

NBA Salary Predictor

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(Theme Pending)

Background

- NBA Contracts
 - For mainstays, very lucrative \Rightarrow almost \$10,000,000 in 2016-17 among players in the league for five years
- TV Deal
 - Close to \$25 Billion
 - Why is that relevant to player contracts
- As time goes on...
 - Bigger player contracts

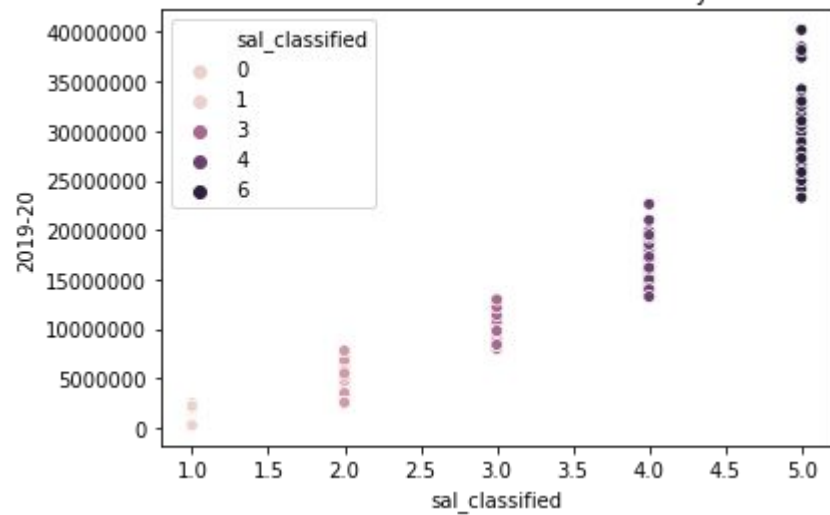
Approach & Process

- EDA
 - Dropping nulls
 - Exploring trends through visualizations
- Decisions
 - Merged statistics from five years with salary -- Why?
 - Worked primarily with three datasets -- Why?
- Originally started as a regression problem
 - Evolved into a classification problem

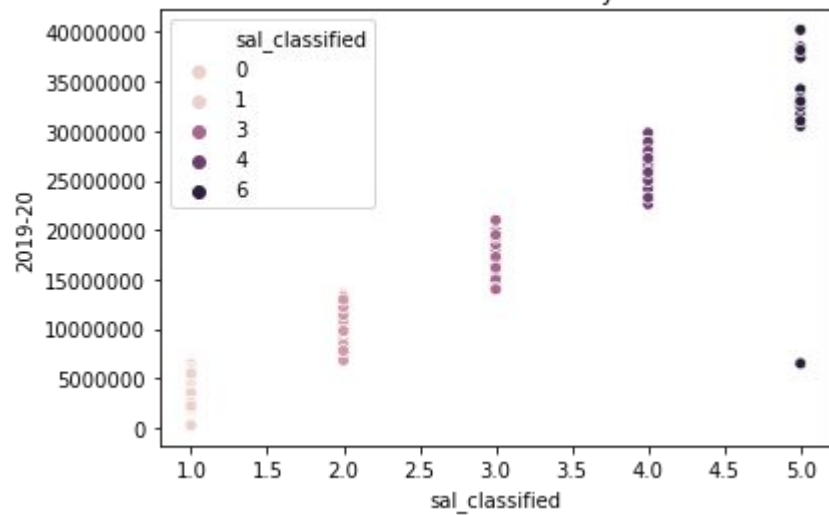
Modeling

- Datasets used
 - 2017, 2018, 2020
- Defining Classes
- Performance
 - Baseline of each model
 - Best model on each dataset
- Trends?
 - Are more predicted above or below their true class?
 - Reason for upwards trend?
- What can we expect going forward?

16-20 dataset classes set Manually



16-20 dataset classes set by Clusters



Strengths and Weaknesses

Strengths:

- Increasing predictive power -- 60% not bad/improves on baseline
- When misclassifying, real-world implications

Weaknesses:

- Amount of data
- Could improve on 60%

Recommendations/Conclusions

- Confusion matrices, more overpaid or underpaid?
- If someone in contract year, can use to see if they should get more or less than current salary
- Likewise, front office management can consider it before bringing in a player
- Expectation: As money increases, accuracy should rise, be able to better predict which class a player is in -- he will be getting more what he “deserves”

Next Steps

- See how model generalizes to the future
- Uncertainty -- pandemic
- Timeseries
- If salaries keep rising, will it be easier to predict salary class?