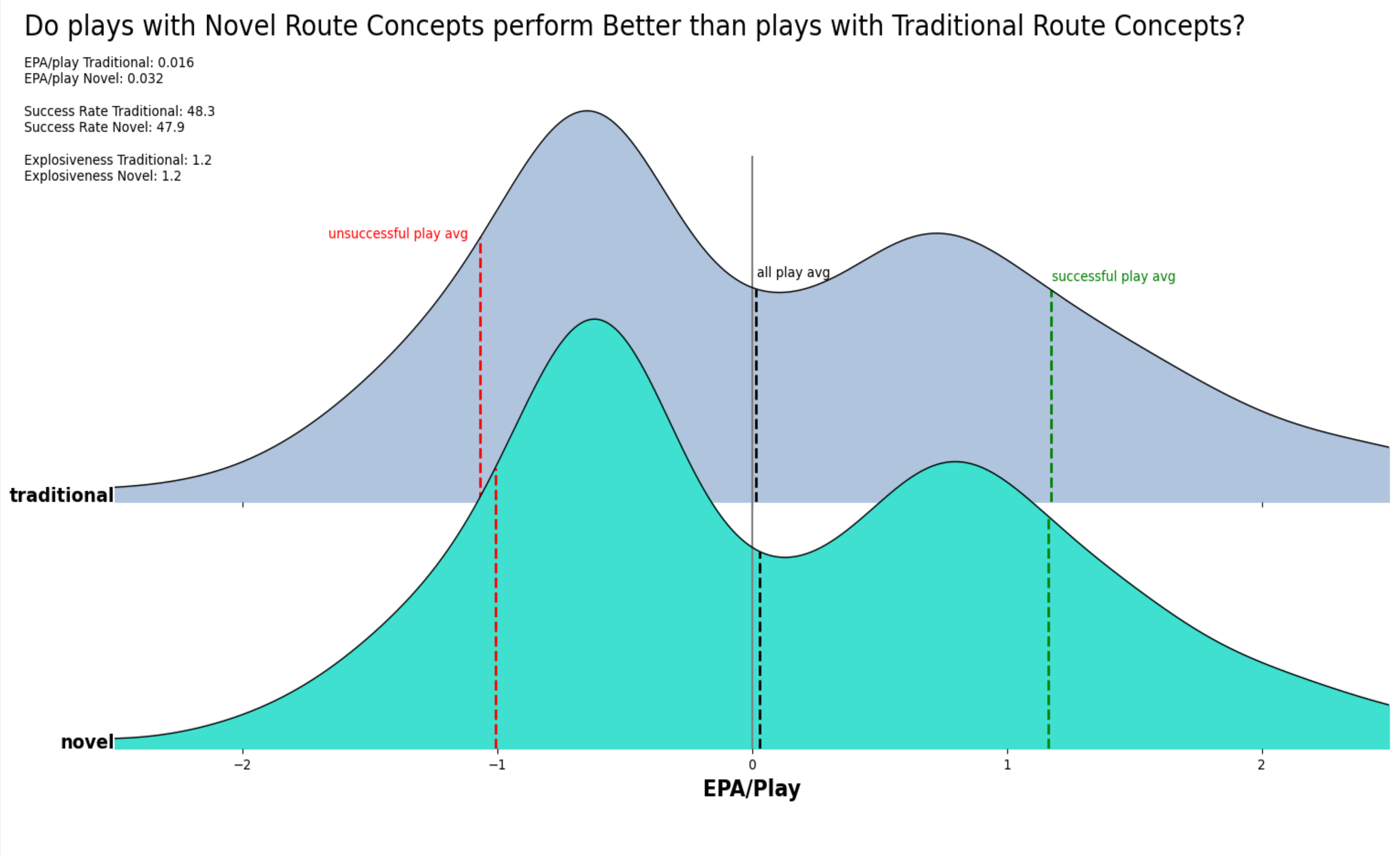
Most concepts saw a minor improvement in EPA/play when run as part of a Run-Pass-Option (RPO)

Two concepts, dino & y-cross demonstrated the most improvement when executed as an RPO

Conversely, hoss & mesh saw worse performance out of RPO execution

This may suggest that RPO dropbacks best compliment route concepts that attack the middle of the field at the mid-to-deep level

Route Concepts in RPO's



Traditional Route Concepts follow route combination dictionary (e.g., traditional hoss = curl+go)

Novel Route Concepts are those identified by our CV model being spatially similar to the traditional definition (e.g., novel hoss = comeback+go)

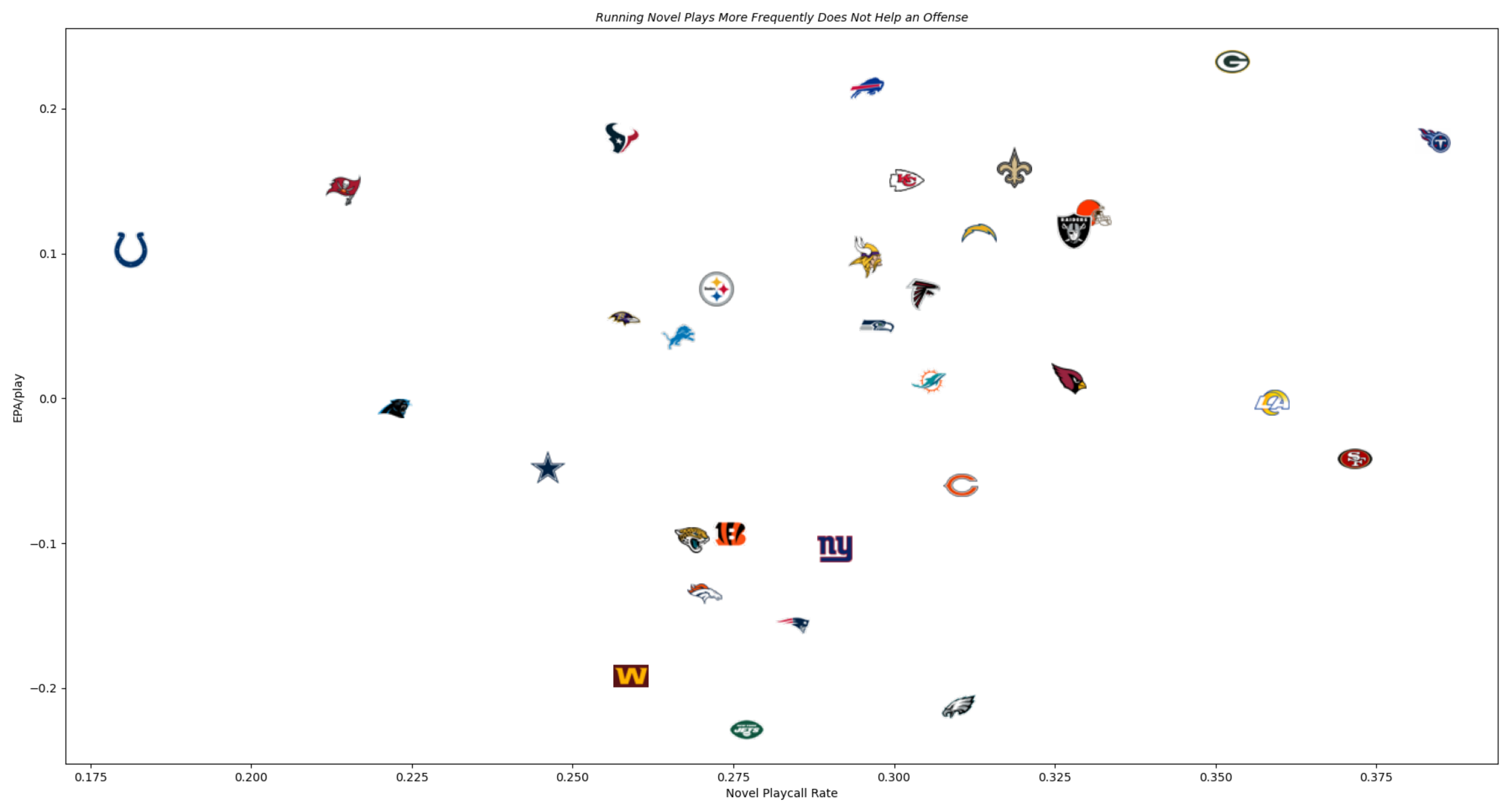
Plays with Novel Route Concepts (n=4,768) performed similarly to plays with Traditional Route Concepts (n=11,580)

Novels Route Concepts demonstrated:

- Slightly higher EPA/play
- Lower Success Rate
- Identical Explosive Play Rate
- Reduced impact on unsuccessful plays

No significant correlation between NFL passing offense performance and Novel Concept playcall rate (next slide)

Novel vs Traditional Route Concepts



Novel vs Traditional Route Concepts

“Explosive” and “On-Schedule” Route Concepts

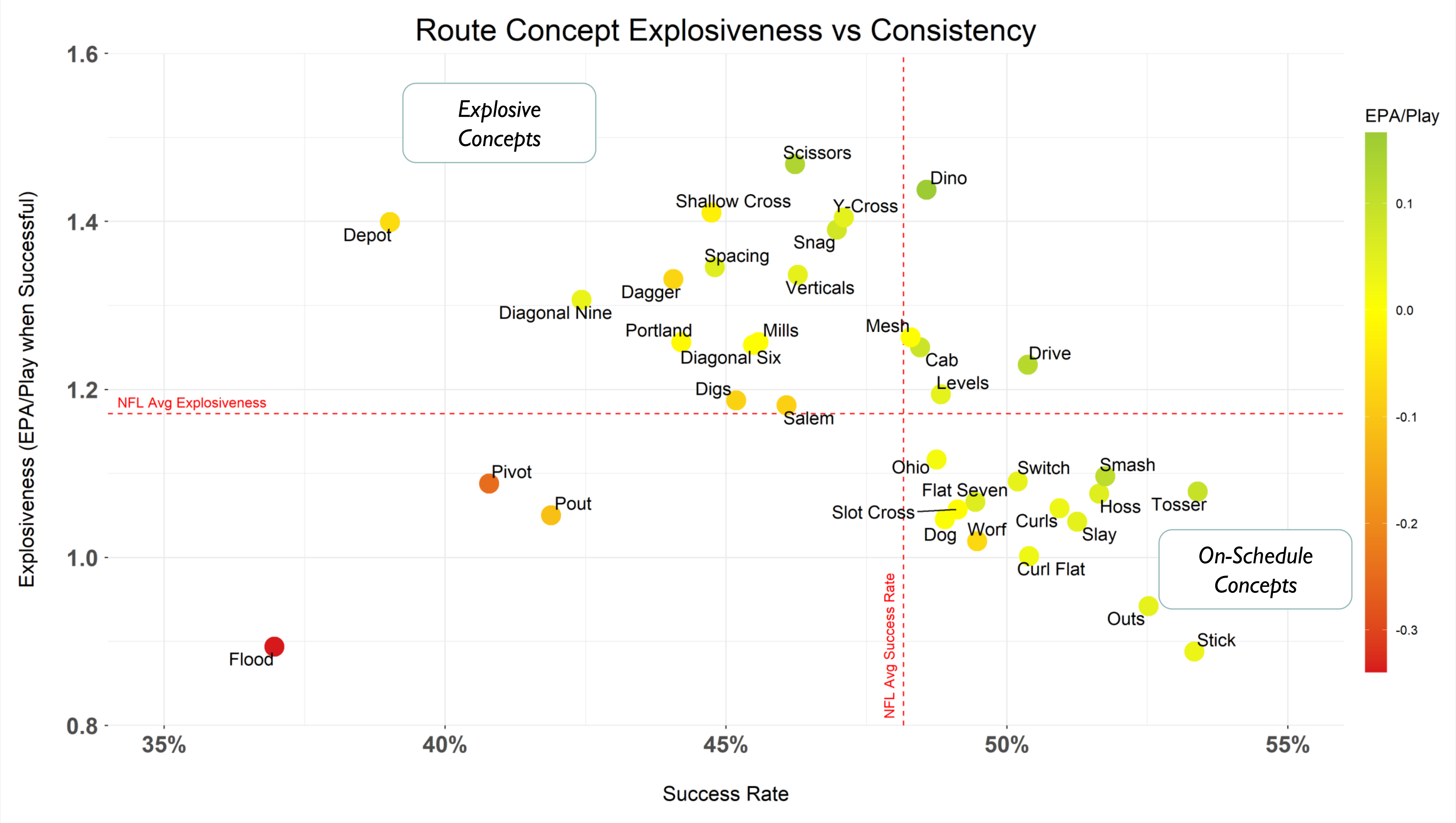
There is a tradeoff between how <u>frequently</u> a route generates a positive EPA, and the <u>magnitude</u> of that positive EPA

Explosive Route Concepts:

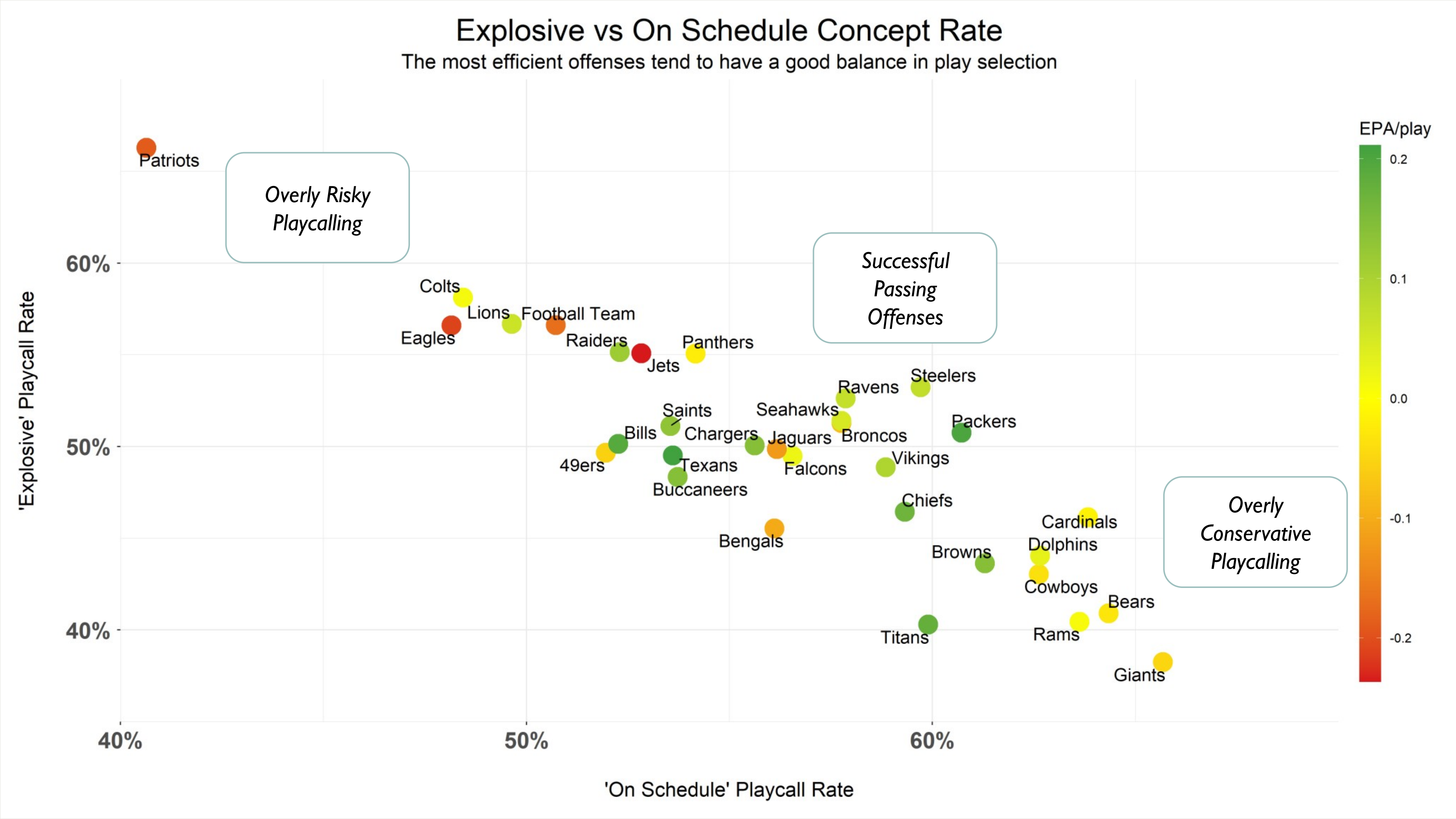
- Generate positive EPA less frequently
- Generate high amounts of EPA on successful plays
- High risk + high reward plays, often vertical passing concepts that are either no gains or big gains
- Example Concepts
  - Verticals
  - Dagger
  - Mills

On-Schedule Route Concepts:

- Generate positive EPA plays more often
- Generally have lower EPA on successful plays
- Quick, reliable concepts that the defense tends to contain
- Example Concepts
  - Stick
  - Outs
  - Curl + Flat



Explosive vs On-Schedule Route Concepts



We looked at the playcalling rate of Explosive & On-Schedule route concepts for NFL teams

The best offenses called a blend of both explosive and efficient route concepts

Lower EPA/play offenses are associated with BOTH overly-conservative and overly-explosive playcalling

What type of route concepts do the best NFL Offenses call?

- Convolution Neural Networks can be used to identify route concepts from play diagrams
- Identified y-cross as the most popular passing offense concepts, while dino was the most effective
- Some route concepts perform well against most coverages, while others are effective only against specific coverages
- Route concepts vary in productivity against MOFO vs MOFC coverage
- Some concepts pair well with other concepts; while others are limited in their complimentary ability
- "Traditional" and "Novel" route concepts perform similarly
- Most route concepts benefited from pairing with an RPO dropback
- Route concepts can be classified as either "Explosive" or "On-Schedule"
- An effective passing offense should utilize a blend of Explosive and On-Schedule route concepts

Conclusions

Shortcomings & Areas of Improvement

CNN model performance could be further optimized to avoid false positive/negative identifications

RB-routes were excluded to help simplify the play images for the CNN model

Sample size issues with many route concepts (e.g., flood)

Sample size issues with many coverages (e.g., Cover 0 & Cover 6)

Sample size issues with RPO/concept pairings

This analysis did not distinguish which route concept deserves credit for the pass target on each play, all concepts on play were assigned the associated play EPA