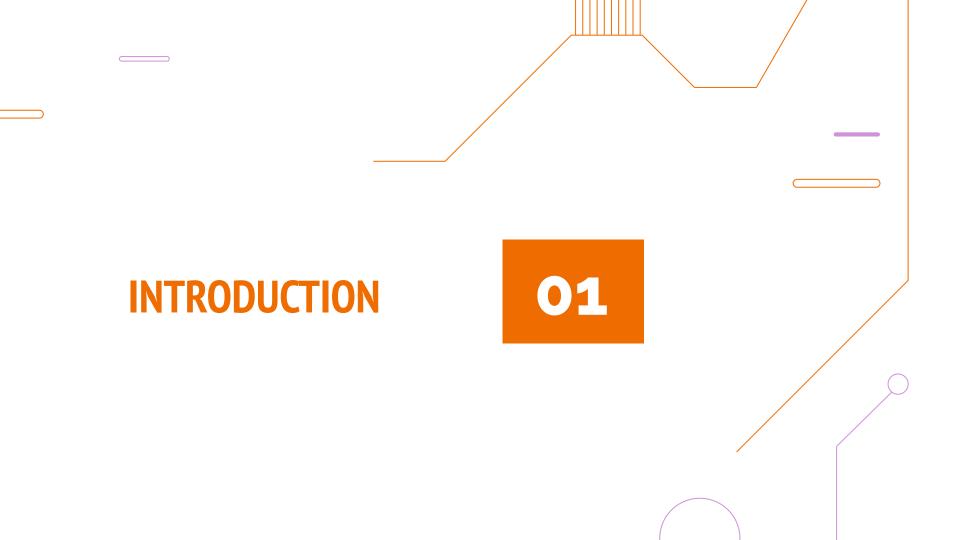
NBA Prediction Lineup

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TOPICS

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Problem Statement

Our problem involves going through historical NBA data, using it to build a machine learning model for predicting the best player for a certain lineup where the given lineup is missing one player.



PROJECT APPROACH 02



PROJECT APPROACH

For the model, we needed to make a few assumptions to improve the performance of the model

- Only players on home team currently playing will be chosen
- Players in future season are not allowed to play in the previous seasons
- If a player is required to be reassigned to a new team, it will be removed from the previous team they were on

FUNCTIONALITY

MODEL FEATURES

Lineup Embedding

The most basic part of the model where it takes all lineups and embeds it where we use cosine to find the closest distance for players

Categorizing Start Time

Some players play more often during earlier start times than others, so this helps categorizing whether a player is more likely to play near the beginning, middle, or end of a game based on the start time

Home/Away Bias

A feature which is used to detect how often the player plays home matches versus away matches

Limiting to players for that home team and 3 seasons before if available

This helps reduce the search space and prevents any player that otherwise be impossible to play during that game in that season

EVALUATION AND FINDINGS



RESULTS EXAMINATION

Results

- Highest Overall Accuracy = 26%
- However when predicting for 2016 lineups, only scored a maximum of 11% accuracy

Loss Function

```
raining samples: 947650
poch 1/30. Loss: 0.3680
poch 2/38, Loss: 8.3418
 ooch 3/38. Loss: 8.3348
poch 5/38, Loss: 8.3275
poch 6/38, Loss: 8,3256
poch 7/30, Loss: 0.3241
poch 8/38, Loss: 8.3229
poch 10/30, Loss: 0.3216
poch 18/30, Loss: 0.3165
poch 21/30, Loss: 0.3154
poch 24/30, Loss: 0.3145
poch 26/30. Loss: 0.3140
poch 27/30, Loss: 0.3137
Epoch 30/30, Loss: 0.3130
raining complete. Model and embeddings saved.
```

Accuracy test



Output File

4	A	В	
1			Fifth_Player
2	2007		Ike Diogu
3	2007		Sebastian Telfair
4	2007		Jacque Vaughn
5	2007		Smush Parker
6	2007	MEM	Tarence Kinsey
7	2007		Desmond Mason
8	2007	MIA	Brian Skinner
9	2007	CLE	LeBron James
10	2007	GSW	Stephen Jackson
11	2007	DEN	Mo Williams
12	2007	MEM	Shareef Abdur-Rahim
13	2007	UTA	Paul Millsap
14	2007	UTA	Kyle Korver
15	2007	POR	Raef LaFrentz
16	2007	MIA	Zach Randolph
17	2007	ORL	Bo Outlaw
18	2007	MIA	Chris Quinn
19	2007	NYK	Jerome James
20	2007	NYK	Jamal Crawford
21	2007	DEN	Andre Iguodala
22	2007	DEN	Allen Iverson
23	2007	LAL	Vladimir Radmanovic
24	2007	NYK	Michael Ruffin
25	2007	GSW	Monta Ellis
26	2007	POR	Steve Blake
27	2007	DET	Rasheed Wallace
28	2007	CLE	Hassan Adams
29	2007	WAS	Dee Brown
30	2007	HOU	Luther Head
31	2007	DET	Antonio McDyess

RESULTS EXAMINATION

For the main testing for the NBA Test, we used the model with 50 epochs to ensure that we achieved the highest accuracy, though overfitting may occur

Number of matches per year within the test dataset

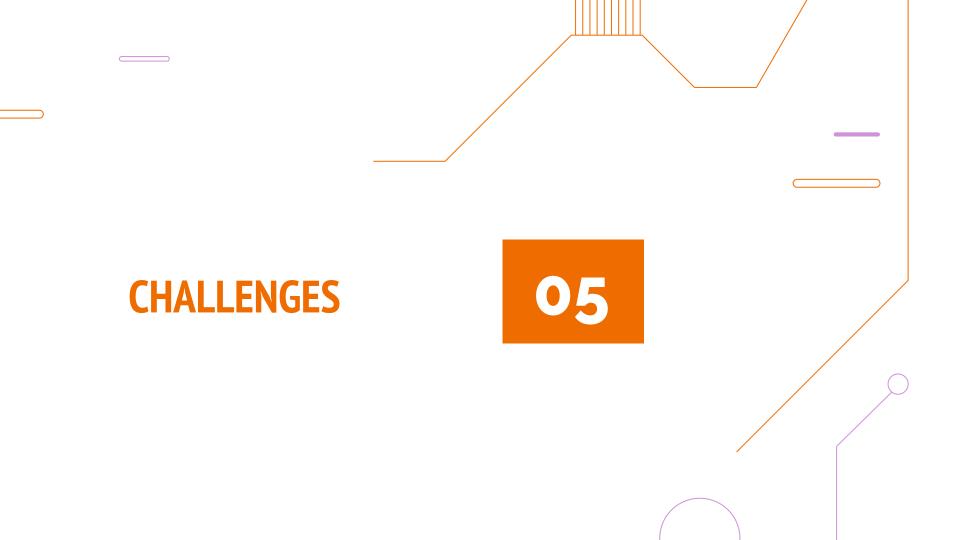
- There are 100 matches per year/season

Average number of matches across the entire dataset.

- 2007: 1230 games
- 2008: 1230 games
- 2010: 1230 games
- 2011: 1229 games
- 2012: 990 games
- 2013: 1229 games
- 2014: 1230 games
- 2015: 1230 games

```
redictions were saved into NBA predictions.
overall accuracy: 18.90% (189 out of 1000)
2007 Test accuracy: 0.00%
0 out of 100 are correct
2008 Test accuracy: 27.00%
27 out of 100 are correct
2009 Test accuracy: 18.00%
18 out of 100 are correct
2010 Test accuracy: 28.00%
28 out of 100 are correct
2011 Test accuracy: 33.00%
33 out of 100 are correct
2012 Test accuracy: 35.00%
35 out of 100 are correct
2013 Test accuracy: 31.00%
31 out of 100 are correct
2014 Test accuracy: 13.00%
13 out of 100 are correct
2015 Test accuracy: 2.00%
2 out of 100 are correct
2016 Test accuracy: 2.00%
 out of 100 are correct
Process finished with exit code 0
```

```
poch [1 out of 50], loss: 0.349735
ooch [2 out of 50], loss: 0.314686
poch [3 out of 50], loss: 0.305646
ooch [4 out of 50], loss: 0.300585
ooch [5 out of 50], loss: 0.296997
ooch [6 out of 50], loss: 0.294470
 och [7 out of 50], loss: 0.292439
poch [8 out of 50], loss: 0.290806
poch [9 out of 50], loss: 0.289370
poch [11 out of 50], loss: 0.287171
poch [12 out of 50], loss: 0.286264
ooch [13 out of 50], loss: 0.285502
poch [14 out of 50], loss: 0.284760
moch [15 out of 50]. loss: 0.284128
poch [16 out of 50], loss: 0,283475
epoch [17 out of 50], loss: 0.283011
epoch [18 out of 50], loss: 0.282479
poch [19 out of 50], loss: 0.281964
poch [20 out of 50], loss: 0.281552
poch [21 out of 50], loss: 0.281097
poch [22 out of 50], loss: 0.280721
poch [23 out of 50], loss: 0.280373
poch [24 out of 50], loss: 0,280005
poch [25 out of 50], loss: 0.279683
poch [26 out of 50], loss: 0.279306
poch [27 out of 50], loss: 0.279020
poch [28 out of 50], loss: 0.278751
poch [29 out of 50], loss: 0.278539
poch [30 out of 50], loss: 0.278245
poch [31 out of 50], loss: 0.278013
poch [32 out of 50], loss: 0.277801
ooch [33 out of 50], loss: 0.277555
poch [34 out of 50], loss: 0.277217
poch [35 out of 50], loss: 0.277063
ooch [36 out of 50], loss: 0.276869
ooch [37 out of 50], loss: 0.276688
poch [38 out of 50], loss: 0.276490
ooch [39 out of 50], loss: 0.276307
ooch [40 out of 50], loss: 0.276067
ooch [41 out of 50], loss: 0.275954
poch [42 out of 50], loss: 0.275732
poch [43 out of 50], loss: 0.275553
poch [44 out of 50], loss: 0.275400
poch [45 out of 50], loss: 0.275236
poch [46 out of 50], loss: 0.275091
poch [47 out of 50], loss: 0.274970
poch [48 out of 50], loss: 0.274833
epoch [49 out of 50], loss: 0.274678
poch [50 out of 50], loss: 0.274524
odel saved
```



CHALLENGES

CHALLENGES	SOLUTION
Many different ways of splitting the data and testing it which required significant changes to the code each time our group wanted to try a different method.	Tested many different ways of splitting the data such as random 80/20 split, leave one out cross validation, stratified split. Ultimately went with 80/20 split
Introducing more features to reduce the search space of the model to improve its accuracy also introduced greater performance overhead when training the model.	Optimizing each feature to reduce the complexity level to ensure that it is able to train within a reasonable amount of time.
Optimizing the model to improve accuracy. There were many times where adding features or small parameter adjustments to the model would lower the accuracy	Trial and error, eventually our data did improve in terms of accuracy, however a lot more trial and error is required for our model



THANK YOU!

From:

Andy Dai, Ashad Ahmed, Kevin Jacob