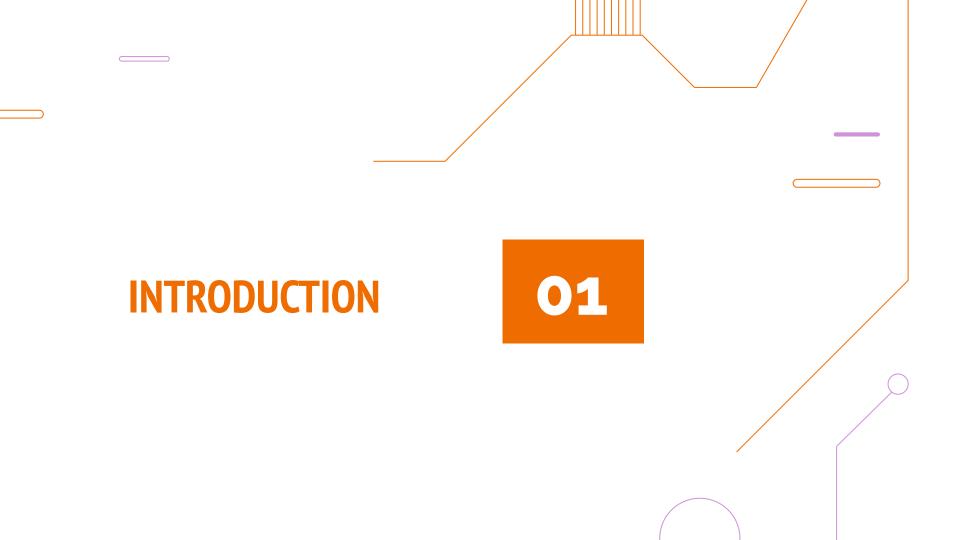
#### **NBA Prediction Lineup**

Group 8: Andy Dai, Ashad Ahmed, Kevin Jacob

#### **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

#### **Team Cohesion**

A feature which is used to detect how often players play with each other, giving a higher weight to those who play with each other more often

#### 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

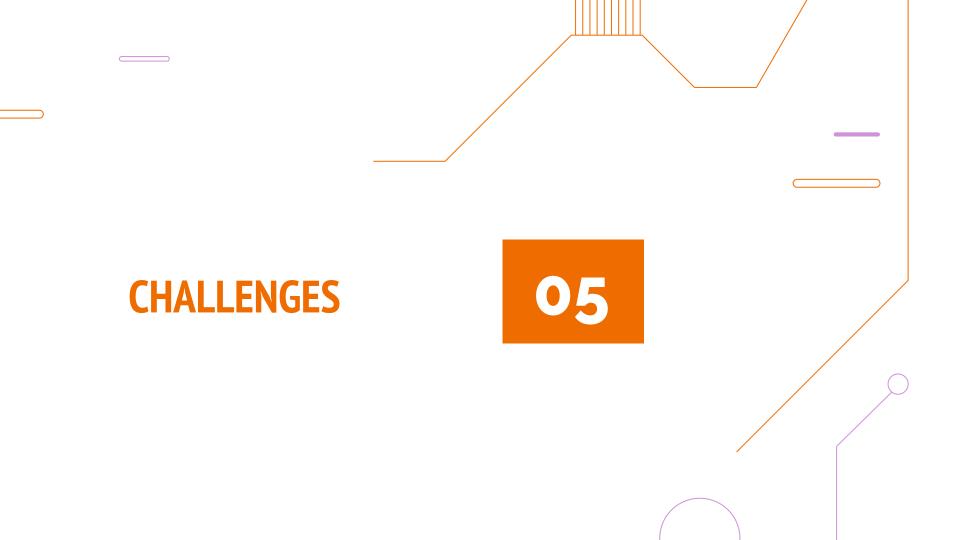
- Highest Overall Accuracy = 26%
- However when predicting for 2016 lineups, only scored a maximum of 11% accuracy

#### Loss Function

```
raining samples: 947650
 poch 1/30. Loss: 0.3680
 poch 2/38, Loss: 8.3418
poch 5/38, Loss: 8.3275
poch 6/38, Loss: 8,3256
 poch 8/38, Loss: 8.3229
Epoch 14/30 Loss: 0.3183
poch 15/30. Loss: 0.3179
 poch 16/30, Loss: 0.3174
 poch 18/30. Loss: 0.3165
poch 21/30, Loss: 0.3154
poch 24/30, Loss: 0.3145
Epoch 26/30. Loss: 0.3140
Epoch 27/30, Loss: 0.3137
Epoch 28/30. Loss: 0.3135
Epoch 29/30, Loss: 0,3133
Epoch 30/30, Loss: 0.3130
```

#### Accuracy test

```
Model loaded successfully!
Prepared 1000 test lineups for predict
Predictions saved to 'NBA_predictions
Overall Accuracy: 21.70% (217/1000)
2007 TESTS - accuracy: 12.00%
2008 TESTS - accuracy: 31.00%
2009 TESTS - accuracy: 22.00%
There are 22/100 correct results
2010 TESTS - accuracy: 28.00%
There are 28/100 correct results
2011 TESTS - accuracy: 40.00%
There are 40/100 correct results
2012 TESTS - accuracy: 32.00%
2013 TESTS - accuracy: 35.00%
There are 35/100 correct results
There are 13/100 correct results
There are 2/100 correct results
2016 TESTS - accuracy: 2.00%
Done!
Process finished with exit code 0
```



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

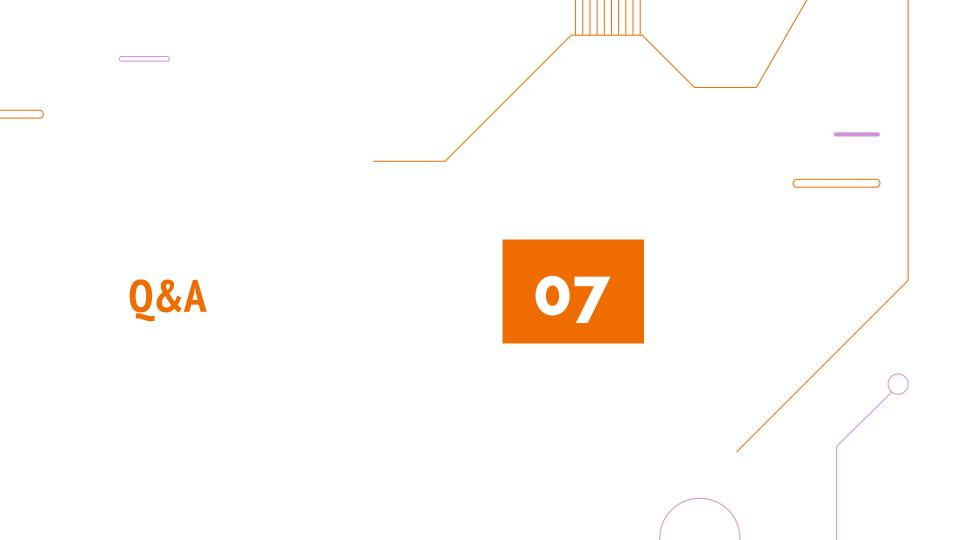
```
redictions were saved into NBA predictions.o
overall accuracy: 18.90% (189 out of 1000)
2007 Test accuracy: 0.00%
0 out of 100 are correct
2008 Test accuracy: 27.00%
27 out of 100 are correct
2009 Test accuracy: 18.00%
18 out of 100 are correct
2010 Test accuracy: 28.00%
28 out of 100 are correct
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
```

```
epoch [1 out of 50], loss: 0.349735
poch [2 out of 50], loss: <u>0.314686</u>
 poch [3 out of 50], loss: 0.305646
poch [4 out of 50], loss: 0.300585
 ooch [5 out of 50], loss: 0.296997
 ooch [6 out of 50], loss: 0.294470
 ooch [7 out of 50], loss: 0.292439
poch [8 out of 50], loss: 0.290806
poch [9 out of 50], loss: 0.289370
 ooch [10 out of 50], loss: 0.288206
poch [11 out of 50], loss: 0.287171
poch [12 out of 50], loss: 0.286264
 poch [13 out of 50], loss: 0.285502
poch [14 out of 50], loss: 0.284760
epoch [15 out of 50], loss: 0.284128
moch [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
epoch [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
moch [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
poch [36 out of 50], loss: 0.276869
poch [37 out of 50], loss: 0.276688
 poch [38 out of 50], loss: 0.276490
poch [39 out of 50], loss: 0.276307
poch [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
epoch [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