Applying Data Mining to Scouting

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AGENDA

Business Use Case

Business Use Case

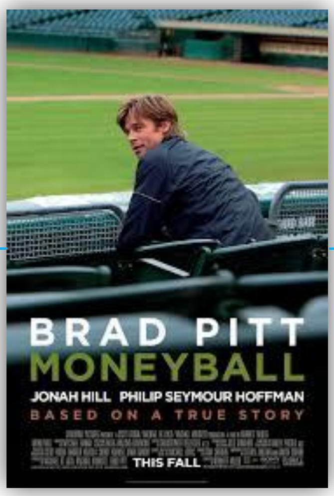
Scouting meets Advanced Analytics

Scouting yesterday		Scouting today

• Observation
• Rudimentary data
• Intuition
	VS	• Advanced analytics
		  • availability of massive data
		  • ability to process & capture insight

The hit movie: Moneyball (2011)

- The potential of unconventional sabermetrics in sport
- Scouting in soccer is a global challenge.



- Poor performing clubs face relegation which has a immediate impact on the club's bottom line
- Important for small $$$ teams to use analytics to compete with larger clubs

Business Objectives

We are positioning ourselves as a scouting agency that:

- uses the **FIFA 2018 dataset** and
- apply various **data mining methods** to:

1. Enhance the **discovery of talents**
2. Help soccer clubs better understand the **dynamics (features)** that come into play when determining the **value** of a player

Key Assumptions

- Our dataset reflects information up to Summer 2018.
- Market values are not biased and reflect the true intrinsic value of the player. We understand that may not be the case, but for the purpose of our models, we assume that it is.
- All feature scores, which are developed by an independent third party, are accurate and reflective of the true player style. These features are reflective of historical performance

Hart Zwingelberg – Manager, Business Intelligence, Chicago Fire

“This (referring to soccer analytics) wasn’t a thing even five years ago,"...“To see (teams) starting to switch to a more analytically based and project-oriented front office, it’s really great. And it’s only going to explode from here.”

Highlights of our meeting with Hart:

- Chicago Fire uses advanced analytics for internal team assessment
- Due to the global nature of the game, the Chicago Fire prefers to outsource its scouting function to 3rd party resources (who include advanced analytics in their arsenal of player assessment)
- Focus on defining success metrics by position that fit within their overall team strategy/style
- Hart sees the potential for advanced analytics in sport and is interested in coordinating a project with the MScA program in the future

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Data Overview, EDA, Engineering

Data - Overview

Dataset

- **CSV**
- **18207(R) x 89(C)**

Features

Profile

• ID	• Club	• Joined
• Name	• Club Logo	• Loaned From
• Age	• Preferred Foot	• Contract Valid Until
• Height	• Weak Foot	• Int. Reputation
• Weight	• Body Type	• Photo
• Nationality	• Real Face	
• Flag	• Jersey Number	

Position Related

• Position	• LS	• LAM	• LWB
	• ST	• CAM	• RWB
	• RS	• RAM	• LB
	• LW	• LM	• LCB
	• LF	• LCM	• CB
	• CF	• CM	• RCB
	• RF	• RCM	• RB
	• RW	• RM	
		• LDM	
		• CDM	
		• RDM	

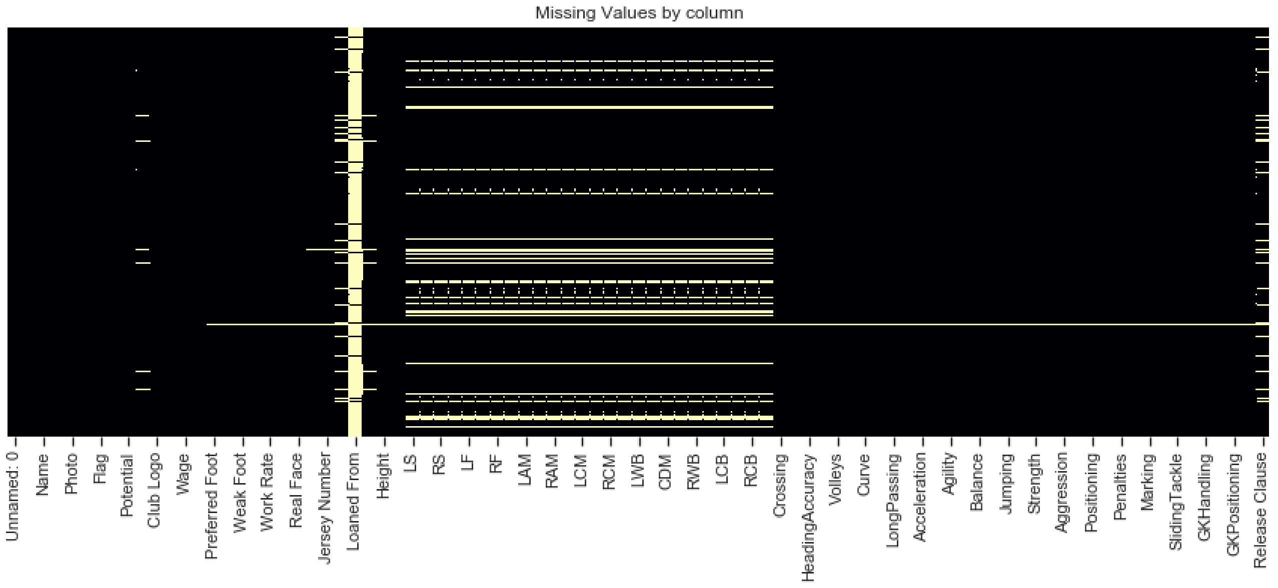
Attributes/Skills

• Overall	• Crossing	• Dribbling	• Acceleration	• ShotPower	• Aggression	• Marking	• GKDiving
• Potential	• Finishing	• Curve	• SprintSpeed	• Jumping	• Interceptions	• StandingTackle	• GKHandling
• Special	• HeadingAccuracy	• FKAccuracy	• Agility	• Stamina	• Positioning	• SlidingTackle	• GKKicking
• Skill Moves	• ShortPassing	• LongPassing	• Reactions	• Strength	• Vision		• GKPositioning
• Work Rate	• Volleys	• BallControl	• Balance	• LongShots	• Penalties		• GKReflexes
					• Composure		

$$$

• Value	• Wage	• Release Clause

MISSING VALUES



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Data Processing & Feature Engineering

Original Data

After Data Processing & Feature Engineering

Feature	Data Type	Missing Values	Processing/Feature Engineering	Imputation / Drop	Data Type
ID	Categorical	-	Dropped	-	-
Name	Text	-	Dropped	-	-
Age	Numerical	-	-	-	Numerical
Height	Text	48	Converted inches to centimeters	48 missing rows dropped	Numerical
Weight	Text	48	Removed the text "lbs" and converted to integer	48 missing rows dropped	Numerical
Nationality	Categorical	-	Dropped and new column "Continent" created to assign continent instead	0	Dummy
Flag	Categorical	-	Dropped	-	-
Club	Categorical	241	Dropped and new column "Club Reputation" created by taking the mean of 'International Reputation' for players for each club	Filled in missing values with "No_club"	Numerical
Club Logo	Text		Dropped	-	-
Preferred Foot	Categorical	48	Converted to Binary: 0 = left, 1 = right	48 missing rows dropped	Categorical
Weak Foot	Numerical	48	No change	48 missing rows dropped	Numerical
Body Type	Categorical	48	Removed one-off body types and replaced them with either "lean", "stocky" and "normal" based on domain knowledge	48 missing rows dropped	Numerical
Real Face	Categorical	48	Converted to Binary: 0 = No, 1 = Yes	48 missing rows dropped	Categorical
Jersey Number	Categorical	60	No change	48 missing rows dropped. 12 remaining missing values were filled in using the mode Jersey Number of the player's position	Categorical
Joined	Date	1553	Converted to int: 2019/1/1 - Joined Date	Filled in missing values with 0	Numerical
Loaned From	Categorical	16943	Converted to Binary: 0 = Not on loan, 1 = On loan	Missing value means the players is not on loan. These missing values are assigned 0	Categorical
Contract Valid Until	Date	289	Converted to int: years of contract left from 2018	Filled in missing values with 0 (expired)	Numerical

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Data Processing & Feature Engineering

Original Data

Feature	Data Type	Missing Values
Position	Categorical	60
LS	Text	2085
.	Text	2085
.	Text	2085
24 columns	Text	2085
.	Text	2085
.	Text	2085
.	Text	2085
RB	Text	2085

After Data Processing & Feature Engineering

Processing/Feature Engineering	Imputation / Drop	Data Type
Position_Group column created that assigns one of the following to the player: Forward, Midfielder, Defender, GoalKeeper, Other (no position)	Players assigned Other originally did not have a position, but later imputed based on the players' max ability from Attacking, Defending, GoalKeeping	Dummy
"+ int" removed and a new column created to capture just the int. Column converted to integer.	2025 missing values are Goalkeepers, who do not have a value for this column	Dummy
"+ int" removed and a new column created to capture just the int. Column converted to integer.	2025 missing values are Goalkeepers, who do not have a value for this column	Dummy
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"+ int" removed and a new column created to capture just the int. Column converted to integer.	2025 missing values are Goalkeepers, who do not have a value for this column	Dummy
"+ int" removed and a new column created to capture just the int. Column converted to integer.	2025 missing values are Goalkeepers, who do not have a value for this column	Dummy

Data Processing & Feature Engineering

Original Data

Feature	Data Type	Missing Values
Overall	Numerical	-
Potential	Numerical	-
Special	Numerical	-
Skill Moves	Numerical	48
Work Rate	Categorical	48
*** Attributes x 34**	Numerical	48
Value	Text	
Wage	Text	
Release Clause	Text	1564

After Data Processing & Feature Engineering

Processing/Feature Engineering	Imputation / Drop	Data Type
-	-	Numerical
-	-	Numerical
-	-	Numerical
-	48 missing rows dropped	Numerical
Dropped and created new columns "Attack_WR" and "Defense_WR"	48 missing rows dropped	Numerical
7 New columns created “Attack”, “Skill”, “Movement”, “Power”, Mentality“, “Defending”, “GoalKeeping” and assigned with means of attributes that belong to the group	48 missing rows dropped	Numerical
Removed currency signs and converted to integer.		Numerical
Removed currency signs and converted to integer.		Numerical
Removed currency signs and converted to integer	Missing values filled in with 0	Numerical

Summary:

18159 rows x 125 columns

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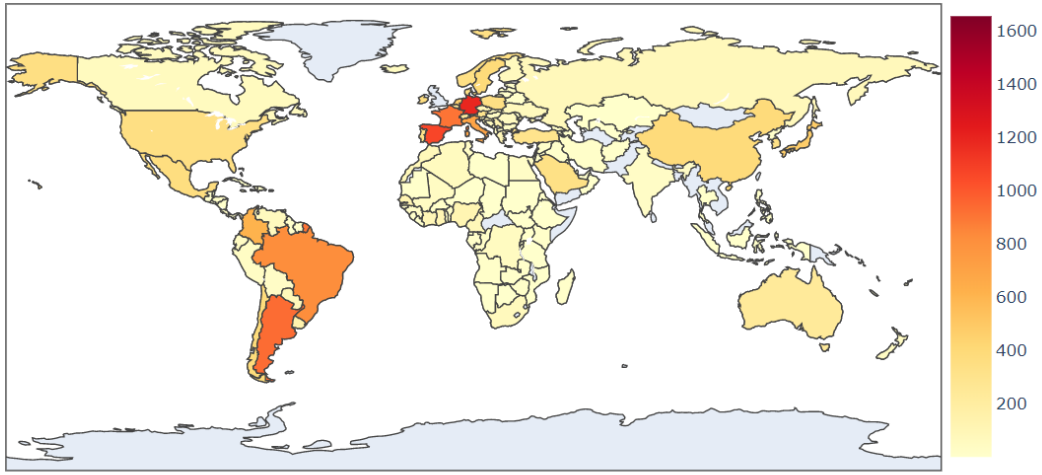
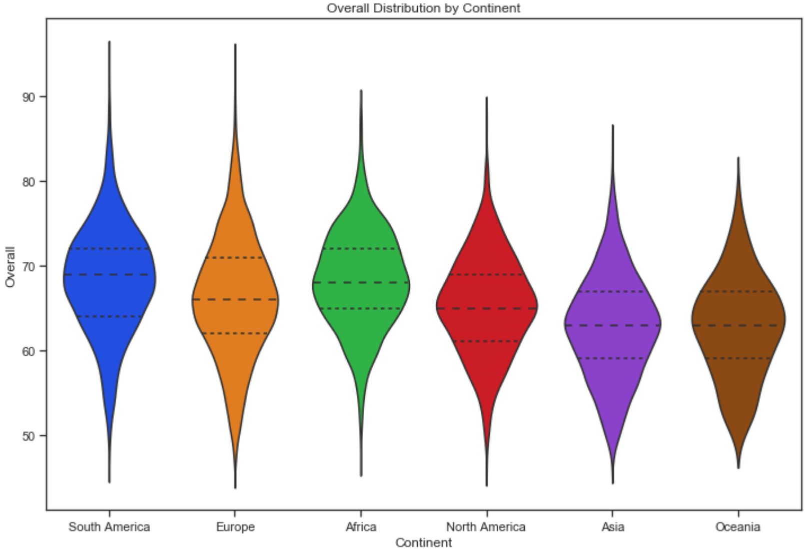
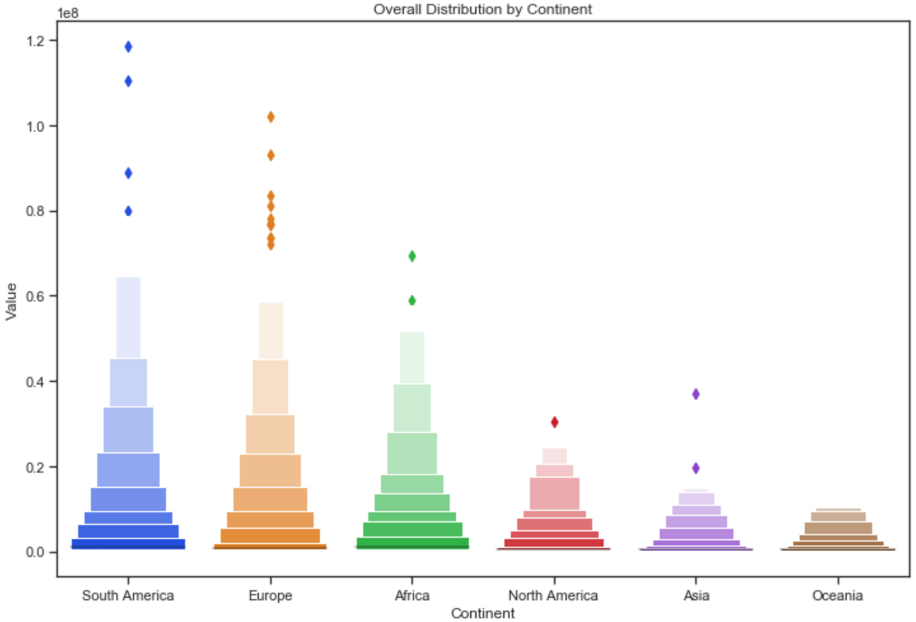
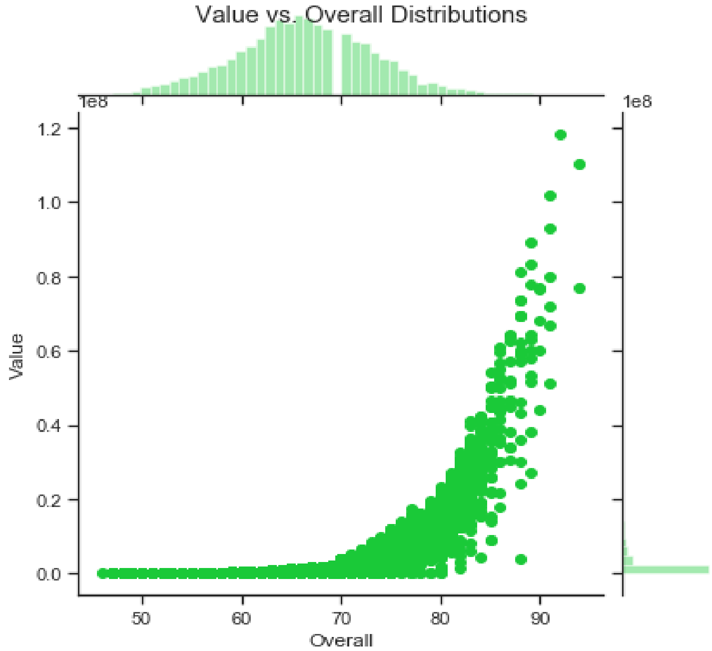
EDA – Visualization (1/3)









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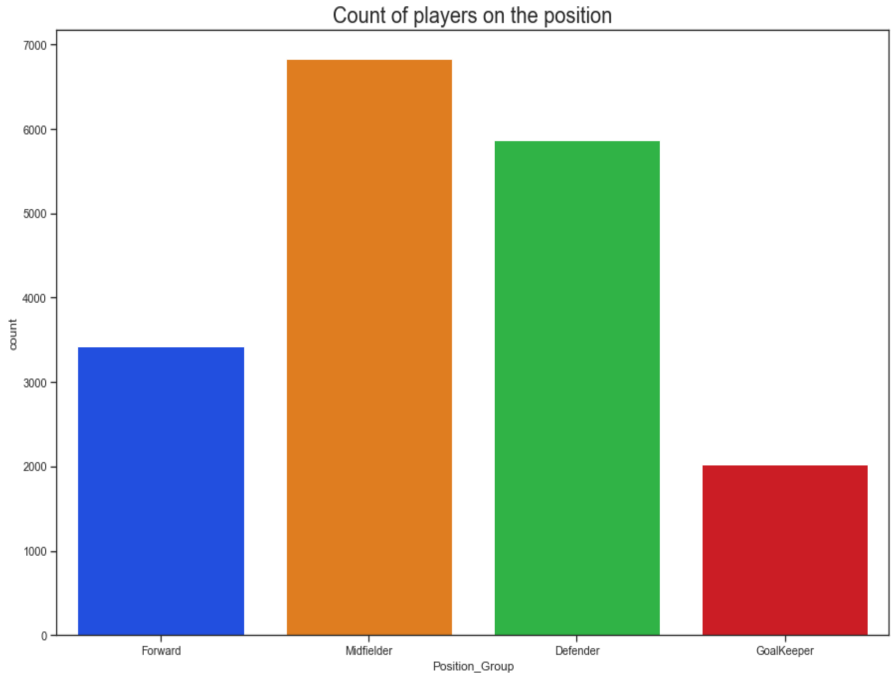
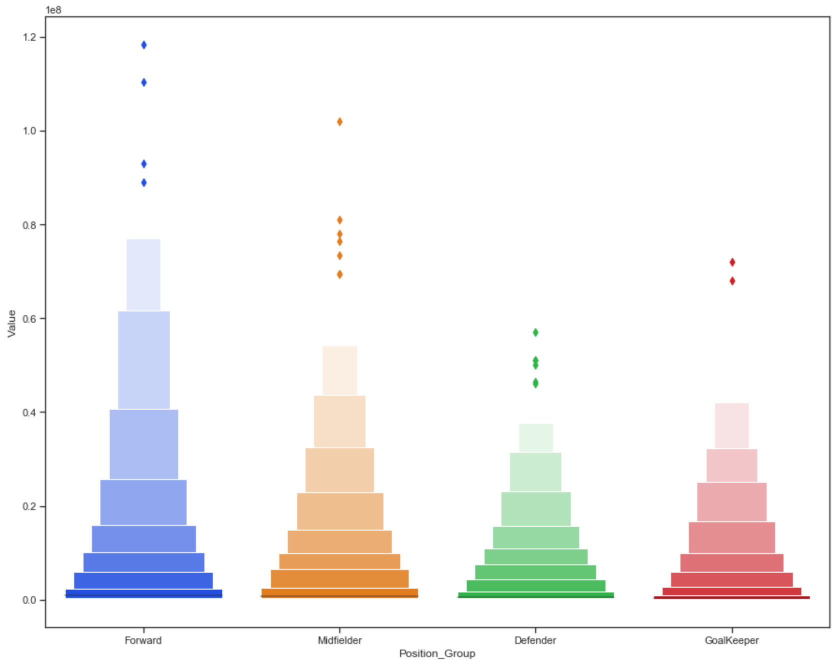
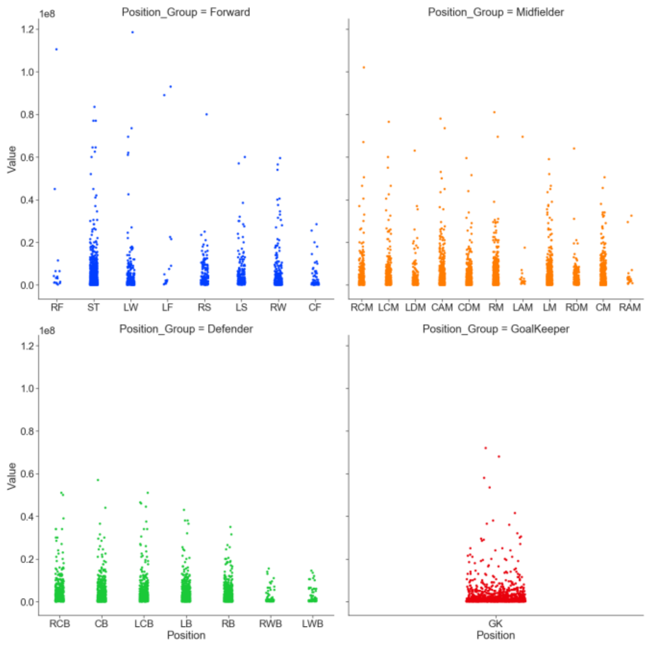
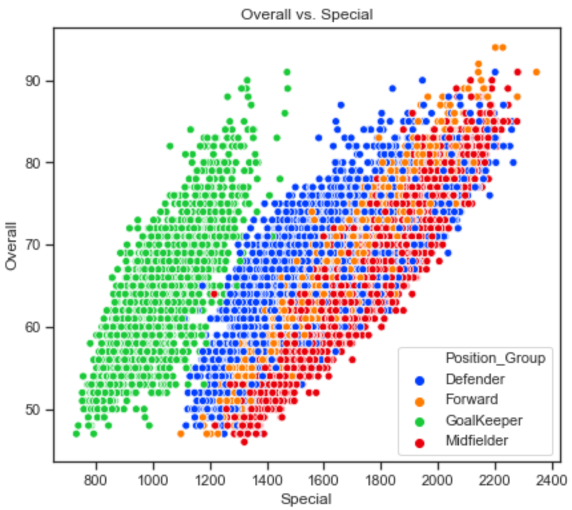
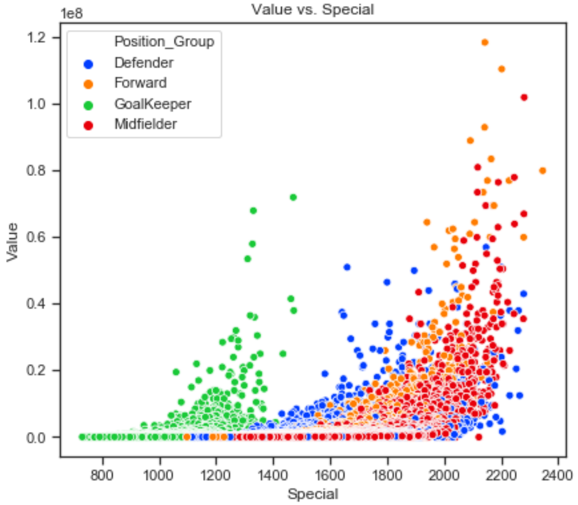
EDA – Visualization (2/3)



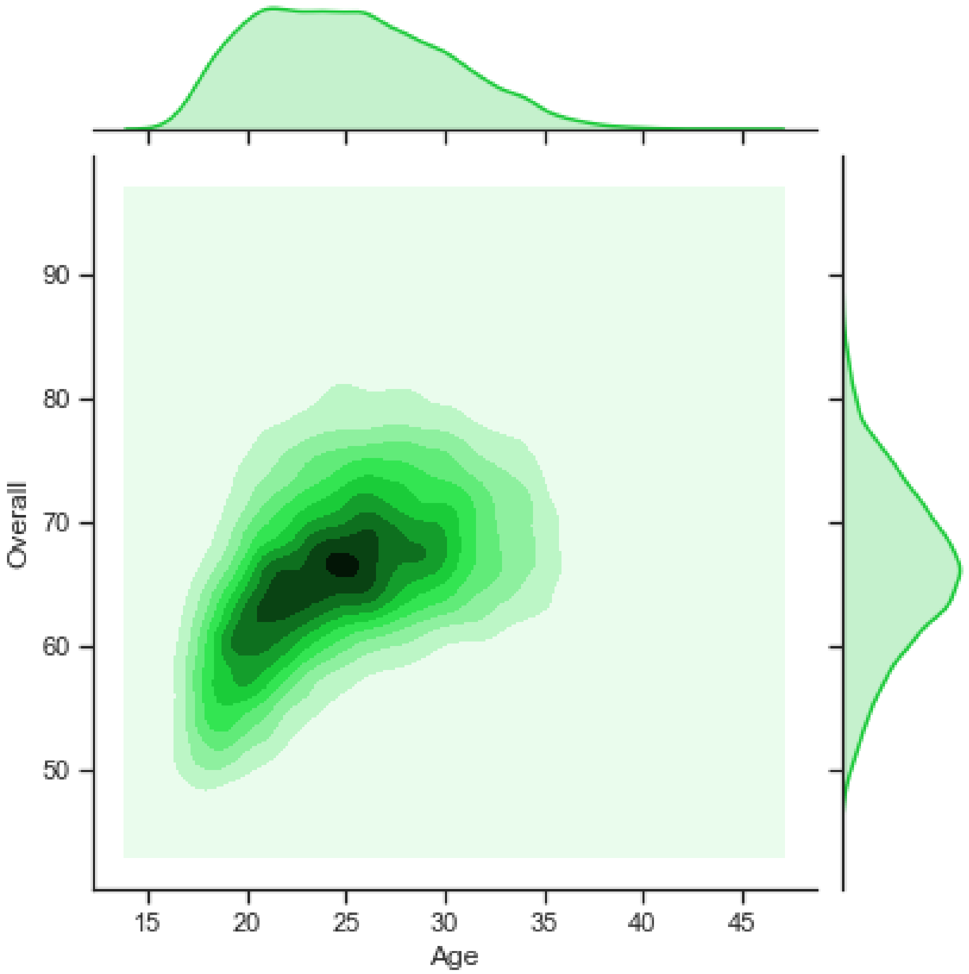


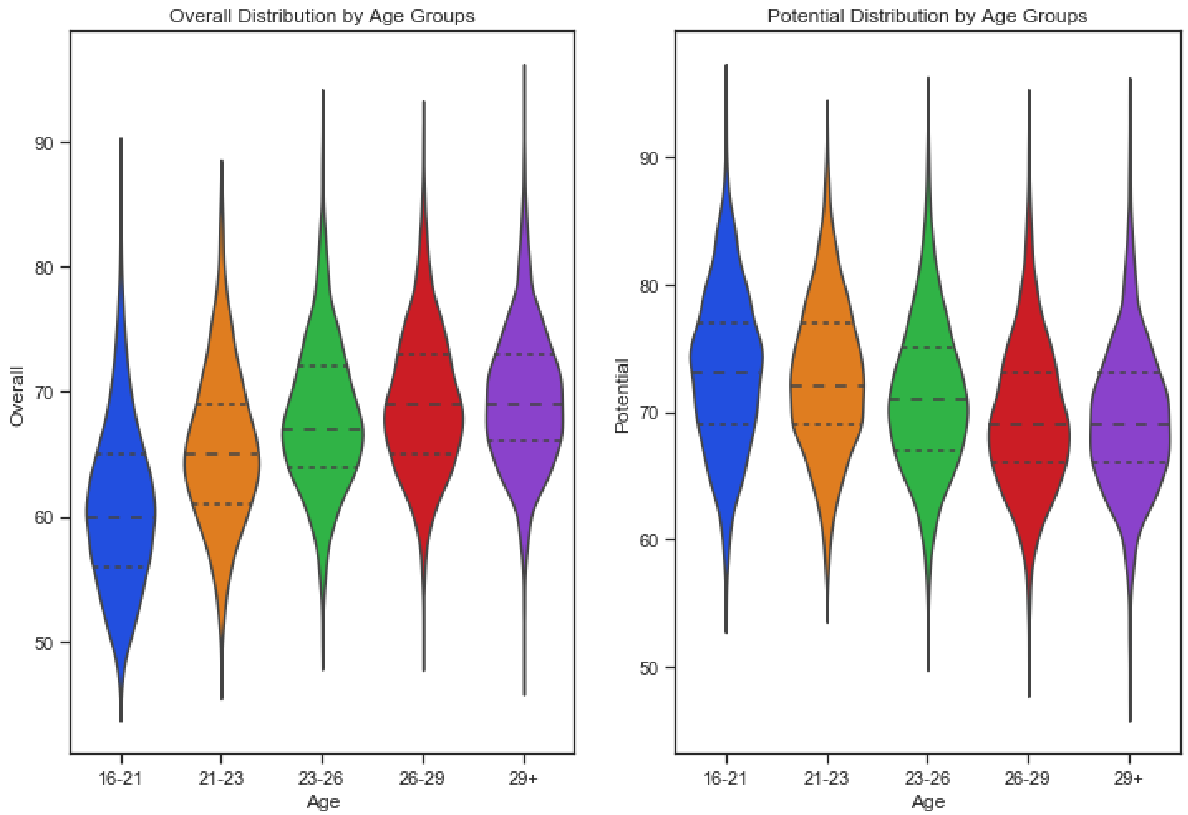






EDA – Visualization (3/3)





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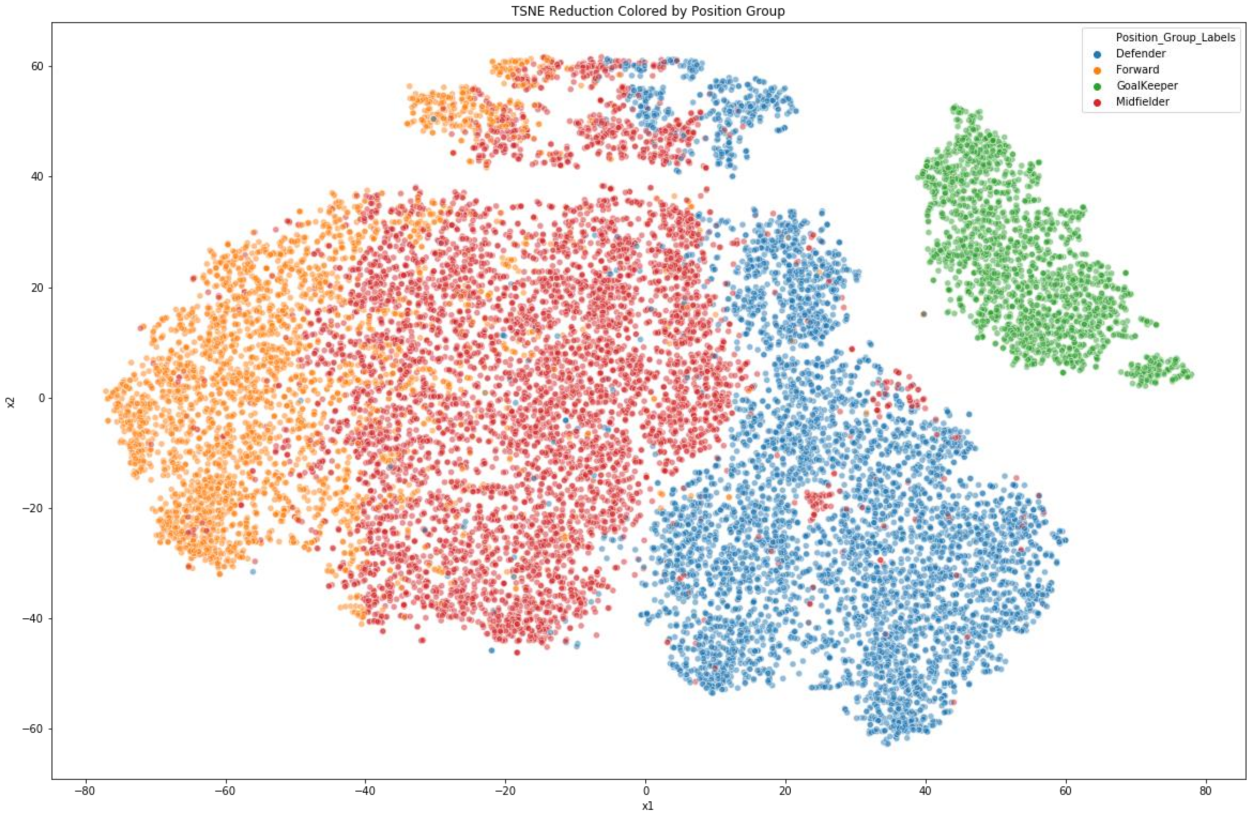
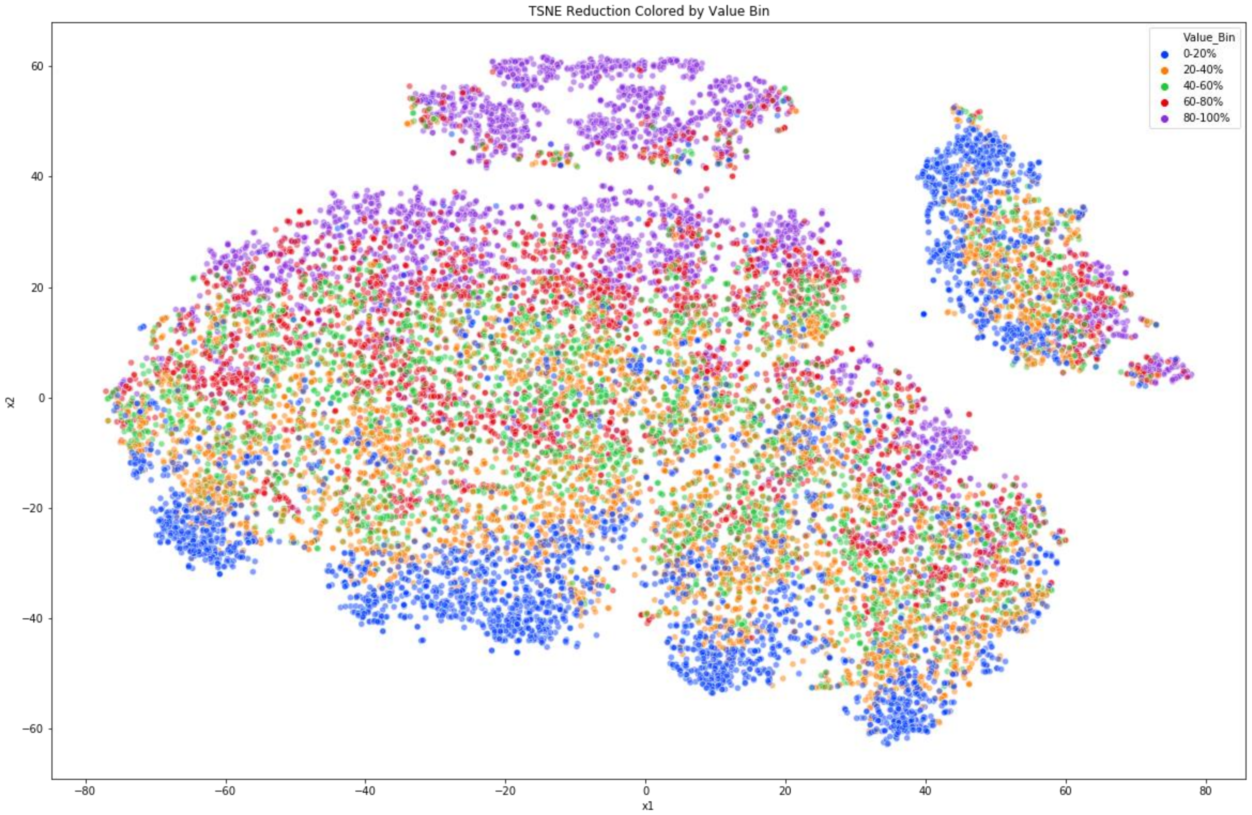
TSNE





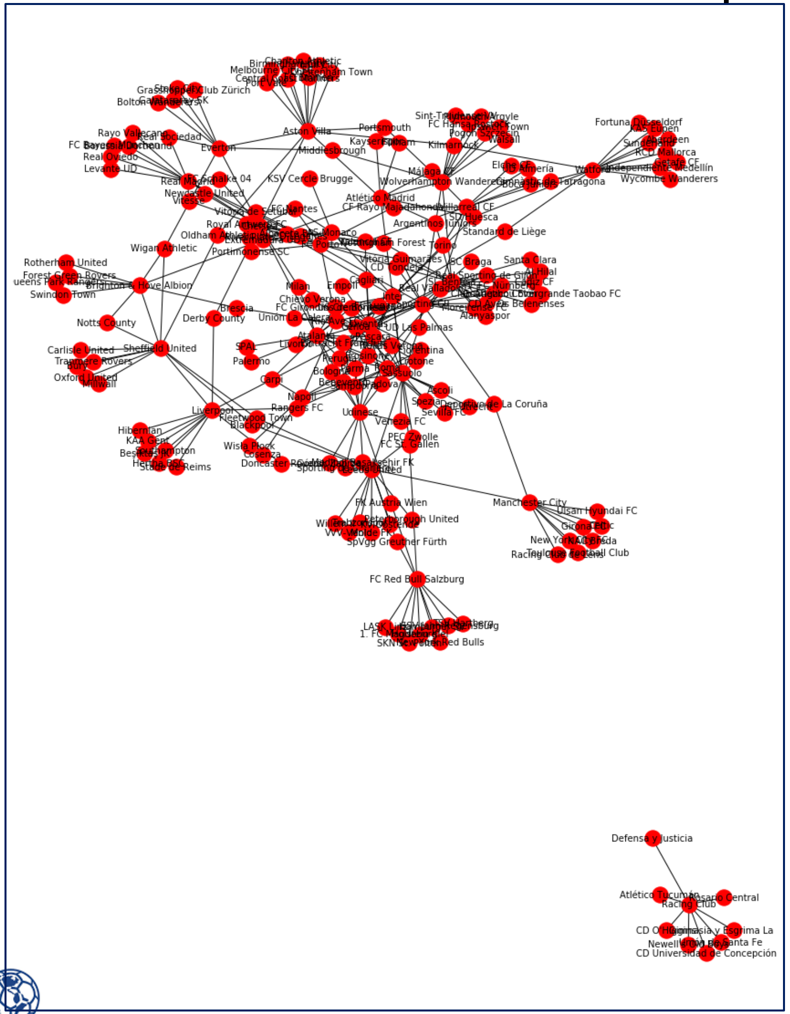
TSNE reduction shows clustering of position groups…

and within these position group clusters there is additional clustering of players by valuation ($) level.

Analysis on players on loan: Graph

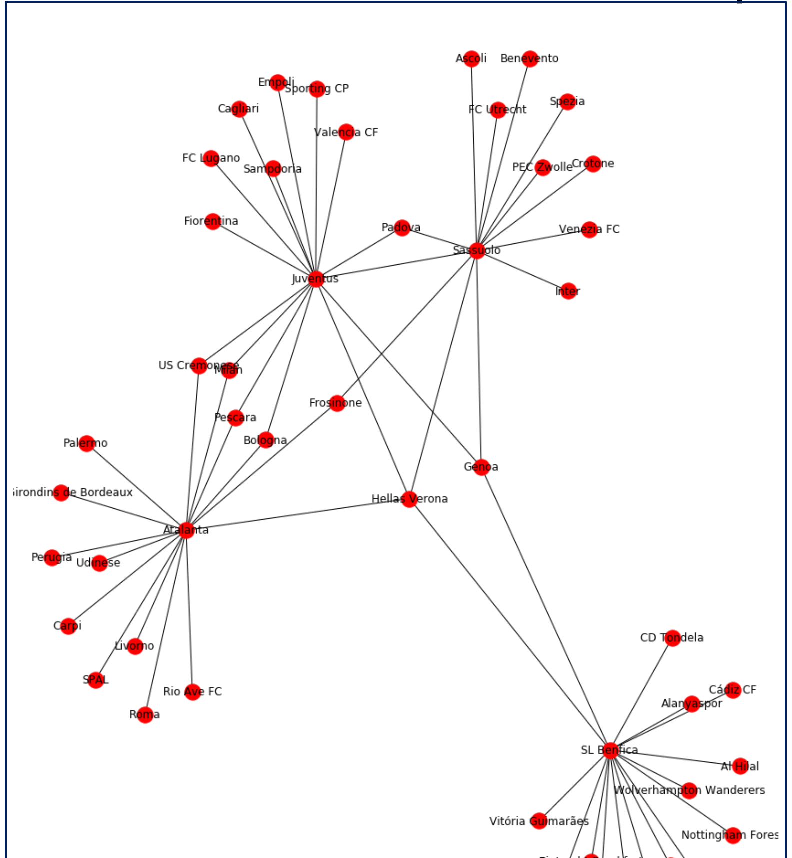
Players on loan: 1265

Clubs that loaned out **10 or more** players



England	10
Italy	8
Portugal	3
Spain	3
France	1
Austria	1

Clubs that loaned out **15 or more** players



Degree centrality

SL Benfica	0.326531
Juventus	0.306122
Atalanta	0.306122
Sassuolo	0.265306

Italy	3
Portugal	1

Why? Italy doesn't have B teams, so they send young players out on loan to give them playing time.

(B teams allowed in Italy from 2019 so this pattern may change)

Client Pipeline Process

01

Create Restricted Set of Recommended Players

- K-Nearest Neighbors

02

Isolate Outlier Players

Anomaly Detection:

- SVM-One Class
- Local Outlier factor
- Isolation Forest
- DBSCAN

03

Predict Bid Price for Isolate Outlier Players

- Linear Regression
- Decision Tree
- Random Forest
- XGBoost
- SVR

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Model Engineering

Client Pipeline Process

Give me 300 hundred players similar to **“M. Salah”**

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Filtering Functions

Option #1:

filter_players(position, ovr_min = 0, ovr_max= 100)

Accepts a position name and overall range and returns a filtered list & dataframe of the players that meet those criteria

Step 1: Enter the position looking for:

CM

Step 2: What is the min overall?:

74

Step 3: What is the max overall?:

86

Output

```
Here are the filtered players based on your criteriea:

['Thiago',
 'S. Milinković-Savić',
 'Jorginho',
 'I. Gündoğan',
 'N. Keïta',
 'C. Tolisso',
 'A. Rabiot',
 'L. Goretzka',
 'J. Draxler',
 'Cesc Fàbregas',
 'M. Dembélé',
 'Rodri',
```

Here are the filtered players' features based on your criteriea:

	Age	Overall	Potential	Special	Preferred Foot	International Reputation	Weak Foot	Skill Moves	Real Face	Height	Weight	LS	ST
67	27	86	86	2190	1	3.0	3.0	5.0	1	175	154	75	75
78	23	85	90	2206	1	2.0	4.0	4.0	1	190	168	81	81
121	26	84	87	2136	1	2.0	3.0	3.0	0	180	148	70	70
136	27	84	84	2138	1	3.0	4.0	4.0	1	180	176	75	75
161	23	83	88	2082	1	2.0	4.0	4.0	1	173	141	73	73
162	23	83	88	2207	1	2.0	3.0	3.0	1	180	179	78	78
168	23	83	87	2184	0	2.0	3.0	3.0	1	193	176	77	77
169	23	83	88	2203	1	3.0	4.0	3.0	1	188	174	77	77
184	24	83	86	2112	1	3.0	5.0	4.0	1	188	170	79	79

Option #2:

recommended_k_players_df(player, k_players = 100)

Accepts a player's name and number of players to recommend and returns a dataframe of the recommended players and a list of their names. The recommendations are limited to players from the same position group.

Step 1: Enter the player you are looking for:

M. Salah

Step 2: Enter the number of similar players you are looking for:

300

Output

```
Here are 300 players similar to M. Salah:

0                   L. Messi
1          Cristiano Ronaldo
2                  Neymar Jr
4              K. De Bruyne
5                  E. Hazard
6                  L. Modrić
7                  L. Suárez
10           R. Lewandowski
11                  T. Kroos
13               David Silva
15                 P. Dybala
16                   H. Kane
17              A. Griezmann
20           Sergio Busquets
21                 E. Cavani
```

Here are the players' features

	Age	Overall	Potential	Special	Preferred Foot	International Reputation	Weak Foot	Skill Moves	Real Face	Height	Weight	LS	ST
G. Bale	28	88	88	2279	0	4.0	3.0	4.0	1	185	181	86	86
A. Griezmann	27	89	90	2246	0	4.0	3.0	4.0	1	175	161	86	86
M. Reus	29	86	86	2172	1	4.0	4.0	4.0	1	180	157	82	82
R. Lewandowski	29	90	90	2152	1	4.0	4.0	4.0	1	183	176	87	87
A. Sánchez	29	85	85	2172	1	4.0	3.0	4.0	1	170	163	81	81
P. Pogba	25	87	91	2247	1	4.0	4.0	5.0	1	193	185	81	81
I. Perišić	29	85	85	2199	1	3.0	5.0	4.0	1	185	176	82	82
E. Cavani	31	89	89	2161	1	4.0	4.0	3.0	1	185	170	85	85

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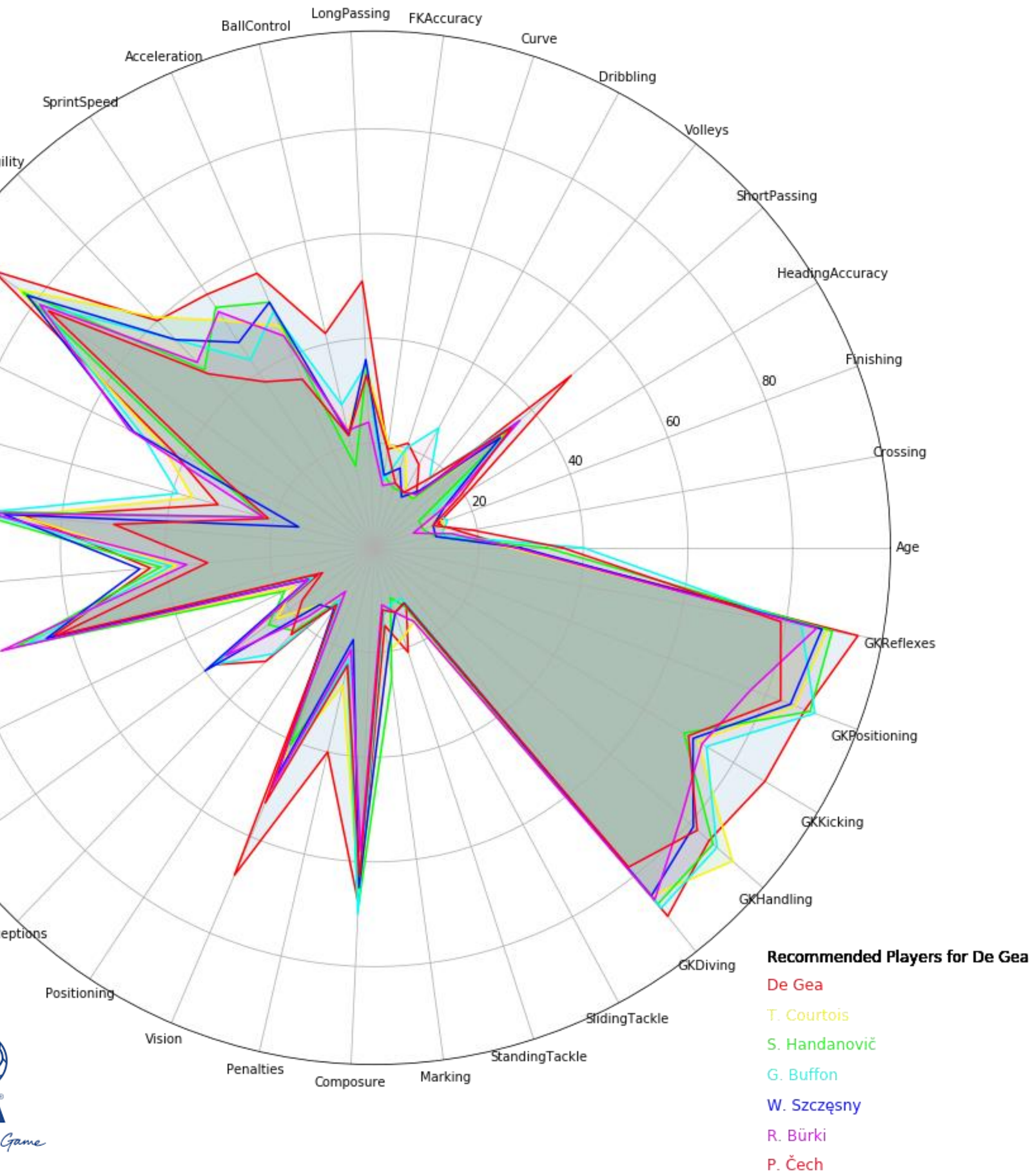
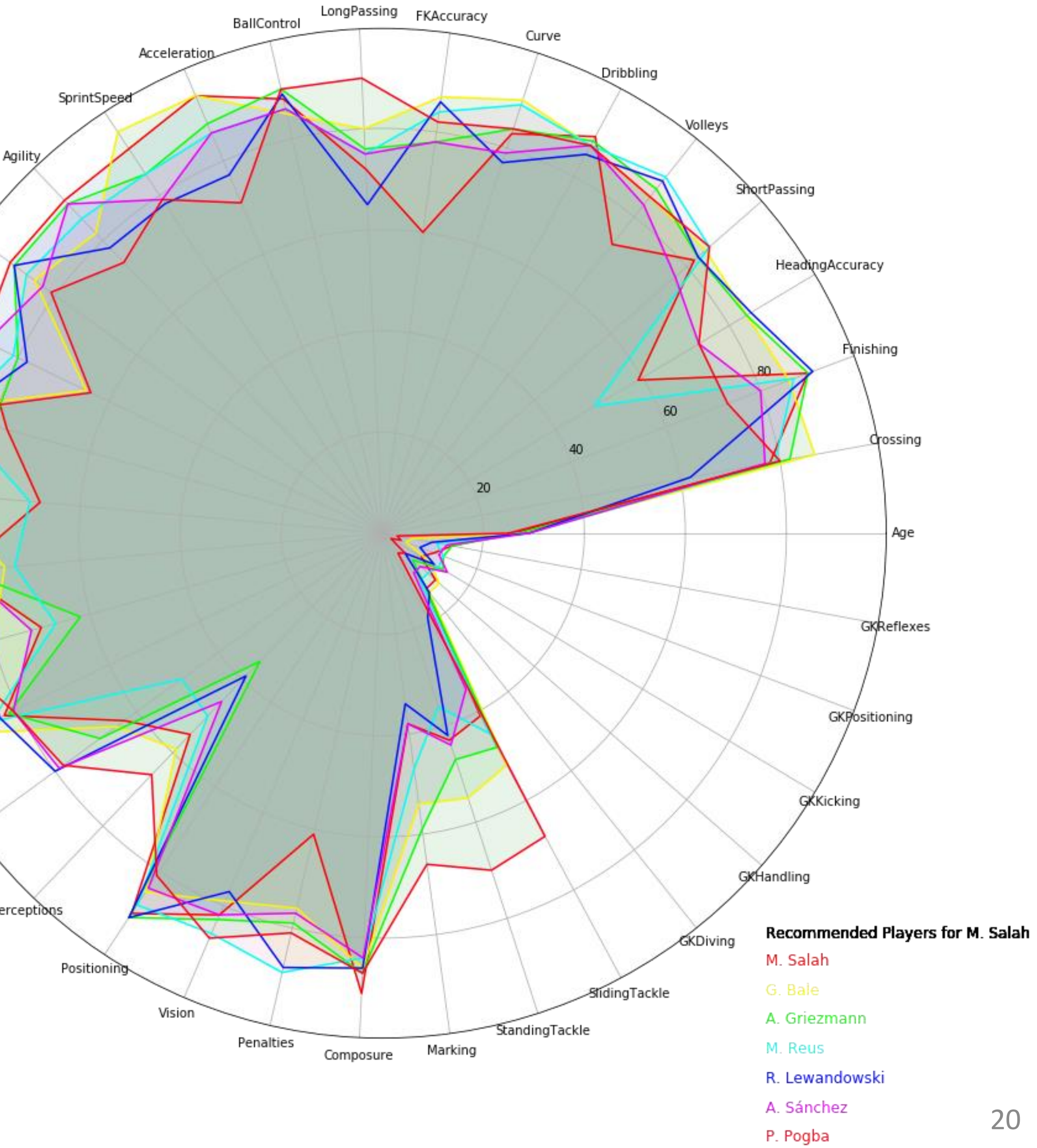
Analyzing Recommendation Feature Similarities

Recommendation Works for Goalkeepers...



...and for Forwards



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Anomaly Detection

Client Pipeline Process

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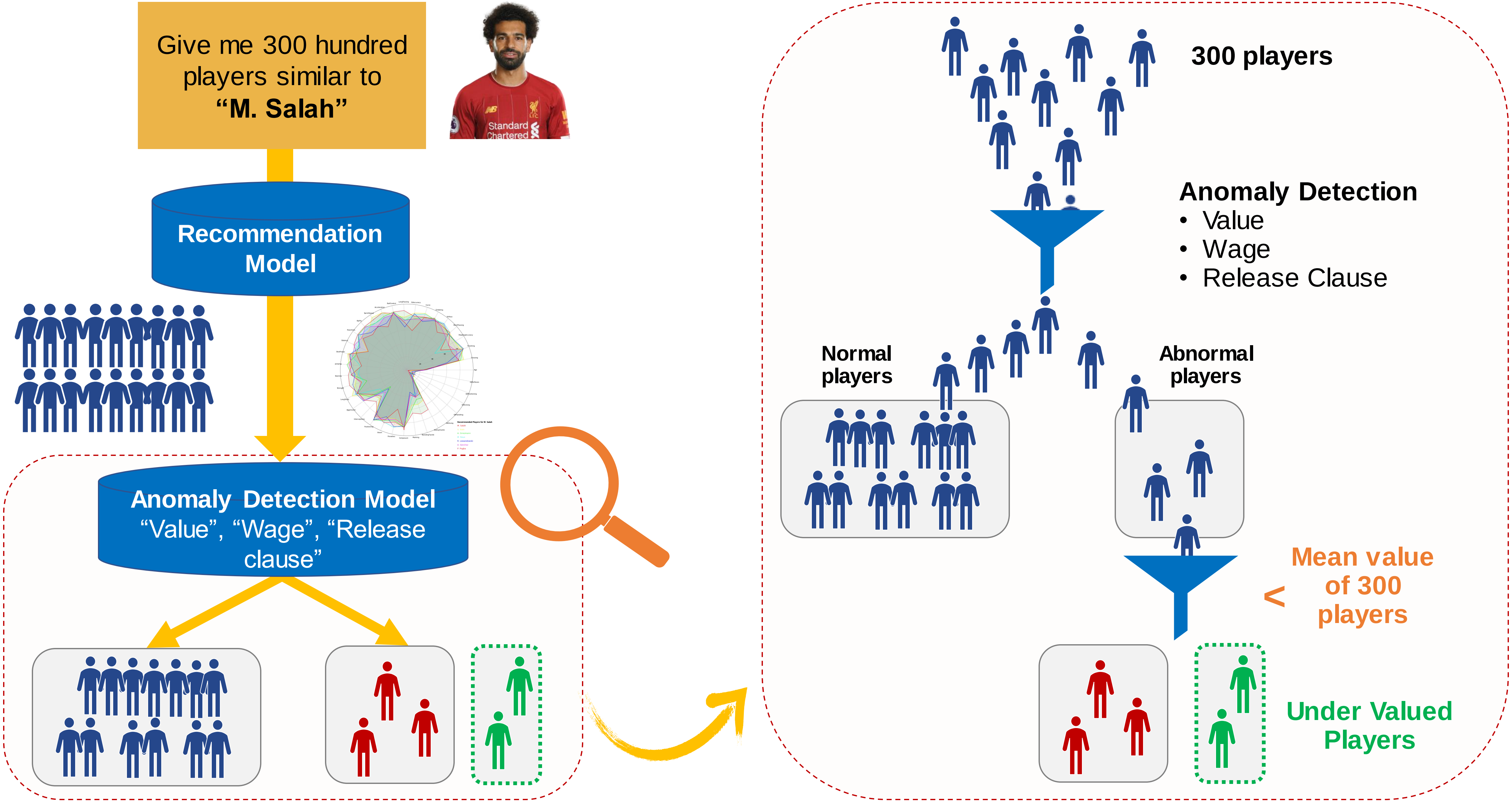
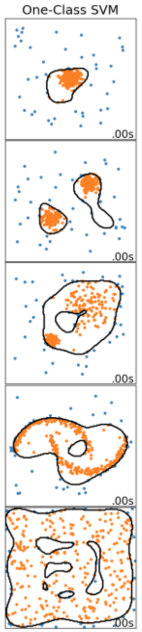
Anomaly Detection Process



Anomaly Detection Methods

Parametric: **OneClass SVM**

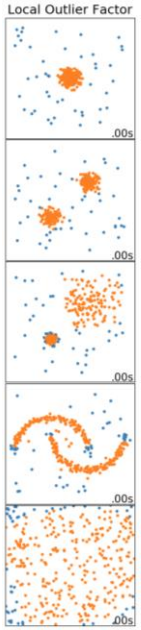


1. Provide normal training data
2. Algorithm creates a representational model of this data (boundary).
3. If newly encountered data is too different it is labeled as out-of-class.

Suitable with novelty detection

Density Based: **LOF**

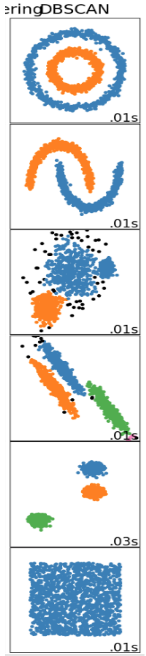
How they work ?



1. Pick a k value (# of neighbors)
2. Calculate k-distance as distance to kth neighbor
3. Smooth k-distance to get reachability distance = max[k-d & d(a,b)]
4. The local reachability density: lrd(a) = 1/(sum(reach-dist(a,n))/k)
5. Compare lrd of 'a' to its k-neighbors and get k-ratio
6. If k-ratio >1 : outlier

Interpret k ratio depends on business knowledge and experience

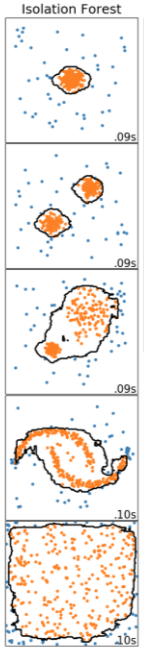
Density Based: **DBSCAN**



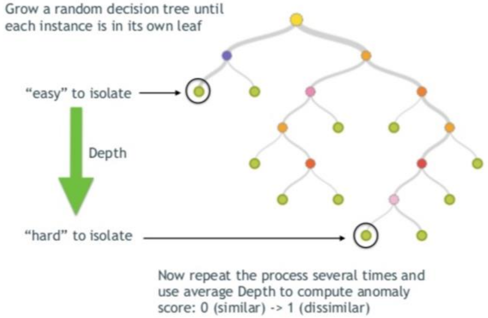
1. Define eps and min.samples
2. Core point if a minimum number of points are within a given distance
3. A point is reachable if there is a path consisting of core points from start to end
4. Any point that is not reachable is considered an outlier

Depends on how we choose eps and min_samples

Ensemble: **Isolation Forest**



1. Build forest of decision trees
2. For each tree, select a random feature and a random split point.
3. Outliers should be identified closer to the roots of the trees on average >> score
4. S = 1: anomaly, S<0.5 normal
5. If all scores close to 0.5, then no clear anomalies.



OneClass SVM

Pros:
- Scales well to high dimensional data

Cons:
- Difficult to understand and interpret the final model
- Difficult to tune hyperparameters gamma & nu
- One-class SVM approach does not control over the false alarm rate (class imbalance)

LOF

Pros:
- Effective when the distribution of values in the feature space can not be assumed.
- Intuitive and easily interpretable

Cons:
- No specific rule of thumb to detect outlier based on k- ratio.
- Need to find appropriate distance metric
- Struggles with high dimensionality data

DBSCAN

Pros:
- Great at handling outliers within dataset
- Separates clusters of high/low density

Cons:
- Struggles with high dimensionality data
- Struggles with clusters of similar density

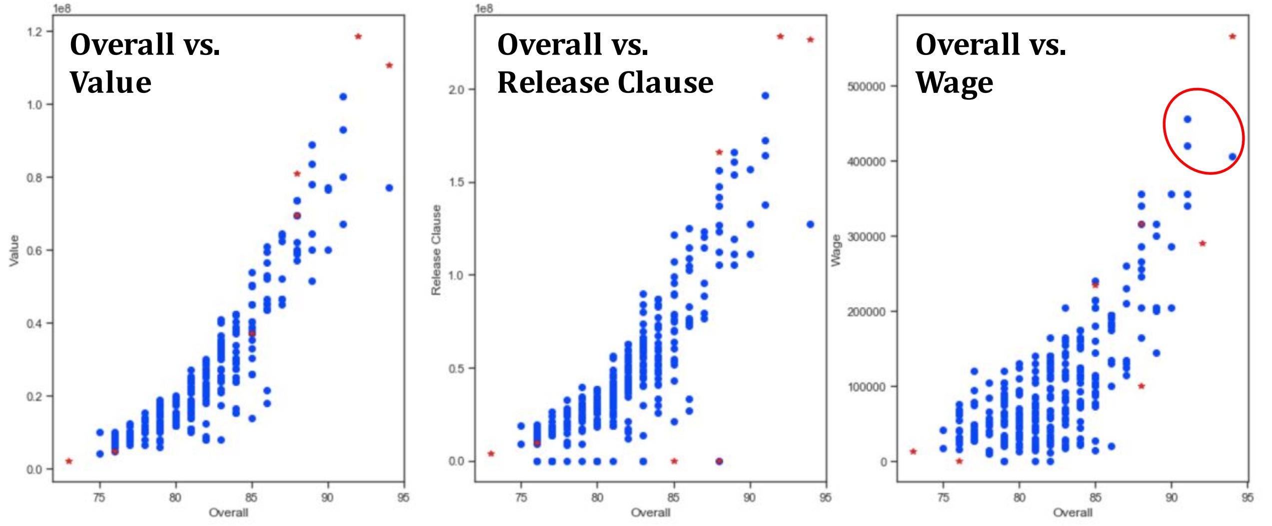
Isolation Forest

Pros:
- Can handle high dimensional data
- Low linear time-complexity and a small memory-requirement
- Does not employ distance/density and only considers isolation

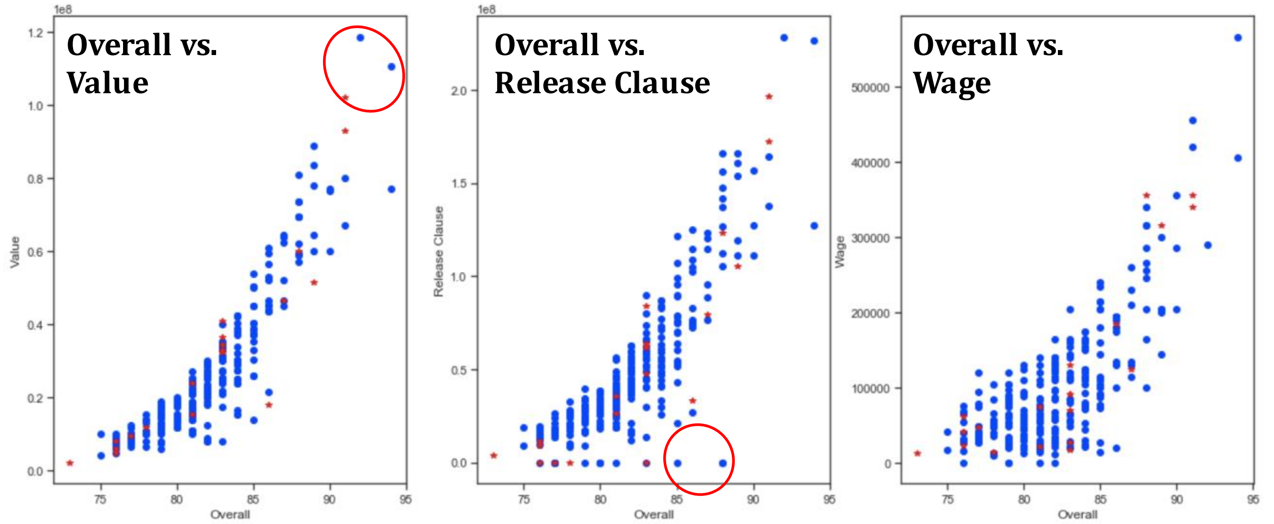
Cons:
- Not ideal if we have a model or good understanding of outliers (I.e. if there is training data)

Anomaly Detection - Compare across methods

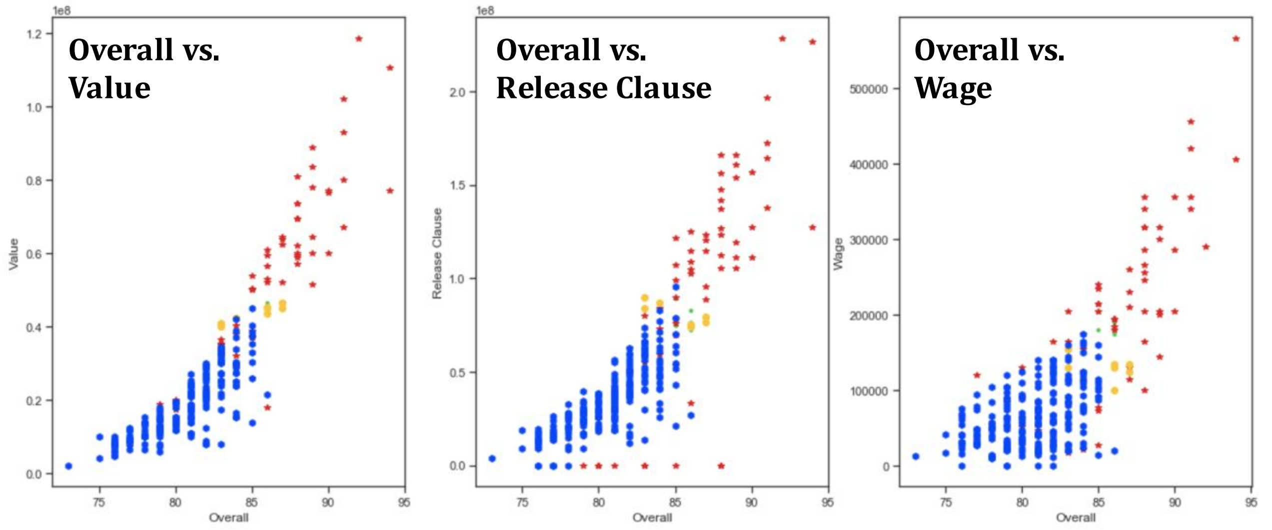
SVM ONE CLASS



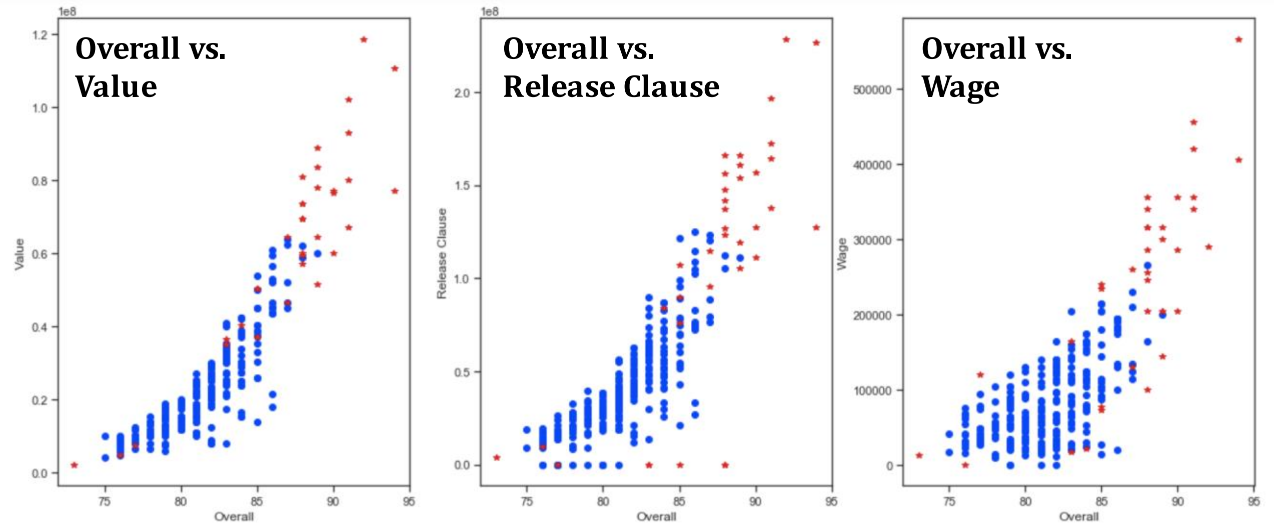
LOCAL OUTLIER FACTOR



DBSCAN



ISOLATION FOREST



Bid Prediction

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- K-Nearest Neighbors

02

Isolate Outlier Players

Anomaly Detection:
- SVM-One Class
- Local Outlier factor
- Isolation Forest
- DBSCAN

03

Predict Bid Price for Player

- Linear Regression
- Decision Tree
- Random Forest
- XGBoost
- SVR

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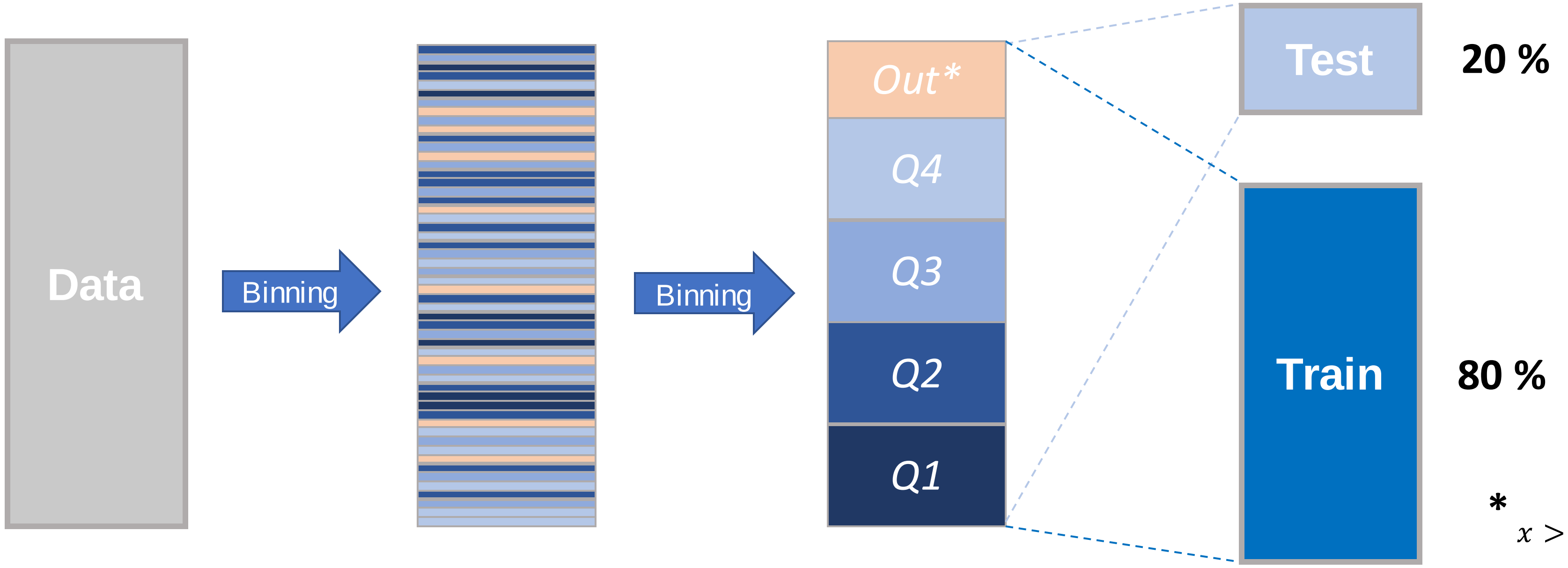
Bid Prediction – Data Pre-Processing

1 Stratified train and test sampling

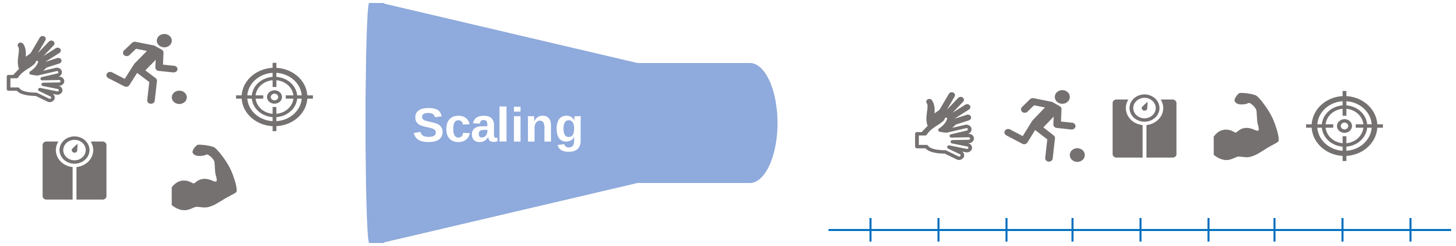


Goal:
Have same distribution of values in training and test set

- Stratified sampling of training and test set based on player value
- Outliers account for ~13% and build their own group
- Remaining data are binned based on quartiles

* $x > Q75_{value} + (Q75_{value} - Q25_{value}) * 1.5 = Outlier$

2 Scaling



Goal:
Normalizing range of independent features

- Scaling all numerical features that are not categorical
- After scaling, each feature has *mean = 0* and *standard deviation = 1*

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Bid Prediction – Model Consideration

Linear

Non-linear

Model Type	Strengths	Weaknesses
Linear Regression	• Simple • Easy to understand relationships (Interpretable coefficients) • Inference focused	• Poor performance with non-linear data relationships between dependent and independent variables • Not naturally flexible enough to capture more complex patterns, and adding the right interaction terms & polynomials difficult.
Support Vector Regression	• Can handle non-linear relationships without changing the explanatory variables through "kernel trick" • Effective in the higher dimension	• Difficult to tune hyperparameters • Difficulty specifying the 'right' kernel function
Decision Tree	• Capable of understanding non-linear relationships • Handles collinearity efficiently. • No assumptions on distribution of data	• Greedy algorithm • Prone to overfit when complexity not controlled
Random Forest	• Same as DT + • More resistant to over-fitting • RF is much easier to tune than GBM. • Biased in favor of categorical variables with attributes with more levels	• Computationally expensive • Not a well descriptive model over the prediction.
Gradient Boosting	• Same as DT + • Learns sequentially • Deals with unbalanced datasets better than RF	• Prone to overfit to noisy data • Slower than RF because trees are built sequentially • Harder to tune than RF

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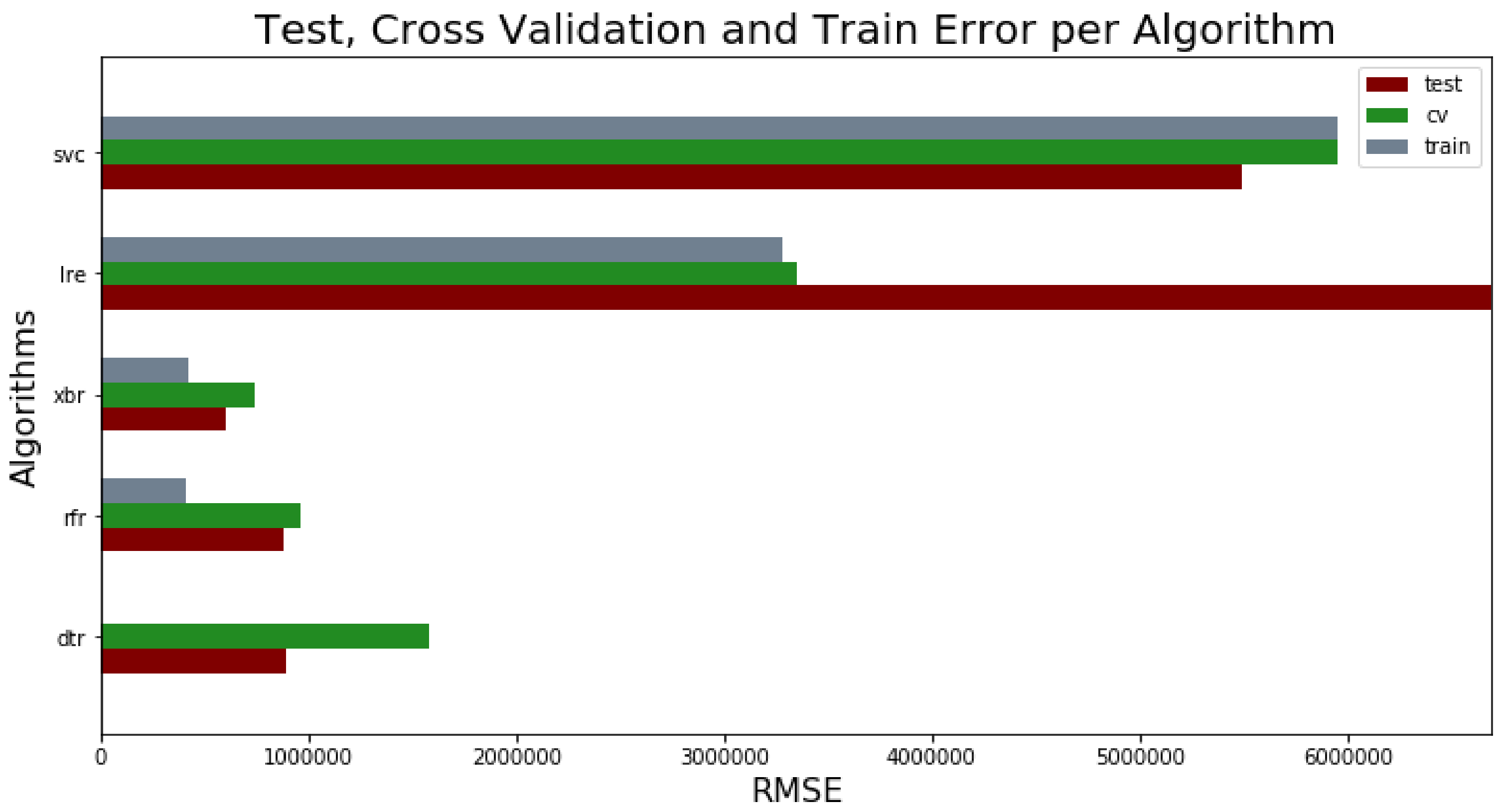
Bid Prediction – Baseline Model Results



- *Using RMSE as evaluation metric**
- Support Vector Regression most stable model
- Linear Regression with extremely high test error
- Decision Tree with virtually no training value
- Random Forest shows some variance, but has a relatively low bias overall
- *XGBoost with the best result, weighing variance and bias*

*

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2}$$

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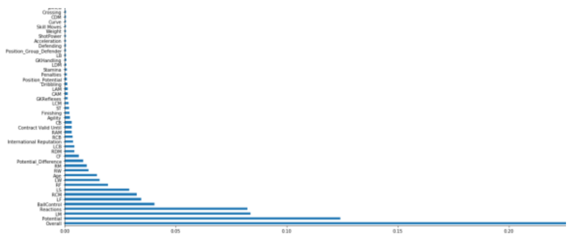
Bid Prediction – Feature Selection

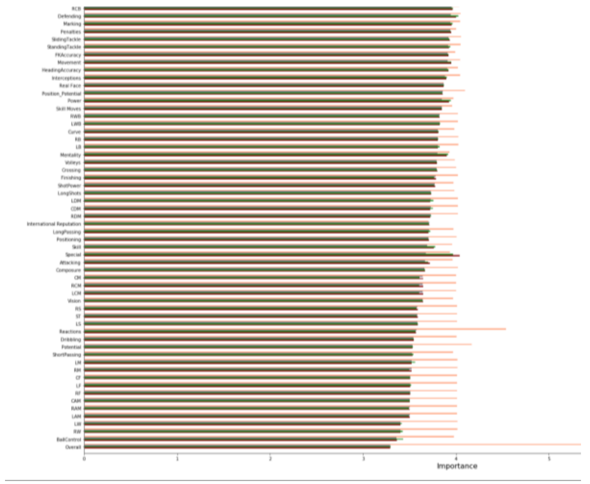
1

	Specs	Score	Expl_percent
5	International Reputation	10926.667128	1.020489e+01
1	Overall	9247.932429	8.637050e+00
75	Club_Reputation	8635.202466	8.064794e+00
2	Potential	7144.411856	6.672479e+00
54	Reactions	5942.582653	5.550038e+00
66	Composure	3632.566134	3.392613e+00
8	Real Face	3565.014584	3.329523e+00
3	Special	2416.453120	2.256832e+00
64	Vision	2126.810904	1.986322e+00
81	Mentality	1937.306594	1.809336e+00
44	ShortPassing	1773.834349	1.656662e+00

2



3



F-Value:

- Start with constant model M_0
- Try all models M_1 consisting of just one feature and pick the best according to the F statistic
- Try all models M_2 consisting of M_1 plus one other feature and pick the best

Tree Regressor

- Based on Extra Tree Regressor (Decision Tree with random splits)
- Total reduction of the criterion brought by that feature (Gini importance)
- Rank by total reduction

RMSE-based:

- Try all models M_1 consisting of just one feature and calculate the RMSE for each of the baseline models
- Rank by lowest RMSE

$$\frac{F_{score}}{\sum_{n=1}^{N} F_{score,n}} > 0.01$$

Top ten features

Top ten features

Final feature selection

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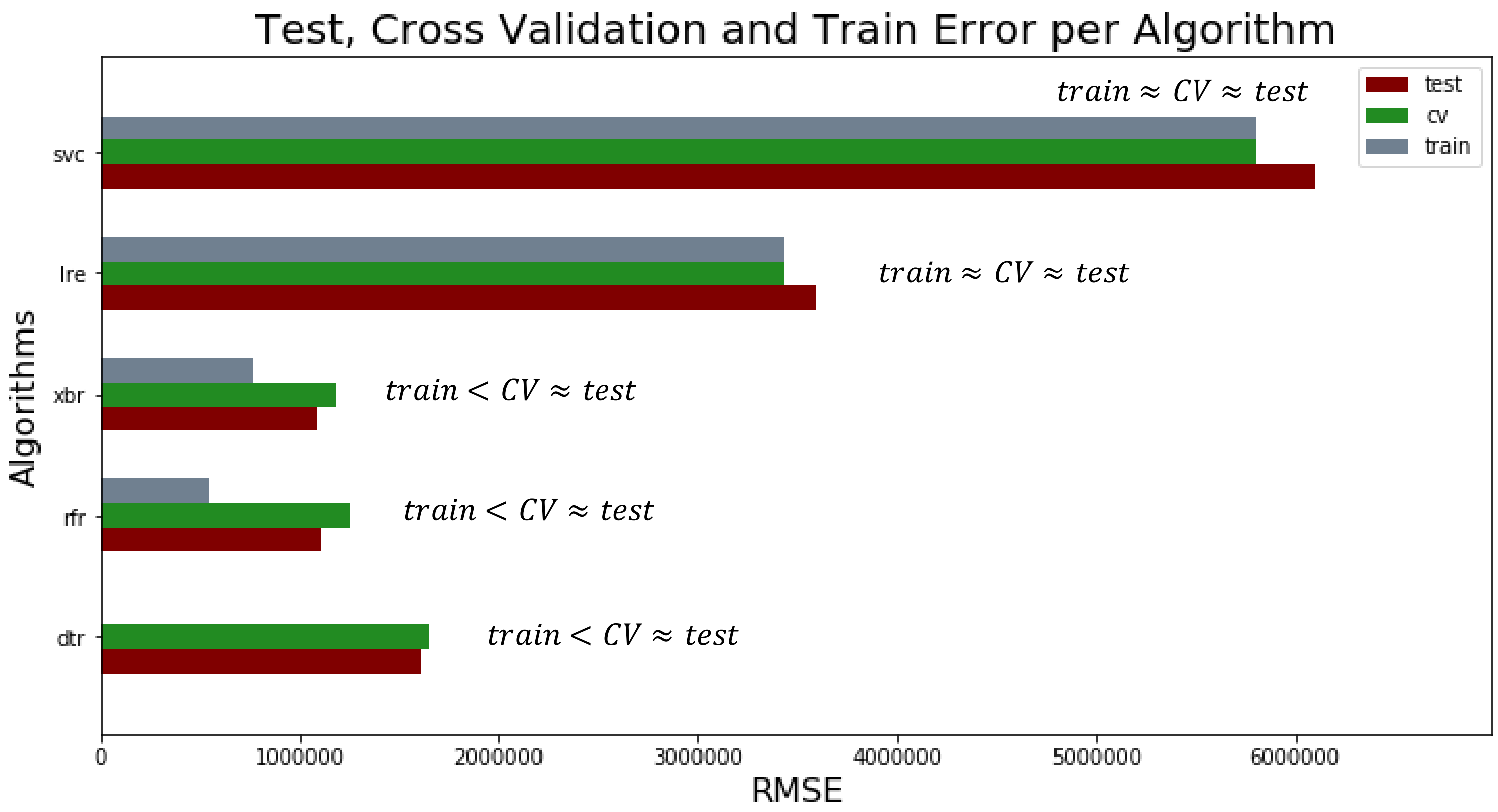
Bid Prediction – Prediction on Reduced Features



- Errors became more stable for most of the models, as compared to baseline model
- Especially Linear Regression improved significantly
- Bias similar to baseline models, therefore, we did not loose much information by reducing number of features

- XGBoost, Random Forest and Decision Tree show signs of overfitting
- Parameter tuning needed

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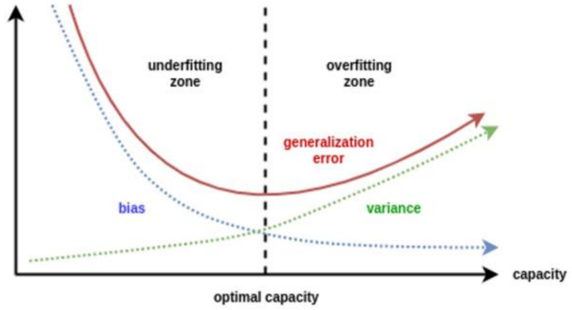
Bid Prediction – Parameter Tuning

1 Setting the goal

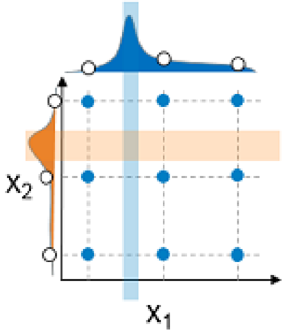
- *Problem:* Setting the optimal parameters for each model to find the sweet spot between variance and bias
- Decrease complexity for XGBoost, Random Forest and Decision Tree
- If possible, decrease bias without significantly increasing variance for all models



2 GridSearch

- GridSearch is an exhaustive method to find optimal hyperparameters

Model	# of parameters	# of fits
Decision Tree	4	8,000
Random Forest	4	243
XGBoost	5	324
Support Vector Reg.	2	60



Standard Grid Search

3 Manual adjustments

- GridSearch is optimizing MSE, but not considering variance-bias tradeoff
- To balance variance and bias, manually adjustment is needed (Trial and Error process)

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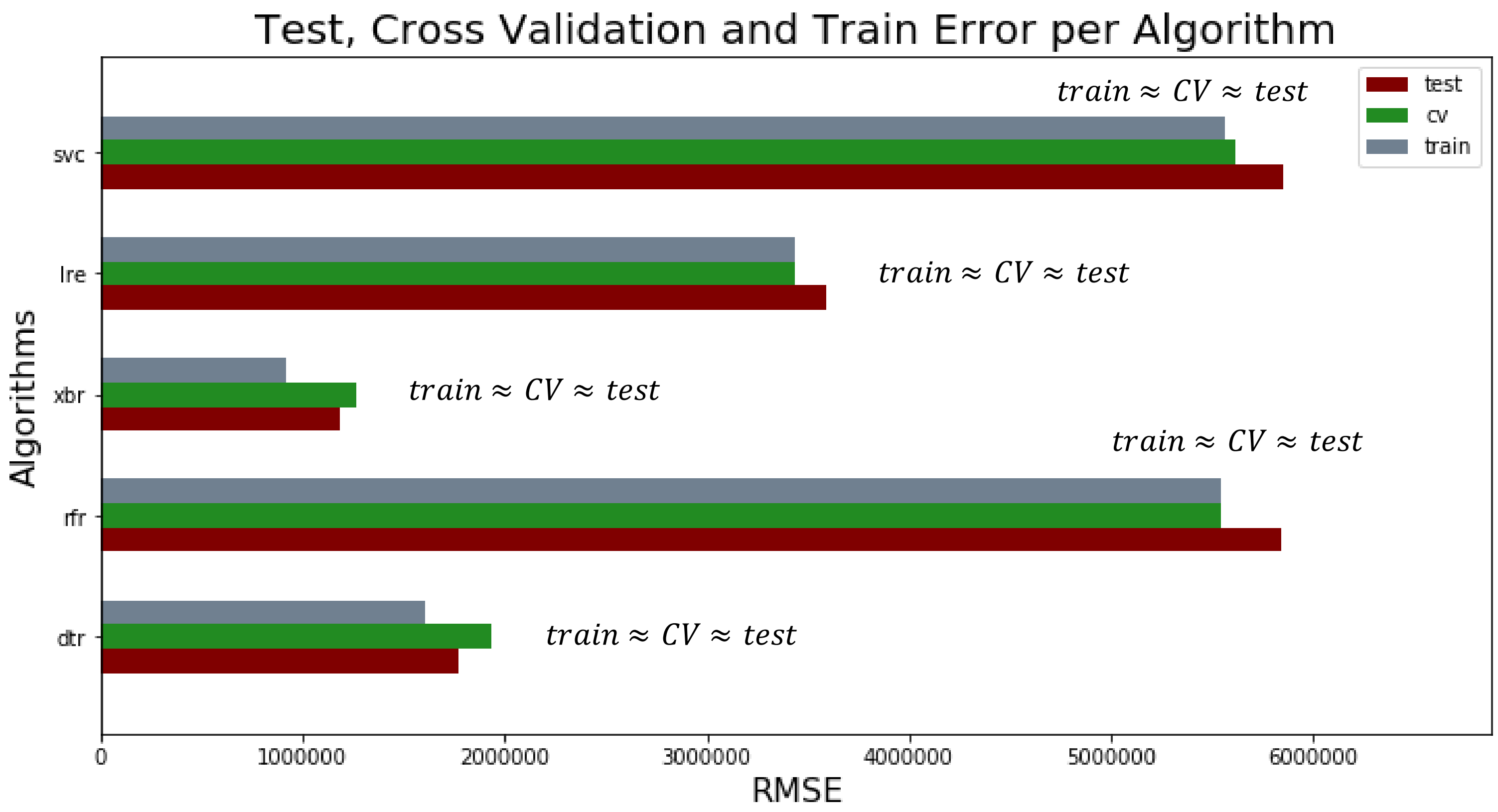
Bid Prediction – Final Evaluation



- In terms of variance, all models are more or less stable
- XGBoost and Decision Tree show somewhat more variance than other models

- Lowest RMSE by far for XGBoost and maybe Decision Tree
- Even though XGBoost show a little more variance, we accept this in turn for a lower bias

Using XGBoost as our model for final bid prediction

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Results

Dashboard

Please choose between the 2 options below:

Option 1: PLAYER

Select a player

Option 2: POSITION AND SCORE

Select a position

CM
CDM
RW
...

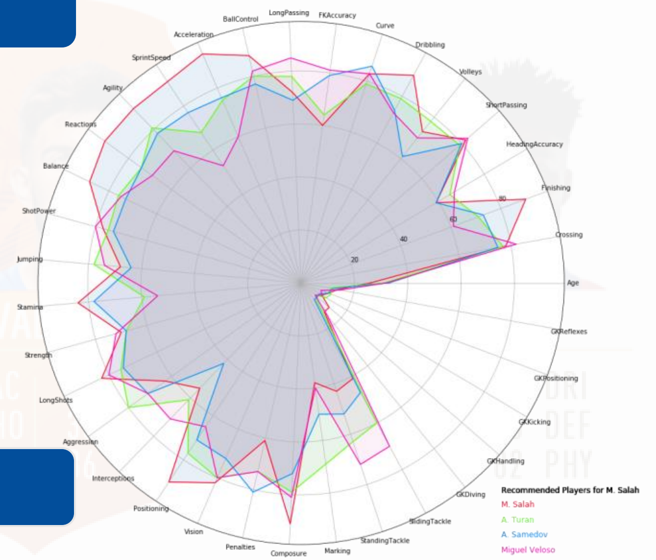
Min Overall score

76

Max Overall score

88

Here is your first bid players suggestion



Suggested value:

3,612,241.2	894,736.06	303,069.7

Next Steps

Next Steps

- Expand dataset to include historical data
- Incorporate intra-match statistics, including geospatial data as well as personal health data such as heart-rate monitoring
- Develop analytics to assess coaching style and style of play
- Maintain communication with the Chicago Fire for future potential projects

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Thank you!