Initial Cleaning and Exploration

In [1]:

```
%matplotlib inline
import warnings
import pandas as pd
from pandas.core.common import SettingWithCopyWarning
warnings.simplefilter(action='ignore', category=SettingWithCopyWarning)
from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import math
df = pd.read_csv("top250-00-19.csv")
df.head()
```

Out[1]:

	Name	Position	Age	Team_from	League_from	Team_to	League_to	Season	Market_value
0	Luís Figo	Right Winger	27	FC Barcelona	LaLiga	Real Madrid	LaLiga	2000-2001	NaN
1	Hernán Crespo	Centre-Forward	25	Parma	Serie A	Lazio	Serie A	2000-2001	NaN
2	Marc Overmars	Left Winger	27	Arsenal	Premier League	FC Barcelona	LaLiga	2000-2001	NaN
3	Gabriel Batistuta	Centre-Forward	31	Fiorentina	Serie A	AS Roma	Serie A	2000-2001	NaN
4	Nicolas Anelka	Centre-Forward	21	Real Madrid	LaLiga	Paris SG	Ligue 1	2000-2001	NaN

In [2]:

```
#mean age of players in the data
rows = df.shape[0]
age_sum = sum(df['Age'])
mean_age = age_sum / rows
print(mean_age)
```

```
24.33872340425532
```

In [3]:

```
print(rows)
```

```
4700
```

In [4]:

```
most_expensive = df[df['Transfer_fee'] == df['Transfer_fee'].max()]
most_expensive
```

Out[4]:

	Name	Position	Age	Team_from	League_from	Team_to	League_to	Season	Market_value
4211	Neymar	Left Winger	25	FC Barcelona	LaLiga	Paris SG	Ligue 1	2017-2018	100000000.0

I've loaded in the dataset and done some initial exploration here. Not surprisingly, Neymar's transfer to PSG is the most expensive one in the dataset.

In [5]:
```
mean_fee=df.groupby('Team_to')['Transfer_fee'].mean().rename('Mean_fee')
count_transfers=df.groupby('Team_to')['Transfer_fee'].size().rename('Transfe
biggest_avg_spender = pd.concat([mean_fee, count_transfers], axis=1).reset_i
biggest_avg_spender.nlargest(10, 'Mean_fee')
```

Out[5]:

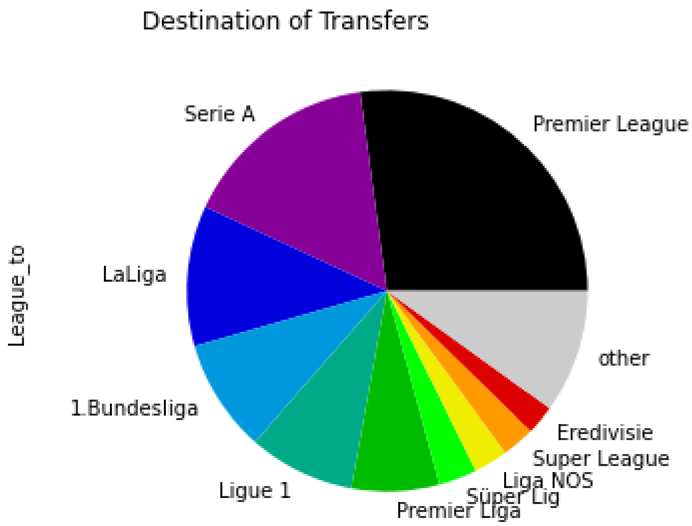
	Team_to	Mean_fee	Transfer_count
257	SIPG	2.598333e+07	6
110	FC Barcelona	2.390057e+07	70
70	CC Yatai	2.330000e+07	1
194	Man Utd	2.303631e+07	65
243	Real Madrid	2.240867e+07	75
221	Paris SG	1.931485e+07	66
192	Man City	1.915447e+07	94
83	Chelsea	1.896510e+07	96
165	Juventus	1.690736e+07	87
184	Liverpool	1.661671e+07	85

The top ten largest average spenders are shown above. SIPG and CC Yatai are both Chinese clubs that I'm not very familiar with, but their transfer count also isn't that high so I won't look into their inclusion too much. Besides those two clubs, there aren't really any surprises in this list.

In [6]:
```
league_to = df['League_to']
count = league_to.value_counts()
count['other'] = sum(count[11:])
count.sort_values(ascending=False)
filtered_counts = count[count > 72]
filtered_counts.rename('League')
#Counts of what leagues transfers go to
```

Out[6]:
```
Premier League    1256
Serie A            739
LaLiga             525
1.Bundesliga       422
Ligue 1            397
Premier Liga       328
Süper Lig          143
Liga NOS           127
Super League       122
Eredivisie         108
other              461
Name: League, dtype: int64
```

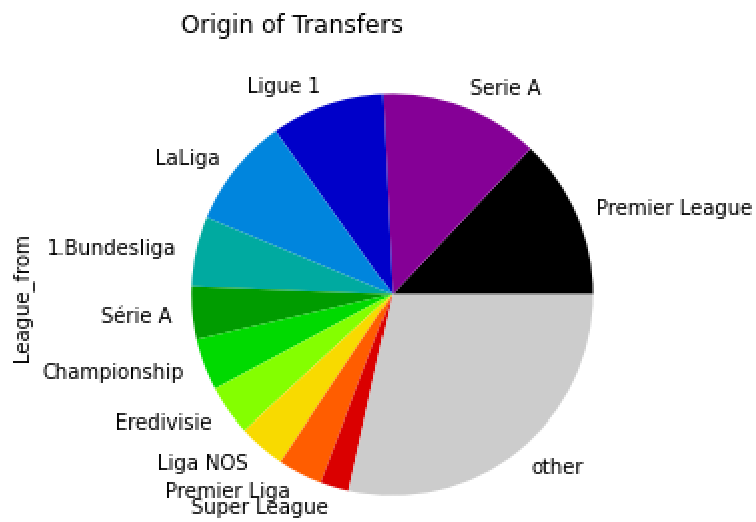
In [7]:
```
colormap = plt.cm.nipy_spectral
filtered_counts.plot(kind="pie", colormap=colormap, title="Destination of Tr
left, right = plt.xlim()
plt.xlim(left - 0.5, right - 0.5)
plt.tight_layout()
plt.show()
```



In [8]:
```
league_from = df["League_from"]
count = league_from.value_counts()
count['other'] = sum(count[11:])
count.sort_values(ascending=False)
filtered_counts = count[count > 100]
filtered_counts.rename('League')
#Counts of what leagues transfers come from
```

Out[8]:
```
Premier League     608
Serie A            602
Ligue 1            428
LaLiga             418
1.Bundesliga       265
Série A            199
Championship       197
Eredivisie         190
Liga NOS           178
Premier Liga       169
Super League       108
other             1338
Name: League, dtype: int64
```

In [9]:
```
colormap = plt.cm.nipy_spectral
filtered_counts.plot(kind="pie", colormap=colormap, title="Origin of Transfe
left, right = plt.xlim()
plt.xlim(left - 0.5, right - 0.5)
plt.tight_layout()
plt.show()
```



The two pie charts above show the destination and origin of the transfers. The first chart shows that the majority of the most expensive transfers go to the traditional top 5 leagues, with the premier league having the greatest percentage. The second pie chart shows the origin of the transfers is similar to the destinations, except that the smaller leagues take up a greater percentage. This makes sense logically, as while many top clubs buy players from other top leagues, they also frequently buy players from smaller leagues. However, it is less common for a club from a smaller league to buy a player from a top league.

Data Cleaning and Aggregating

Now I do some more data cleaning. There are many similar positions listed in the dataset, so I am going to group similar positions together, such as Left-Winger and Left-Midfielder in order to get a simpler dataset with less different positions.

In [10]:
```
#Now we will explore the average cost based on position
df['Position'].value_counts()
```

Out[10]:
```
Centre-Forward        1218
Centre-Back            714
Central Midfield       487
Attacking Midfield     426
Defensive Midfield     411
Right Winger           305
Left Winger            267
Left-Back              225
Right-Back             181
Goalkeeper             180
Second Striker         130
Left Midfield           87
Right Midfield          63
Forward                  3
Sweeper                  1
Defender                 1
Midfielder               1
Name: Position, dtype: int64
```

In [11]:
```
#Clean the data to group similar positions together
df.loc[df.Position == 'Left Winger', 'Position'] = 'Left Midfield'
df.loc[df.Position == 'Second Striker', 'Position'] = 'Centre-Forward'
df.loc[df.Position == 'Right Winger', 'Position'] = 'Right Midfield'
df.loc[df.Position == 'Sweeper', 'Position'] = 'Centre-Back'
df.loc[df.Position == 'Defender', 'Position'] = 'Centre-Back'
df.loc[df.Position == 'Midfielder', 'Position'] = 'Central Midfield'
df.loc[df.Position == 'Forward', 'Position'] = 'Centre-Forward'
df['Position'].value_counts()
```

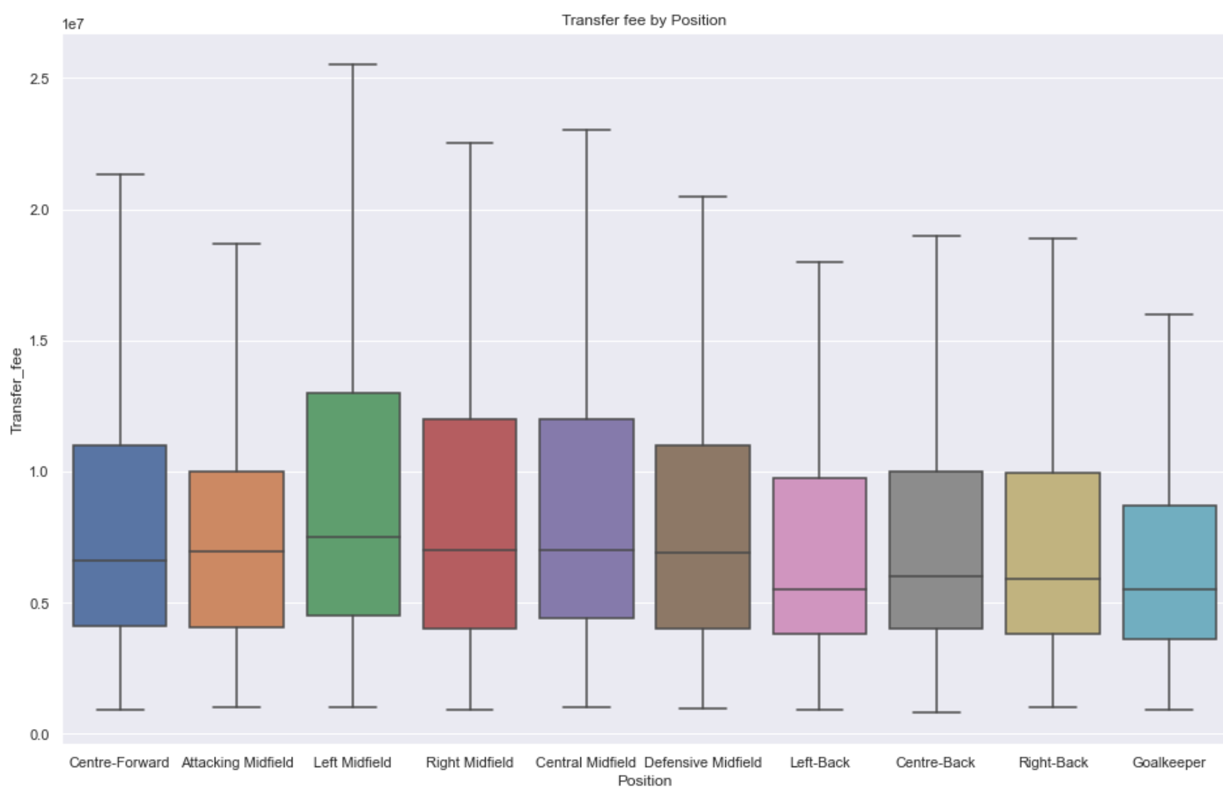
Out[11]:
```
Centre-Forward        1351
Centre-Back            716
Central Midfield       488
Attacking Midfield     426
Defensive Midfield     411
Right Midfield         368
Left Midfield          354
Left-Back              225
Right-Back             181
Goalkeeper             180
Name: Position, dtype: int64
```

In [12]:
```
average_costs = df.groupby('Position', as_index=False)['Transfer_fee'].mean(
print(average_costs)
```

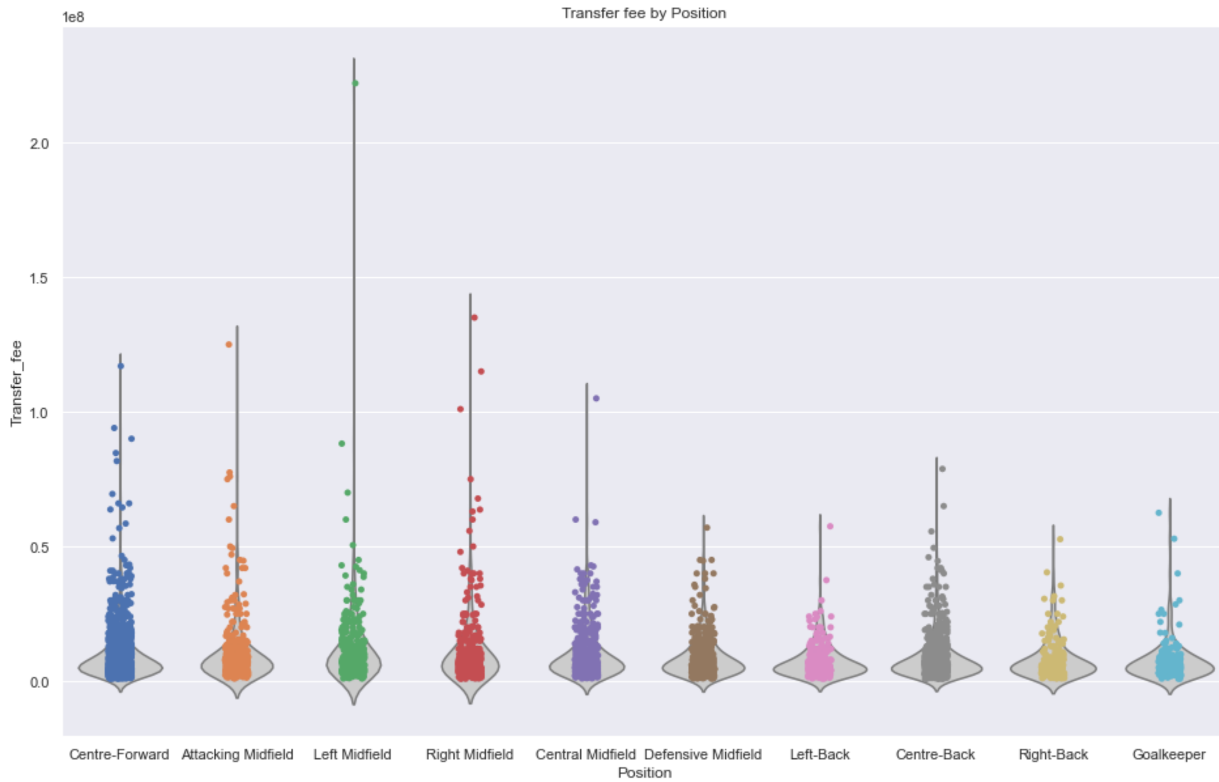
```
             Position  Transfer_fee
0  Attacking Midfield  9.824178e+06
1    Central Midfield  1.007787e+07
2         Centre-Back  8.430929e+06
3      Centre-Forward  9.496869e+06
4  Defensive Midfield  8.992019e+06
5          Goalkeeper  7.622667e+06
6       Left Midfield  1.138398e+07
7           Left-Back  7.718933e+06
8      Right Midfield  1.115549e+07
9          Right-Back  8.254309e+06
```

Visualizations

In [13]:
```
sns.set(rc={'figure.figsize':(16,10)})
sns.boxplot(x='Position', y='Transfer_fee',data=df[['Position', 'Transfer_fe
                                   "Defensive Midfield", "Left-Back", "Centr
None
```

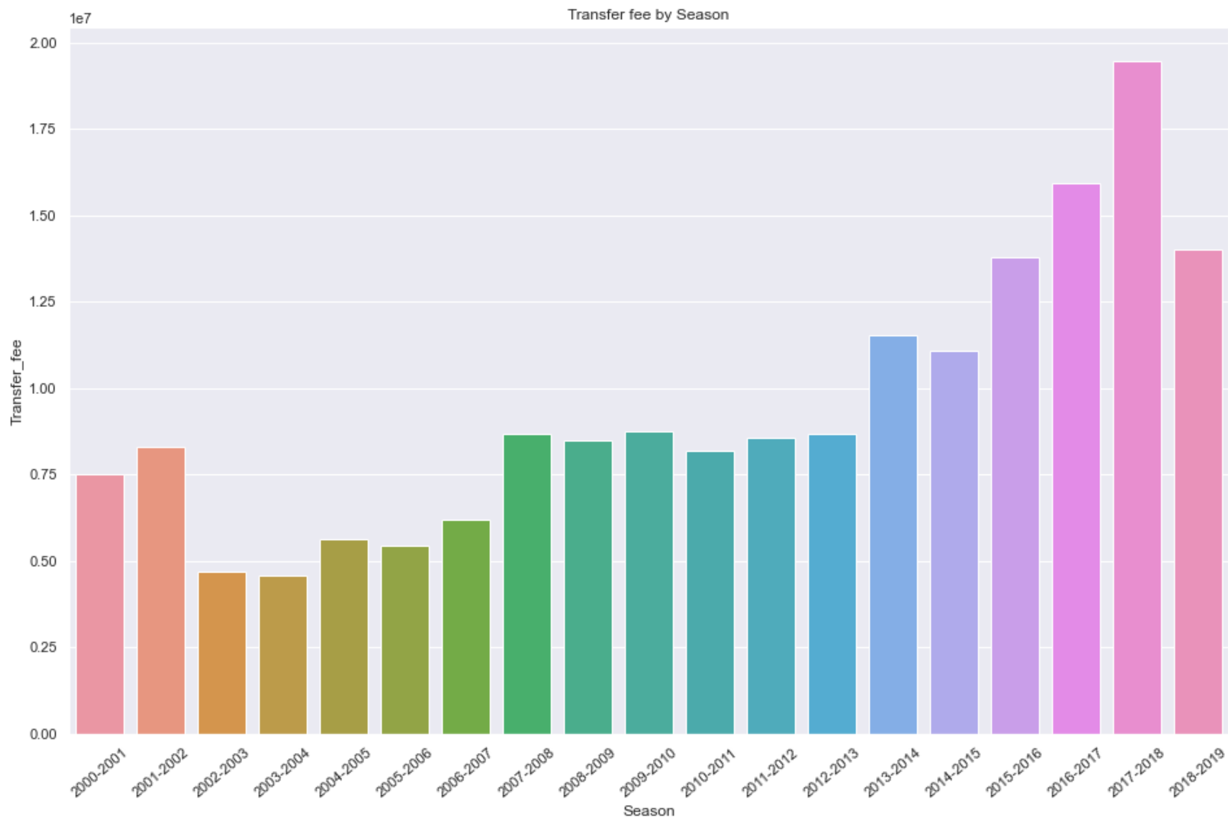


```
In [14]: ax = sns.violinplot(x='Position', y='Transfer_fee', data=df[['Position', 'Tra
                              inner=None, color=".8", order=["Centre-Forward", "Attacki
                                             "Defensive Midfield", "Left-Back", "Centre
         ax = sns.stripplot(x='Position', y='Transfer_fee', data=df[['Position', 'Tran
                                             "Defensive Midfield", "Left-Back", "Centre
         ax.set_title("Transfer fee by Position")
         None
```



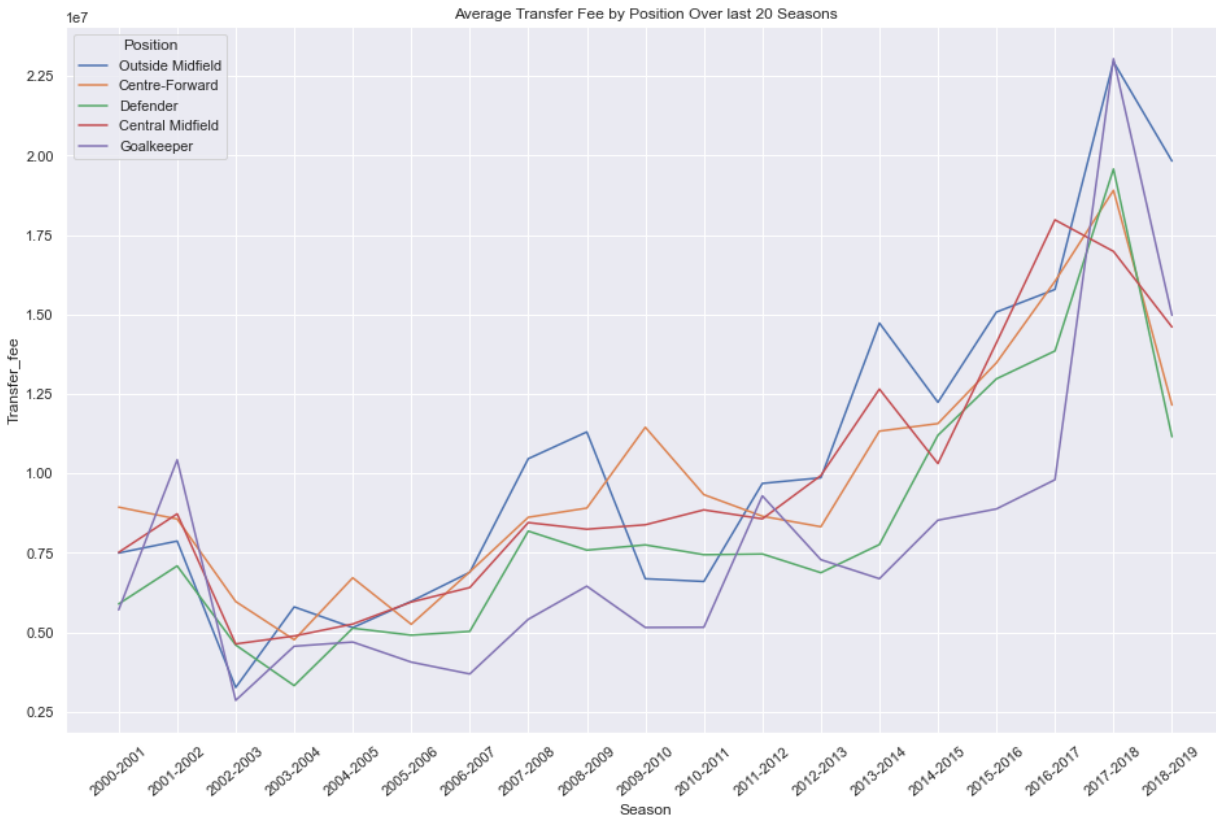
The two cells above both show the average transfer fee by position in similar but slightly different ways. They both show the mean and convey information about the spread of the data, but the width of the base oval in the second plot also conveys the variance of transfer fees for each position. It's not very surprising that attackers (particularly the most elite ones) generally cost more than defenders.

In [15]:
```
sns.barplot(x='Season', y='Transfer_fee', data=df[['Season', 'Transfer_fee']
            ci=None).set_title('Transfer fee by Season')
plt.xticks(rotation=40)
None
```



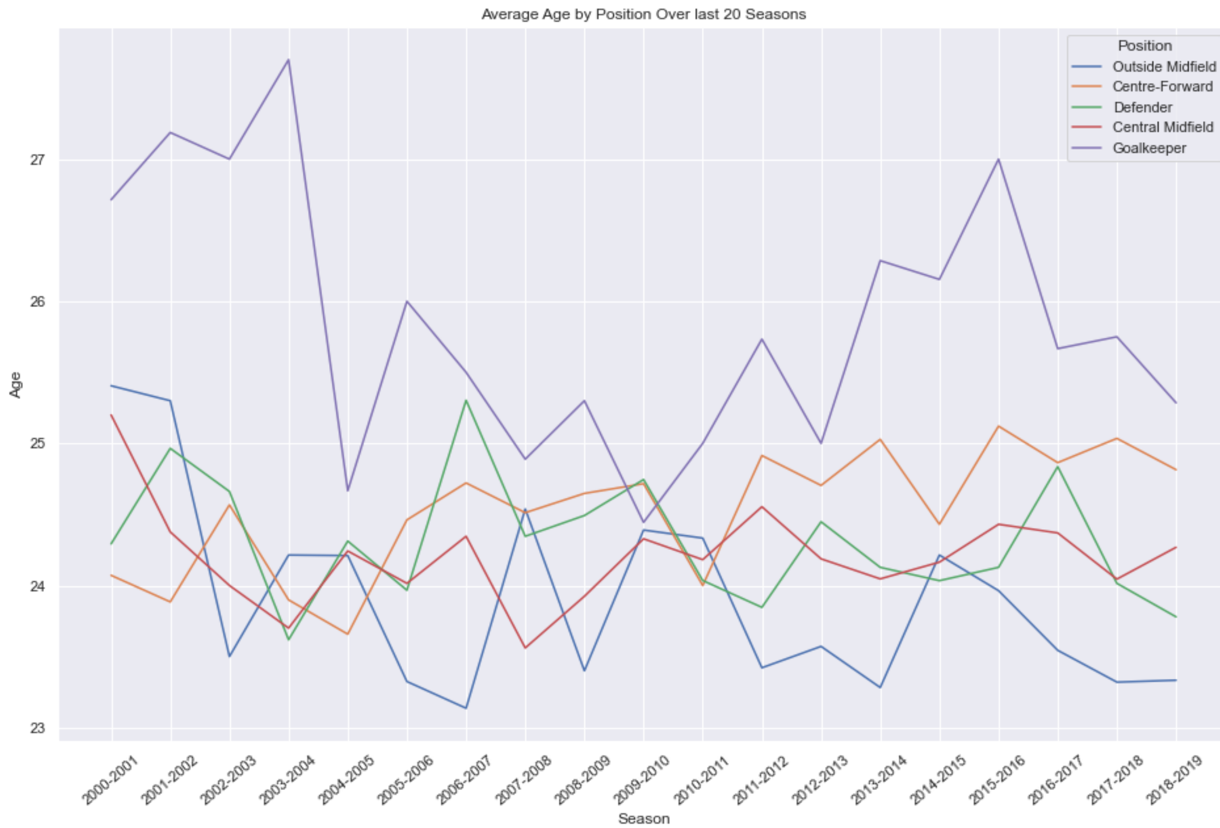
This bar chart shows the average transfer fee by each season without going into any further detail. Transfer fees clearly rose over time, despite taking slight dips or pauses during periods of economic downturn, such as the dot com burst and and great recession.

In [16]:
```
simplified = df.copy()
simplified.loc[simplified.Position == 'Right Midfield', 'Position'] = 'Outsi
simplified.loc[simplified.Position == 'Left Midfield', 'Position'] = 'Outsic
simplified.loc[simplified.Position == 'Attacking Midfield', 'Position'] = 'C
simplified.loc[simplified.Position == 'Defensive Midfield', 'Position'] = 'C
simplified.loc[simplified.Position == 'Centre-Back', 'Position'] = 'Defender
simplified.loc[simplified.Position == 'Left-Back', 'Position'] = 'Defender'
simplified.loc[simplified.Position == 'Right-Back', 'Position'] = 'Defender'
sns.lineplot(x='Season', y='Transfer_fee',
                 data=simplified[['Season', 'Transfer_fee', 'Position']],
                 hue='Position', ci=None).set_title('Average Transfer Fee by

plt.xticks(rotation=40)
None
```



The above chart further breaks down how transfer fees have changed over the season by position. Different trends in each position are very interesting, such as goalkeeper and defender consistently remaining lower than some of the more attacking positions.

In [17]:
```
sns.lineplot(x='Season', y='Age',
                    data=simplified[['Season', 'Age', 'Position']],
                    hue='Position', ci=None).set_title('Average Age by Positior

plt.xticks(rotation=40)
None
```



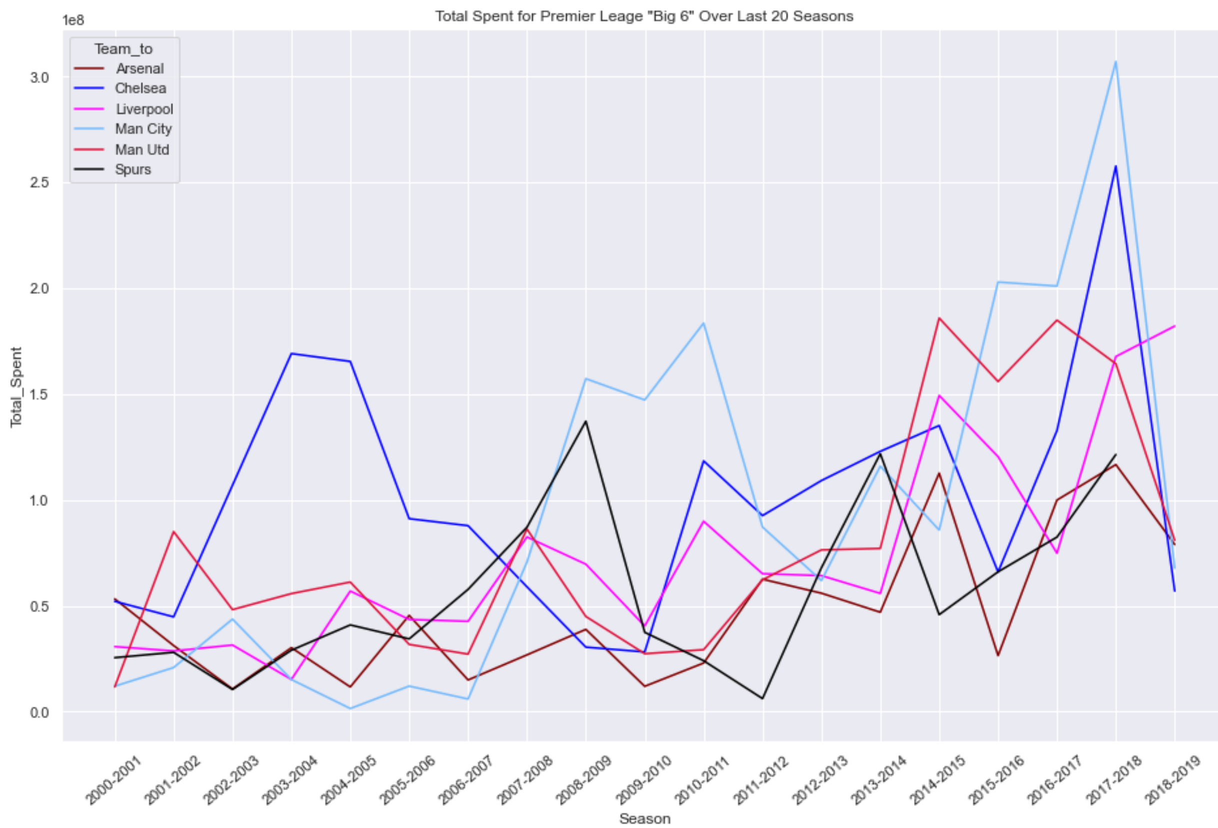
The chart above shows the average age of the trasnfers in each position for each season. Not surprisingly, goalkeepers are generally much older than other positions, as they can play until they are much older and generally also take longer to reach the prime of their career (when their transfer fee would be the greatest). Another interesting trend is that in recent years, centre-forwards have been older than outside midfielders. Perhaps teams prefer slightly more experience for their centre-forwards, but are willing to gamble on younger players at the outside midfield position.

In [18]:
```
sum_spent = df.groupby(['Team_to', 'Season'])['Transfer_fee'].sum().reset_in
prem_top_6 = sum_spent[sum_spent['Team_to'].isin(['Arsenal', 'Chelsea', 'Man
prem_top_6 = prem_top_6.rename({'Transfer_fee': 'Total_Spent'}, axis='column
prem_top_6.head()
```

Out[18]:

	Team_to	Season	Total_Spent
145	Arsenal	2000-2001	53300000
146	Arsenal	2001-2002	31250000
147	Arsenal	2002-2003	10730000
148	Arsenal	2003-2004	30250000
149	Arsenal	2004-2005	11700000

In [19]:
```
sns.lineplot(x='Season', y='Total_Spent',
             data = prem_top_6[['Team_to', 'Season', 'Total_Spent']],
             hue='Team_to',
             palette = {'Arsenal':'Maroon', 'Chelsea': 'Blue', 'Man Utd': 'C
                        'Man City': 'xkcd:sky blue', 'Liverpool': 'Magenta',
             ci=None).set_title('Total Spent for Premier Leage "Big 6" Over 
plt.xticks(rotation=40)
None
```



This is my favorite chart, as I am especially a fan of the English Premier League. This chart shows the total spent by the traditional 'big 6' clubs over the last 19 seasons. I feel that this chart shows, more than anything, that it takes significant spending to be successful in the Premier League. We can see spending spikes from Chelsea just before they started becoming successful in the mid 2000s and also very recently. We can also see a significant spending spike from Manchester City just before they began their period of sustained success in the mid 2010s. Similar spikes exist for Liverpool and Manchester United. However, spending also does not guarantee success, as there are a number of spikes from Spurs and Arsenal, but both teams have had limited success in recent years. One trend that I find particularly interesting is how Arsenal (my favorite team) consistently spend less than their 'big 6' rivals. This trend backs up the sentiment that many Arsenal fans feel, that their owners do not spend enough money for them to be competitive.

Machine Learning

I will now build a number of machine learning models to predict a player's transfer fee from all of the other data we have on the transfer. I will first use classification to approach this problem, by predicting a bucketed range that the transfer fee will fall into. I will then use regression to try to predict the exact transfer fee rather than a bucketed range.

I will first use classification to develop a machine learning model capable of predicting a player's transfer fee based on the other attributes (besides name for obvious reasons and market value due to presence of a lot of Nan's).

In [20]:
```
class_df = df.drop(columns=["Name", "Market_value"])
class_df.head()
```

Out[20]:

	Position	Age	Team_from	League_from	Team_to	League_to	Season	Transfer_fee
0	Right Midfield	27	FC Barcelona	LaLiga	Real Madrid	LaLiga	2000-2001	60000000
1	Centre-Forward	25	Parma	Serie A	Lazio	Serie A	2000-2001	56810000
2	Left Midfield	27	Arsenal	Premier League	FC Barcelona	LaLiga	2000-2001	40000000
3	Centre-Forward	31	Fiorentina	Serie A	AS Roma	Serie A	2000-2001	36150000
4	Centre-Forward	21	Real Madrid	LaLiga	Paris SG	Ligue 1	2000-2001	34500000

Now we will add a column showing the bucket a transfer fee falls into. A classification machine learning algorithm cannot predict discrete values and is suited to predicting categorical values. Transfer_fee is obviously a discrete value, so we will use buckets to make this into a categorical value.

In [21]:
```
class_df["Transfer_fee"].describe()
```

Out[21]:
```
count    4.700000e+03
mean     9.447586e+06
std      1.043772e+07
min      8.250000e+05
25%      4.000000e+06
50%      6.500000e+06
75%      1.082000e+07
max      2.220000e+08
Name: Transfer_fee, dtype: float64
```

In [22]:
```
#params: function to create buckets for the transfer fee where data is the c
#returns: a new dataframe where "bucket" exists as a column and the "Transfe
def create_buckets(data, n):
    out_df = data.copy()
    out_df["bucket"] = pd.qcut(out_df["Transfer_fee"], q=n)
    out_df = out_df.drop(columns=["Transfer_fee"])
    return out_df
```

Data Encoding

A key problem with this dataset at the moment is that I have lots of categorical variables, but computers only see numbers. Thus, I need to encode my categorical variables to be numerical values. There are two options for each column, label encoding, in which I just assign each unique value in a column a unique number. This works well for ordinal categorical variables such as season because it the assignment of a unique number forces the algorithm to interpret unique relationships in the same order as what you would expect. (i.e. first season gets assigned 0 and second season gets assigned 1). However, this would not work well for something like Position because there is no ordinal relationship there. For columns where there is not an ordinal relationship, I will use one-hot encoding, in which I essentially create a dummy variable for each unique value in the column.

In [23]:
```
from sklearn.model_selection import train_test_split, GridSearchCV, cross_va
from sklearn.preprocessing import LabelEncoder
import patsy as pts

bucketed_df = create_buckets(class_df, 10)

#Label Encoding on Season and Bucket columns
season_le = LabelEncoder()
bucketed_df['Season'] = season_le.fit_transform(bucketed_df['Season'])
target_le = LabelEncoder().fit(bucketed_df['bucket'])
bucketed_df['bucket'] = target_le.transform(bucketed_df['bucket'])

#Performing one-hot encoding on Position, Team_from, League_from, Team_to, a

Y, X = pts.dmatrices('bucket ~ C(Position) + Age + C(Team_from) + C(League_f
                     data = bucketed_df,
                     return_type='dataframe')
None
```

In [24]:
```
np_Y = Y['bucket'].to_numpy()
```

In the code cell below, I scale the data columns to have a mean of 0 and standard deviation of 1. I found that this led to a general improvement in the models performance, which makes sense because many of the columns of the input do not follow a normal distribution and some of them use different scales.

In [25]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = pd.DataFrame(scaler.fit_transform(X),columns = X.columns)
X.head()
```

Out[25]:

	Intercept	C(Position) [T.Central Midfield]	C(Position) [T.Centre-Back]	C(Position) [T.Centre-Forward]	C(Position) [T.Defensive Midfield]	C(Position) [T.Goalkeeper]	C(Position) [T.Left Midfield]	C(Positior [T.Left Back
0	0.0	-0.340381	-0.423933	-0.635141	-0.309559	-0.199557	-0.285402	-0.22423
1	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423
2	0.0	-0.340381	-0.423933	-0.635141	-0.309559	-0.199557	3.503832	-0.22423
3	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423
4	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423

5 rows × 1086 columns

Custom Classification Report

I want to include cross validation in my method comparison, so I will write a quick function for a custom classification report using nested cross validation. This means that I will perform cross validation on 5 different folds of data (outer folds), and then I will perform a grid search on inner folds for each of the 5 outer folds in order to find optimal hyperparameters for each model.

In [26]:
```
from sklearn.metrics import classification_report, accuracy_score, make_scor

originalclass = []
predictedclass = []

def custom_classification_scoring(y_true, y_pred, is_training=True):
    originalclass.extend(y_true)
    predictedclass.extend(y_pred)
    '''
    print("originalclass")
    print(originalclass)
    print("predictedclass")
    print(predictedclass)
    '''
    # Custom Accuracy function to measure the distance of the predicted valu
    # accuracy score that only determines if the datapoint was correctly cla
    diff = np.abs(y_true - y_pred) / 10.0
    score = (1.0 - diff)
    ret_val = score.mean()
    if is_training:
        print("Mean Relative Accuracy of this outer fold is: ")
        print(ret_val)
    return ret_val

def run_model(model, parameters, X, Y):
    clf = GridSearchCV(estimator=model, param_grid=parameters, n_jobs = -1)
    clf.fit(X, Y)
    nested_score = cross_val_score(clf, X=X, y=Y, scoring=make_scorer(custom
    return classification_report(originalclass, predictedclass, zero_divisio
```

In [27]:
```
X_train, X_test, y_train, y_test = train_test_split( X, np_Y, test_size=0.2,
```

Now that I have split my data into a training and testing set and written methods for cross validation, grid searching, and custom scoring, I am ready to compare different models.

Model Comparison

KNN

In [28]:
```
from sklearn.neighbors import KNeighborsClassifier

originalclass = []
predictedclass = []

params = {
    'n_neighbors': np.arange(3, 16),
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean']
}

knn_report, knn_best_params, knn_nested_score = run_model(KNeighborsClassifi
print(knn_best_params)
print(knn_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(knn_nested_score)

test_model = KNeighborsClassifier(n_neighbors=knn_best_params['n_neighbors']
                                  weights=knn_best_params['weights'],
                                  metric=knn_best_params['metric'],
                                  n_jobs = -1).fit(X_train, y_train)
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.7351063829787233
[CV] END ................................ score: (test=0.735) total time=
12.0s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   12.0s remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7398936170212768
[CV] END ................................ score: (test=0.740) total time=
11.4s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   23.4s remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7208776595744681
[CV] END ................................ score: (test=0.721) total time=
11.4s
Mean Relative Accuracy of this outer fold is:
0.7232712765957447
[CV] END ................................ score: (test=0.723) total time=
11.4s
Mean Relative Accuracy of this outer fold is:
0.7363031914893617
[CV] END ................................ score: (test=0.736) total time=
11.2s
{'metric': 'euclidean', 'n_neighbors': 8, 'weights': 'distance'}
              precision    recall  f1-score   support
```

```
         0.0       0.34      0.19      0.24       403
         1.0       0.16      0.11      0.13       358
         2.0       0.15      0.12      0.14       438
         3.0       0.09      0.07      0.08       305
         4.0       0.13      0.14      0.13       394
         5.0       0.14      0.13      0.14       464
         6.0       0.08      0.06      0.07       254
         7.0       0.12      0.12      0.12       392
         8.0       0.14      0.19      0.16       385
         9.0       0.23      0.48      0.31       367

    accuracy                           0.16      3760
   macro avg       0.16      0.16      0.15      3760
weighted avg       0.16      0.16      0.16      3760

Mean Relative Accuracy of all outer folds is:
0.731090425531915
The accuracy on the test dataset is:

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   57.4s finished

0.7243617021276597
```

We can see the results form KNN Classification above. We see the 'Mean Relative Accuracy' for each outer fold, the output of the classification report (which uses exact accuracy rather than the 'Mean Relative Accuracy'), and then we can see the average MRA on all folds and on the test set after being trained on the entire training set. We will now continue to repeat this process with various other classification methods.

Random Forest

In [29]:
```
from sklearn.ensemble import RandomForestClassifier

originalclass = []
predictedclass = []

#I could do more hyperparamter tuning than this, but it honestly just takes
params = {
    'bootstrap': [True],
    'max_depth': [10, 50],
    'max_features': ['auto', 'sqrt'],
    'n_estimators': [200, 1000]
}

rf_report, rf_best_params, rf_nested_score = run_model(RandomForestClassifie
print(rf_best_params)
print(rf_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(rf_nested_score)

test_model = RandomForestClassifier(bootstrap=rf_best_params['bootstrap'],
                                    max_depth=rf_best_params['max_depth'],
                                    max_features=rf_best_params['max_feature
                                    n_estimators=rf_best_params['n_estimator
                                    n_jobs = -1).fit(X_train, y_train)
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.8125
[CV] END ................................ score: (test=0.812) total time=
1.8min

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  1.8min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.8053191489361703
[CV] END ................................ score: (test=0.805) total time=
1.8min

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  3.6min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.8085106382978723
[CV] END ................................ score: (test=0.809) total time=
1.8min
Mean Relative Accuracy of this outer fold is:
0.8050531914893618
[CV] END ................................ score: (test=0.805) total time=
1.8min
Mean Relative Accuracy of this outer fold is:
0.8143617021276596
[CV] END ................................ score: (test=0.814) total time=
1.8min
```

```
{'bootstrap': True, 'max_depth': 50, 'max_features': 'sqrt', 'n_estimator
s': 200}
              precision    recall  f1-score   support

         0.0       0.44      0.83      0.58       403
         1.0       0.27      0.16      0.20       358
         2.0       0.23      0.26      0.24       438
         3.0       0.15      0.06      0.09       305
         4.0       0.15      0.09      0.11       394
         5.0       0.19      0.25      0.22       464
         6.0       0.10      0.03      0.04       254
         7.0       0.21      0.20      0.20       392
         8.0       0.22      0.21      0.22       385
         9.0       0.40      0.58      0.47       367

    accuracy                           0.28      3760
   macro avg       0.24      0.27      0.24      3760
weighted avg       0.24      0.28      0.25      3760

Mean Relative Accuracy of all outer folds is:
0.8091489361702129

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  9.1min finished

The accuracy on the test dataset is:
0.8093617021276597
```

AdaBoost

In [30]:
```
from sklearn.ensemble import AdaBoostClassifier

originalclass = []
predictedclass = []

#I could do more hyperparamter tuning than this, but it honestly just takes
params = {
    'n_estimators': [100, 200],
    'learning_rate': [0.001, 0.01, 0.1, 0.2, 0.5]
}

ada_report, ada_best_params, ada_nested_score = run_model(AdaBoostClassifier
print(ada_best_params)
print(ada_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(ada_nested_score)

test_model = AdaBoostClassifier(learning_rate=ada_best_params['learning_rate
                                n_estimators=ada_best_params['n_estimators']
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.7542553191489362
[CV] END ................................ score: (test=0.754) total time=
2.1min

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  2.1min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7631648936170214
[CV] END ................................ score: (test=0.763) total time=
2.0min

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  4.1min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7515957446808511
[CV] END ................................ score: (test=0.752) total time=
2.1min
Mean Relative Accuracy of this outer fold is:
0.7640957446808511
[CV] END ................................ score: (test=0.764) total time=
2.0min
Mean Relative Accuracy of this outer fold is:
0.7664893617021278
[CV] END ................................ score: (test=0.766) total time=
2.0min
{'learning_rate': 0.01, 'n_estimators': 200}
              precision    recall  f1-score   support

         0.0       0.35      0.98      0.51       403
         1.0       0.32      0.19      0.24       358
```

```
         2.0       0.20      0.44      0.27       438
         3.0       0.00      0.00      0.00       305
         4.0       0.00      0.00      0.00       394
         5.0       0.17      0.49      0.25       464
         6.0       0.00      0.00      0.00       254
         7.0       0.09      0.00      0.00       392
         8.0       0.18      0.05      0.08       385
         9.0       0.25      0.01      0.02       367

    accuracy                           0.24      3760
   macro avg       0.16      0.22      0.14      3760
weighted avg       0.17      0.24      0.15      3760

Mean Relative Accuracy of all outer folds is:
0.7599202127659576

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed: 10.2min finished

The accuracy on the test dataset is:
0.7672340425531915
```

Support Vector Machine

In [31]:
```
from sklearn.svm import SVC

originalclass = []
predictedclass = []

params = {
    'C': [0.1,0.5,1],
    'gamma': [0.1,0.5,1.0],
    'kernel': ['rbf','linear']
}

svm_report, svm_best_params, svm_nested_score = run_model(SVC(), params, X_t
print(svm_best_params)
print(svm_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(svm_nested_score)

test_model = SVC(C=svm_best_params['C'],
                 gamma=svm_best_params['gamma'],
                 kernel=svm_best_params['kernel']).fit(X_train, y_train)
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.7868351063829788
[CV] END ............................... score: (test=0.787) total time=
4.6min

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  4.6min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7848404255319149
[CV] END ............................... score: (test=0.785) total time=
4.6min

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  9.2min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7908244680851064
[CV] END ............................... score: (test=0.791) total time=
4.6min
Mean Relative Accuracy of this outer fold is:
0.785372340425532
[CV] END ............................... score: (test=0.785) total time=
4.6min
Mean Relative Accuracy of this outer fold is:
0.7970744680851064
[CV] END ............................... score: (test=0.797) total time=
4.6min
{'C': 0.5, 'gamma': 0.1, 'kernel': 'linear'}
              precision    recall  f1-score   support

         0.0       0.43      0.36      0.39       403
```

```
         1.0       0.19      0.21      0.20       358
         2.0       0.16      0.17      0.17       438
         3.0       0.12      0.10      0.11       305
         4.0       0.12      0.13      0.13       394
         5.0       0.18      0.18      0.18       464
         6.0       0.09      0.08      0.08       254
         7.0       0.15      0.15      0.15       392
         8.0       0.20      0.20      0.20       385
         9.0       0.46      0.50      0.48       367

    accuracy                           0.21      3760
   macro avg       0.21      0.21      0.21      3760
weighted avg       0.21      0.21      0.21      3760

Mean Relative Accuracy of all outer folds is:
0.7889893617021277

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed: 23.1min finished

The accuracy on the test dataset is:
0.7888297872340425
```

Gaussian Naive Bayes

In [32]:
```
from sklearn.naive_bayes import GaussianNB
originalclass = []
predictedclass = []

params = {'var_smoothing': np.logspace(0,-9, num=10)}

gnb_report, gnb_best_params, gnb_nested_score = run_model(GaussianNB(), para
print(gnb_best_params)
print(gnb_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(gnb_nested_score)

test_model = GaussianNB(var_smoothing=gnb_best_params['var_smoothing']).fit(
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.7308510638297873
[CV] END ................................ score: (test=0.731) total time=
2.4s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.4s remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7308510638297872
[CV] END ................................ score: (test=0.731) total time=
2.1s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    4.6s remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7417553191489361
[CV] END ................................ score: (test=0.742) total time=
2.1s
Mean Relative Accuracy of this outer fold is:
0.730186170212766
[CV] END ................................ score: (test=0.730) total time=
2.0s
Mean Relative Accuracy of this outer fold is:
0.7400265957446809
[CV] END ................................ score: (test=0.740) total time=
2.1s
{'var_smoothing': 1e-05}
              precision    recall  f1-score   support

         0.0       0.47      0.15      0.23       403
         1.0       0.21      0.11      0.15       358
         2.0       0.23      0.07      0.11       438
         3.0       0.15      0.11      0.13       305
         4.0       0.16      0.09      0.12       394
         5.0       0.16      0.07      0.09       464
         6.0       0.10      0.20      0.13       254
         7.0       0.12      0.09      0.10       392
```

```
         8.0       0.13      0.20      0.16       385
         9.0       0.24      0.79      0.37       367

    accuracy                           0.18      3760
   macro avg       0.20      0.19      0.16      3760
weighted avg       0.20      0.18      0.16      3760

Mean Relative Accuracy of all outer folds is:
0.7347340425531914
The accuracy on the test dataset is:
0.7159574468085106

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   10.7s finished
```

Neural Network

In [33]:
```
from sklearn.neural_network import MLPClassifier
from warnings import simplefilter
from sklearn.exceptions import ConvergenceWarning
simplefilter("ignore", category=ConvergenceWarning)
originalclass = []
predictedclass = []

params = {
    'hidden_layer_sizes': [(10,30,10),(20,)],
    'activation': ['tanh', 'relu'],
    'solver': ['sgd', 'adam'],
    'alpha': [0.0001, 0.05],
    'learning_rate': ['constant','adaptive'],
}

mlp_report, mlp_best_params, mlp_nested_score = run_model(MLPClassifier(verb
print(mlp_best_params)
print(mlp_report)
print("Mean Relative Accuracy of all outer folds is: ")
print(mlp_nested_score)

test_model = MLPClassifier(verbose=False,
                           learning_rate=mlp_best_params['learning_rate'],
                           activation=mlp_best_params['activation'],
                           hidden_layer_sizes=mlp_best_params['hidden_layer_
                           solver=mlp_best_params['solver'],
                           alpha=mlp_best_params['alpha']).fit(X_train, y_tr
print("The accuracy on the test dataset is: ")
print(custom_classification_scoring(y_test, test_model.predict(X_test), is_t
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Mean Relative Accuracy of this outer fold is:
0.7888297872340426
[CV] END ................................ score: (test=0.789) total time=
6.7min

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  6.7min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7736702127659574
[CV] END ................................ score: (test=0.774) total time=
6.7min

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed: 13.4min remaining:
0.0s

Mean Relative Accuracy of this outer fold is:
0.7753989361702126
[CV] END ................................ score: (test=0.775) total time=
6.7min
Mean Relative Accuracy of this outer fold is:
0.777127659574468
[CV] END ................................ score: (test=0.777) total time=
6.8min
Mean Relative Accuracy of this outer fold is:
```

```
0.7997340425531916
[CV] END ................................ score: (test=0.800) total time=
6.7min
{'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (10, 30, 1
0), 'learning_rate': 'adaptive', 'solver': 'sgd'}
              precision    recall  f1-score   support

         0.0       0.32      0.33      0.33       403
         1.0       0.17      0.17      0.17       358
         2.0       0.17      0.17      0.17       438
         3.0       0.14      0.10      0.12       305
         4.0       0.15      0.13      0.14       394
         5.0       0.16      0.17      0.16       464
         6.0       0.05      0.04      0.05       254
         7.0       0.14      0.14      0.14       392
         8.0       0.19      0.19      0.19       385
         9.0       0.39      0.55      0.46       367

    accuracy                           0.20      3760
   macro avg       0.19      0.20      0.19      3760
weighted avg       0.19      0.20      0.20      3760

Mean Relative Accuracy of all outer folds is:
0.7829521276595744

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed: 33.6min finished

The accuracy on the test dataset is:
0.7898936170212766
```

RF Classification Visualization

Based on both the Mean Relative Accuracy on all outer folds on the training dataset and then also on the testing dataset, the Random Forest Classifier performs the best. Here's a Graph of the Random Forest Classifier's predicted output vs actual value on the test set when trained on the entire dataset.

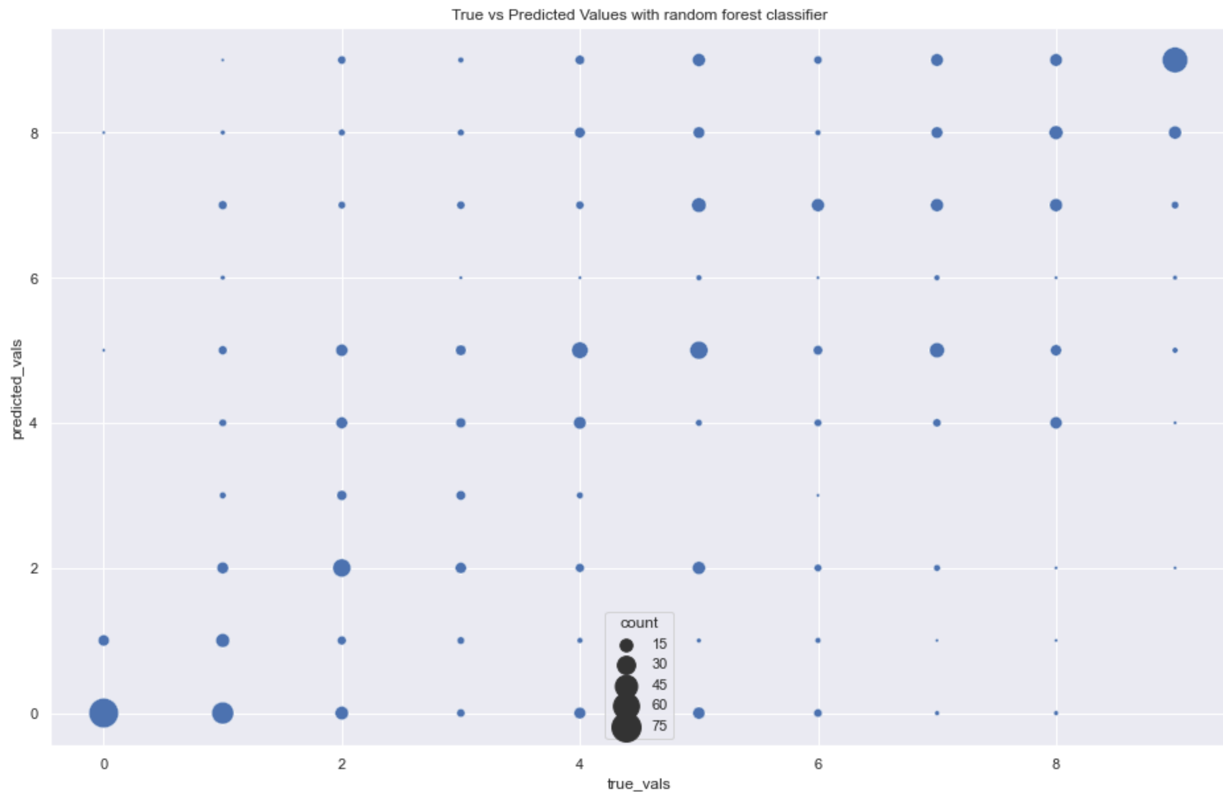
In [34]:
```
test_model = RandomForestClassifier(bootstrap=rf_best_params['bootstrap'],
                                    max_depth=rf_best_params['max_depth'],
                                    max_features=rf_best_params['max_feature
                                    n_estimators=rf_best_params['n_estimato
                                    n_jobs = -1).fit(X_train, y_train)
plotting_data = pd.DataFrame({'true_vals': y_test, 'predicted_vals': test_mo
```

In [35]:
```
counts = plotting_data.value_counts()
counts_dic = counts.to_dict()
plotting_data['count'] = np.zeros((plotting_data.shape[0],))
for index, row in plotting_data.iterrows():
    row['count'] = counts_dic[(row['true_vals'], row['predicted_vals'])]
```

In [36]:
```
plotting_data['count'].value_counts()
```

Out[36]:
```
16.0    96
78.0    78
13.0    65
30.0    60
59.0    59
7.0     49
15.0    45
44.0    44
14.0    42
6.0     36
12.0    36
18.0    36
8.0     32
5.0     30
4.0     28
9.0     27
2.0     26
25.0    25
11.0    22
21.0    21
20.0    20
10.0    20
3.0     18
17.0    17
1.0      8
Name: count, dtype: int64
```

In [37]:
```
sns.scatterplot(x='true_vals', y='predicted_vals',
                data = plotting_data, size='count', sizes=(0, 500)
                ).set_title('True vs Predicted Values with random forest classi
None
```



Most predictions do seem to be pretty close to their true value. Obviously, some are very far off, but the accuracy achieved is surprisingly good for how little data we have.

Regression Modeling

Now I will try to solve the same problem with a slightly different approach. I will treat the problem as regression rather than classification, still trying to predict a player's transfer fee. Note, I will need to use slightly different metrics to evaluate these models because the 'Mean Relative Accuracy' from the classification problems is no longer applicable due to this being a regression problem rather than classification into 10 different categories. The scoring that I have chosen to use is the classic R Squared metric for regression. I have also included information about the explained variance in each outer fold. Other than that, the cross validation process is very similar to what it was when performing classification.

In [38]:
```
reg_season_le = LabelEncoder()
class_df['Season'] = reg_season_le.fit_transform(class_df['Season'])

class_df.sort_values('Season')
```

Out[38]:

	Position	Age	Team_from	League_from	Team_to	League_to	Season	Transfer_fee
0	Right Midfield	27	FC Barcelona	LaLiga	Real Madrid	LaLiga	0	60000000
157	Left Midfield	23	Atlético Madrid	LaLiga2	Real Madrid	LaLiga	0	3500000
158	Defensive Midfield	24	Hamburger SV	1.Bundesliga	Everton	Premier League	0	3500000
159	Centre-Forward	23	Busan IPark	Korea, South	Perugia	Serie A	0	3500000
160	Attacking Midfield	27	Sevilla FC	LaLiga2	AEK Athens	Super League	0	3500000
...	...	...	...	...	...	...	...	...
4541	Left Midfield	23	Norwich	Championship	Cardiff	Premier League	18	11400000
4542	Attacking Midfield	25	Bristol City	Championship	Cardiff	Premier League	18	11350000
4543	Attacking Midfield	20	Sheffield Utd.	Championship	Bournemouth	Premier League	18	11300000
4545	Right Midfield	26	Huddersfield	Premier League	Stoke City	Championship	18	11200000
4699	Centre-Back	27	Swansea	Championship	West Brom	Championship	18	4500000

4700 rows × 8 columns

In [39]:
```
forming one-hot encoding on Position, Team_from, League_from, Team_to, and Le

 = pts.dmatrices('Transfer_fee ~ C(Position) + Age + C(Team_from) + C(League_
                 data = class_df,
                 return_type='dataframe')

 = Y['Transfer_fee'].to_numpy()
er = StandardScaler()
od.DataFrame(scaler.fit_transform(X),columns = X.columns)
ad()
```

Out[39]:

	Intercept	C(Position) [T.Central Midfield]	C(Position) [T.Centre-Back]	C(Position) [T.Centre-Forward]	C(Position) [T.Defensive Midfield]	C(Position) [T.Goalkeeper]	C(Position) [T.Left Midfield]	C(Positior [T.Left Back
0	0.0	-0.340381	-0.423933	-0.635141	-0.309559	-0.199557	-0.285402	-0.22423
1	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423
2	0.0	-0.340381	-0.423933	-0.635141	-0.309559	-0.199557	3.503832	-0.22423
3	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423
4	0.0	-0.340381	-0.423933	1.574454	-0.309559	-0.199557	-0.285402	-0.22423

5 rows × 1086 columns

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split( X, np_Y, test_size=0.2,
```

In [41]:
```
from sklearn.metrics import r2_score
from sklearn.metrics import explained_variance_score
from sklearn.metrics import mean_squared_error
def reg_scorer(y_true, y_pred, is_training=True):
    originalclass.extend(y_true)
    predictedclass.extend(y_pred)
    '''
    print("originalclass")
    print(originalclass)
    print("predictedclass")
    print(predictedclass)
    '''
    # Custom Accuracy function to measure the distance of the predicted valu
    # accuracy score that only determines if the datapoint was correctly cla
    exp_var = explained_variance_score(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)
    if is_training:
        print("Explained Variance of this outer fold is: ")
        print(exp_var)
        print("The R2 of this outer fold is: ")
        print(r2)
    return r2

def run_reg_model(model, parameters, X, y):
    clf = GridSearchCV(estimator=model, param_grid=parameters, n_jobs = -1)
    clf.fit(X, y)
    nested_r2 = cross_val_score(model, X=X, y=y, scoring=make_scorer(reg_sco
    return clf.best_params_, nested_r2
```

Model Selection

Now I have prepared my training and testing datasets similarly to before and written a custom regression scoring function. Let's compare the various regression models.

KNN Regressor

In [42]:
```
from sklearn.neighbors import KNeighborsRegressor
params = {
    'n_neighbors': np.arange(3, 16),
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean']
}

originalclass = []
predictedclass = []

rknn_best_params, rknn_nested_score = run_reg_model(KNeighborsRegressor(n_jo
print("The best parameters are: ")
print(rknn_best_params)
print("Mean r squared of all outer folds is: ")
print(rknn_nested_score)

test_model = KNeighborsRegressor(n_neighbors=rknn_best_params['n_neighbors']
                                  weights=rknn_best_params['weights'],
                                  metric=rknn_best_params['metric'],
                                  n_jobs = -1).fit(X_train, y_train)
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
-0.1817561913683461
The R2 of this outer fold is:
-0.27081315217402024
[CV] END ............................. score: (test=-0.271) total time=
0.2s
Explained Variance of this outer fold is:
0.050448153041256605
The R2 of this outer fold is:
0.00036678298815839 84
[CV] END .............................. score: (test=0.000) total time=
0.2s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.2s remaining:
0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.4s remaining:
0.0s

Explained Variance of this outer fold is:
-0.04437572009403001
The R2 of this outer fold is:
-0.1311301950953807
[CV] END ............................. score: (test=-0.131) total time=
0.2s
Explained Variance of this outer fold is:
-0.008762301897099478
The R2 of this outer fold is:
-0.049942968236491136
[CV] END ............................. score: (test=-0.050) total time=
0.2s
Explained Variance of this outer fold is:
```

```
-0.452933640600268
The R2 of this outer fold is:
-0.7282773376972558
[CV] END ............................. score: (test=-0.728) total time=
0.2s
The best parameters are:
{'metric': 'euclidean', 'n_neighbors': 11, 'weights': 'distance'}
Mean r squared of all outer folds is:
-0.23595937404299788
The r squared on the test dataset is:
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    0.9s finished
-0.05521216482953273
```

Linear Regressor

In [43]:
```
from sklearn.linear_model import LinearRegression

originalclass = []
predictedclass = []
#Note there are no parameters to optimize for Linear Regression
_ , rlr_nested_score = run_reg_model(LinearRegression(), {}, X_train, y_trai
print("Mean r squared of all outer folds is: ")
print(rlr_nested_score)

test_model = LinearRegression().fit(X_train, y_train)
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
-3.131901606994099e+28
The R2 of this outer fold is:
-3.132507019177874e+28
[CV] END ... score: (test=-31325070191778738790148866048.000) total time=
0.5s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.5s remaining:
0.0s

Explained Variance of this outer fold is:
-3.046767324440288e+28
The R2 of this outer fold is:
-3.0507405237411085e+28
[CV] END ... score: (test=-30507405237411085286232817664.000) total time=
0.5s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    1.0s remaining:
0.0s

Explained Variance of this outer fold is:
-2.1100450830669877e+28
The R2 of this outer fold is:
-2.114849348654067 2e+28
[CV] END ... score: (test=-21148493486540672208809754624.000) total time=
0.4s
Explained Variance of this outer fold is:
-1.9725058659260144e+28
The R2 of this outer fold is:
-1.9754110756270493e+28
[CV] END ... score: (test=-19754110756270493082924875776.000) total time=
0.4s
Explained Variance of this outer fold is:
-7.605559975500181e+28
The R2 of this outer fold is:
-7.607516355561761e+28
[CV] END ... score: (test=-76075163555617608687813656576.000) total time=
0.4s
Mean r squared of all outer folds is:
-3.576204864552372e+28

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    2.2s finished
```

```
The r squared on the test dataset is:
-2.3731710499587237e+28
```

Decision Tree Regressor

In [44]:
```
from sklearn.tree import DecisionTreeRegressor

params = {'max_depth': range(1, 11),
          'min_samples_split': range(10, 60, 10)
}
originalclass = []
predictedclass = []

rdt_best_params, rdt_nested_score = run_reg_model(DecisionTreeRegressor(), p
print("The best parameters are: ")
print(rdt_best_params)
print("Mean r squared of all outer folds is: ")
print(rdt_nested_score)

test_model = DecisionTreeRegressor(max_depth=rdt_best_params['max_depth'],
                                   min_samples_split=rdt_best_params['min_sam
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
/Users/jarrettbrunner/miniconda3/lib/python3.6/site-packages/joblib/exter
nals/loky/process_executor.py:706: UserWarning: A worker stopped while so
me jobs were given to the executor. This can be caused by a too short wor
ker timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
0.001077868694062678
The R2 of this outer fold is:
-0.011855568745091638
[CV] END ............................. score: (test=-0.012) total time=
0.3s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s remaining:
0.0s

Explained Variance of this outer fold is:
0.07509413581816493
The R2 of this outer fold is:
0.06726752710740036
[CV] END .............................. score: (test=0.067) total time=
0.3s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.6s remaining:
0.0s

Explained Variance of this outer fold is:
-0.05838898907601986
The R2 of this outer fold is:
-0.060285860372569555
[CV] END ............................. score: (test=-0.060) total time=
0.3s
Explained Variance of this outer fold is:
-0.10262455817205329
The R2 of this outer fold is:
-0.11176802616324744
[CV] END ............................. score: (test=-0.112) total time=
```

```
0.3s
Explained Variance of this outer fold is:
-0.05139187153799485
The R2 of this outer fold is:
-0.05438673423412954
[CV] END .............................. score: (test=-0.054) total time=
0.3s
The best parameters are:
{'max_depth': 10, 'min_samples_split': 50}
Mean r squared of all outer folds is:
-0.03420573248152756
The r squared on the test dataset is:
0.30901309606355787

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    1.4s finished
```

Random Forest Regressor

In [45]:
```
from sklearn.ensemble import RandomForestRegressor


params = {
    'bootstrap': [True],
    'max_depth': [10, 50],
    'max_features': ['auto', 'sqrt'],
    'n_estimators': [200, 1000]
}


originalclass = []
predictedclass = []

rrf_best_params, rrf_nested_score = run_reg_model(RandomForestRegressor(n_jo
print("The best parameters are: ")
print(rrf_best_params)
print("Mean r squared of all outer folds is: ")
print(rrf_nested_score)

test_model = RandomForestRegressor(bootstrap=rrf_best_params['bootstrap'],
                                  max_depth=rrf_best_params['max_depth'],
                                  max_features=rrf_best_params['max_features
                                  n_estimators=rrf_best_params['n_estimators
                                  n_jobs = -1).fit(X_train, y_train)
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
0.3576710679533307
The R2 of this outer fold is:
0.34978063337483734
[CV] END ................................ score: (test=0.350) total time=
7.5s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    7.5s remaining:
0.0s

Explained Variance of this outer fold is:
0.35536387823967186
The R2 of this outer fold is:
0.3489073947125245
[CV] END ................................ score: (test=0.349) total time=
7.0s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   14.5s remaining:
0.0s

Explained Variance of this outer fold is:
0.2693106057080349
The R2 of this outer fold is:
0.2672742587883862
[CV] END ................................ score: (test=0.267) total time=
7.7s
Explained Variance of this outer fold is:
```

```
0.35707509258638215
The R2 of this outer fold is:
0.3487129523901078
[CV] END ................................ score: (test=0.349) total time=
7.6s
Explained Variance of this outer fold is:
0.39833877353341895
The R2 of this outer fold is:
0.39794157748922887
[CV] END ................................ score: (test=0.398) total time=
7.2s
The best parameters are:
{'bootstrap': True, 'max_depth': 50, 'max_features': 'auto', 'n_estimator
s': 1000}
Mean r squared of all outer folds is:
0.3425233633510169

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   37.0s finished

The r squared on the test dataset is:
0.3139591415876605
```

Lasso Regression

In [46]:
```
from sklearn.linear_model import Lasso

params = {
    'alpha' : np.arange(0, 1, 0.1)
}


originalclass = []
predictedclass = []

rlm_best_params, rlm_nested_score = run_reg_model(Lasso(), params, X_train,
print("The best parameters are: ")
print(rlm_best_params)
print("Mean r squared of all outer folds is: ")
print(rlm_nested_score)

test_model = Lasso(alpha=rlm_best_params['alpha']).fit(X_train, y_train)
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
0.25992610731383314
The R2 of this outer fold is:
0.2573756399474405
[CV] END ................................ score: (test=0.257) total time=
2.6s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.6s remaining:
0.0s

Explained Variance of this outer fold is:
0.3038445723965032
The R2 of this outer fold is:
0.30344542875728286
[CV] END ................................ score: (test=0.303) total time=
2.8s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    5.4s remaining:
0.0s

Explained Variance of this outer fold is:
0.14344342037552626
The R2 of this outer fold is:
0.14209500521064067
[CV] END ................................ score: (test=0.142) total time=
2.8s
Explained Variance of this outer fold is:
0.33454273821820424
The R2 of this outer fold is:
0.33336747861064686
[CV] END ................................ score: (test=0.333) total time=
2.7s
Explained Variance of this outer fold is:
0.11549449447807247
The R2 of this outer fold is:
```

```
0.10487440959572736
[CV] END ................................ score: (test=0.105) total time=
2.5s
The best parameters are:
{'alpha': 0.9}
Mean r squared of all outer folds is:
0.2282315924243476

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   13.4s finished

The r squared on the test dataset is:
0.2599573877665836
```

Elastic Net Regression

In [47]:
```
from sklearn.linear_model import ElasticNet


params = {
    'alpha' : np.arange(0, 1, 0.1)
}


originalclass = []
predictedclass = []

ren_best_params, ren_nested_score = run_reg_model(ElasticNet(), params, X_tr
print("The best parameters are: ")
print(ren_best_params)
print("Mean r squared of all outer folds is: ")
print(ren_nested_score)

test_model = ElasticNet(alpha=ren_best_params['alpha']).fit(X_train, y_trai
print("The r squared on the test dataset is: ")
print(reg_scorer(y_test, test_model.predict(X_test), is_training=False))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent w
orkers.

Explained Variance of this outer fold is:
0.32146767839687307
The R2 of this outer fold is:
0.31952201645973266
[CV] END .............................. score: (test=0.320) total time=
0.2s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.2s remaining:
0.0s

Explained Variance of this outer fold is:
0.30926027780851106
The R2 of this outer fold is:
0.30911735441081045
[CV] END .............................. score: (test=0.309) total time=
0.2s

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.5s remaining:
0.0s

Explained Variance of this outer fold is:
0.22944962921316003
The R2 of this outer fold is:
0.22784273227408536
[CV] END .............................. score: (test=0.228) total time=
0.3s
Explained Variance of this outer fold is:
0.3513590655812793
The R2 of this outer fold is:
0.34991758103033765
[CV] END .............................. score: (test=0.350) total time=
0.2s
Explained Variance of this outer fold is:
0.3348139809487163
```

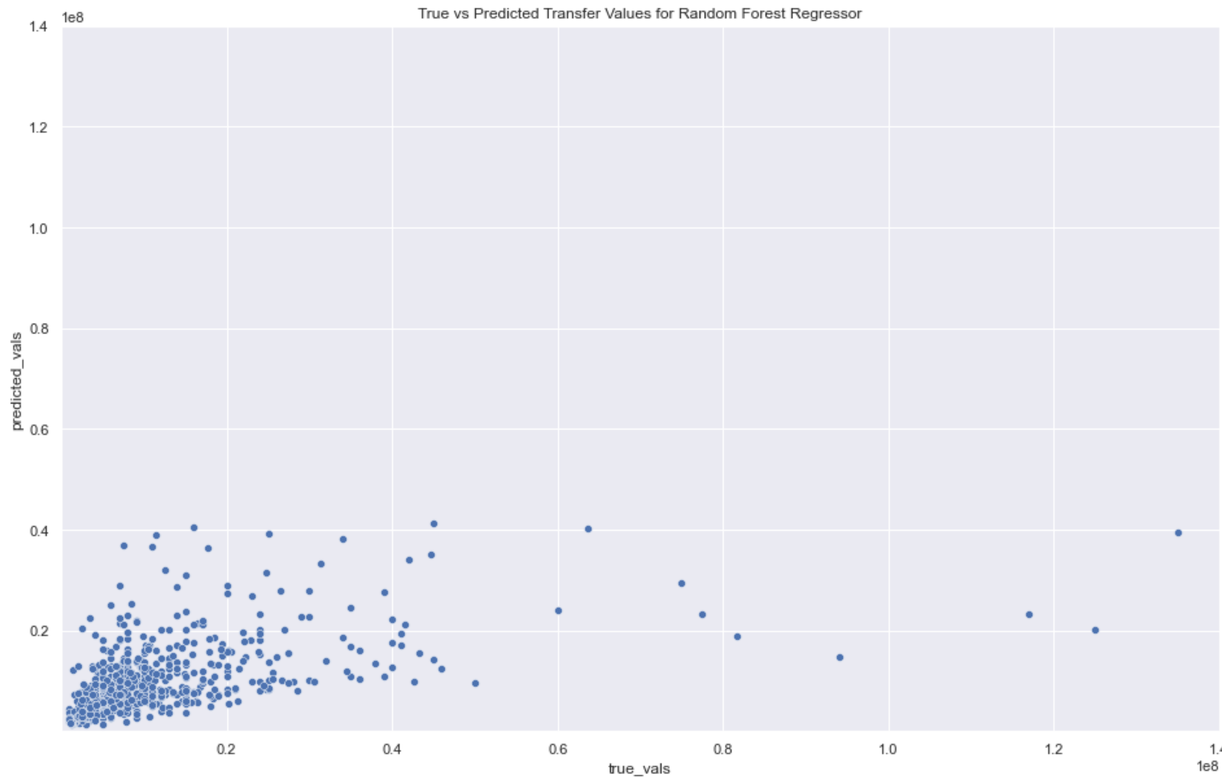
```
The R2 of this outer fold is:
0.31827191285389966
[CV] END .............................. score: (test=0.318) total time=
0.2s
The best parameters are:
{'alpha': 0.7000000000000001}
Mean r squared of all outer folds is:
0.3049343194057732

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    1.1s finished

The r squared on the test dataset is:
0.285552494348429
```

RF Regressor Visualization

It was close, but it looks like the best regression model is the Random Forest. I will now make a graph for the true vs predicted values similarl to the one I made for the classification.

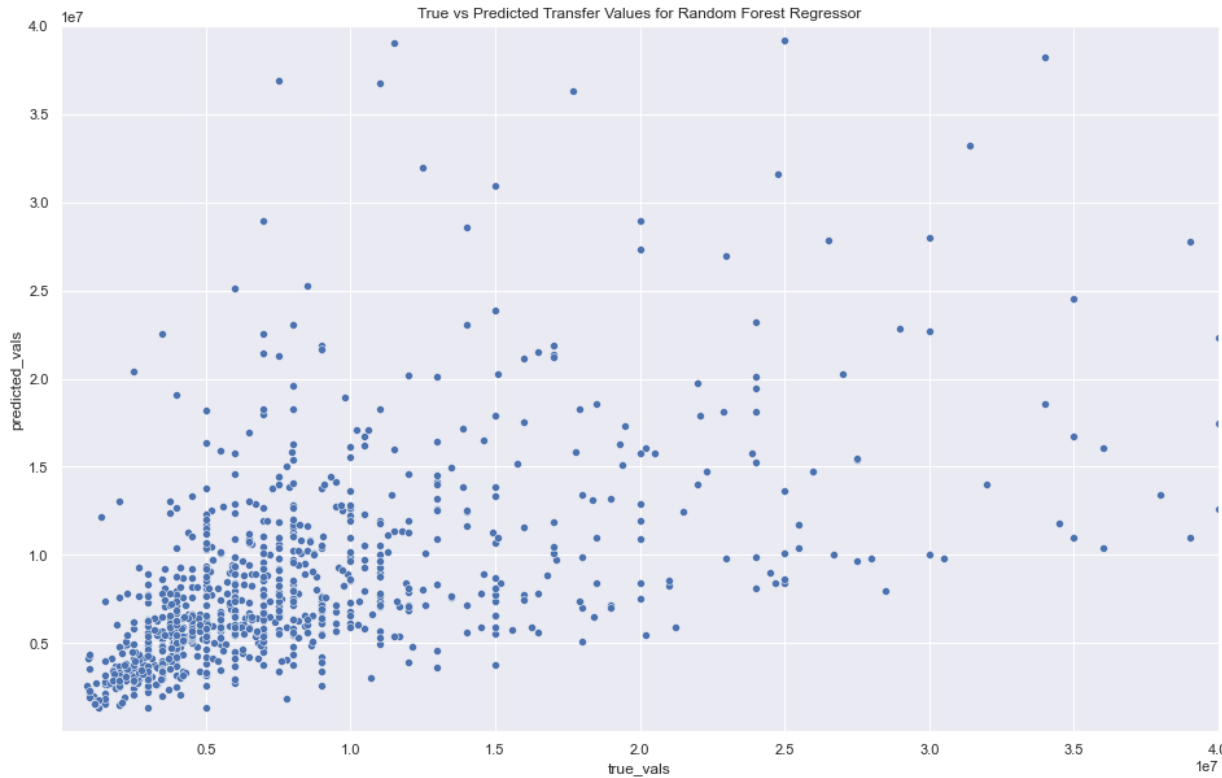
In [48]:
```
test_model = RandomForestRegressor(bootstrap=rrf_best_params['bootstrap'],
                                    max_depth=rrf_best_params['max_depth'],
                                    max_features=rrf_best_params['max_featu
                                    n_estimators=rrf_best_params['n_estimato
                                    n_jobs = -1).fit(X_train, y_train)
plotting_data = pd.DataFrame({'true_vals': y_test, 'predicted_vals': test_mo
```

In [49]:
```
fig, ax = plt.subplots()
sns.scatterplot(x='true_vals', y='predicted_vals',
                data = plotting_data, ax=ax).set_title('True vs Predicted Trans

ax.set_xlim(1,1.4e8)
ax.set_ylim(1,1.4e8)
plt.show()
None
```



As we can see the data does seem to generally follow the line of x=y, which is what we were hoping for. It should be noted that our regression is definitely skewed towards predicting lower transfer fees than what happens in reality, as a number of true values are over 0.4e8 (40 million), while our model only predicts 3 transfers to be over 40 million. I'll do another plot that doesn't include some of the outliers to get a better picture of what is happening with the majority of the data.

In [50]:
```
fig, ax = plt.subplots()
sns.scatterplot(x='true_vals', y='predicted_vals',
                data = plotting_data, ax=ax).set_title('True vs Predicted Trans
ax.set_xlim(1,0.4e8)
ax.set_ylim(1,0.4e8)
plt.show()
None
```



This graph confirms our previous suspicions. The model performs really well in predicting transfers with very low transfer fees, but the predictions begin to vary more as the true value of the transfer increases.

Trying a Time Series Split

In all of our previous ML models, we used a standard Train_Test_Split method to create training and testing datasets. This however, may not be the best method for this dataset, because it could be argued that these transfers are a time series of approximately twenty seasons. Thus, I will use the two best models from the previous sections (Random Forest Classifier and Random Forest Regressor) and train them using a TimeSeriesSplit.

In [51]:
```
unique_seasons = bucketed_df['Season'].nunique()
bucketed_df.sort_values('Season')
Y, X = pts.dmatrices('bucket ~ C(Position) + Age + C(Team_from) + C(League_f
                    data = bucketed_df,
                    return_type='dataframe')
np_Y = Y['bucket'].to_numpy()
scaler = StandardScaler()
X = pd.DataFrame(scaler.fit_transform(X),columns = X.columns)
```

In [52]:
```
from sklearn.model_selection import TimeSeriesSplit

tscv = TimeSeriesSplit(n_splits=unique_seasons - 1)
for train_index, test_index in tscv.split(X):
    X_train, X_test = X.loc[train_index], X.loc[test_index]
    y_train, y_test = np_Y[train_index], np_Y[test_index]
    model = RandomForestClassifier(bootstrap=rf_best_params['bootstrap'],
                                   max_depth=rf_best_params['max_depth'],
                                   max_features=rf_best_params['max_feature
                                   n_estimators=rf_best_params['n_estimato
                                   n_jobs = -1).fit(X_train, y_train)
    yhat = model.predict(X_test)
    custom_classification_scoring(y_test, yhat)
```

```
Mean Relative Accuracy of this outer fold is:
0.520242914979757
Mean Relative Accuracy of this outer fold is:
0.7497975708502026
Mean Relative Accuracy of this outer fold is:
0.8352226720647774
Mean Relative Accuracy of this outer fold is:
0.7886639676113361
Mean Relative Accuracy of this outer fold is:
0.7704453441295546
Mean Relative Accuracy of this outer fold is:
0.7388663967611337
Mean Relative Accuracy of this outer fold is:
0.6979757085020243
Mean Relative Accuracy of this outer fold is:
0.7834008097165992
Mean Relative Accuracy of this outer fold is:
0.7902834008097168
Mean Relative Accuracy of this outer fold is:
0.7931174089068828
Mean Relative Accuracy of this outer fold is:
0.7789473684210526
Mean Relative Accuracy of this outer fold is:
0.7963562753036437
Mean Relative Accuracy of this outer fold is:
0.7607287449392713
Mean Relative Accuracy of this outer fold is:
0.817004048582996
Mean Relative Accuracy of this outer fold is:
0.7680161943319839
Mean Relative Accuracy of this outer fold is:
0.8202429149797572
Mean Relative Accuracy of this outer fold is:
0.8639676113360324
Mean Relative Accuracy of this outer fold is:
0.8238866396761135
```

As we can see in the later folds (in which the model is trained on most of the data and then tested on the later years), the TimeSeriesSplit is actually slightly better for Random Forest Classifier than the normal TrainTestSplit is. Now we will do the same thing, but with Random Forest Regression.

In [53]:
```
Y, X = pts.dmatrices('Transfer_fee ~ C(Position) + Age + C(Team_from) + C(Le
                     data = class_df,
                     return_type='dataframe')

np_Y = Y['Transfer_fee'].to_numpy()
scaler = StandardScaler()
X = pd.DataFrame(scaler.fit_transform(X),columns = X.columns)
```

In [54]:
```
tscv = TimeSeriesSplit(n_splits=unique_seasons - 1)
for train_index, test_index in tscv.split(X):
    X_train, X_test = X.loc[train_index], X.loc[test_index]
    y_train, y_test = np_Y[train_index], np_Y[test_index]
    model = RandomForestRegressor(bootstrap=rrf_best_params['bootstrap'],
                                  max_depth=rrf_best_params['max_depth'],
                                  max_features=rrf_best_params['max_featu
                                  n_estimators=rrf_best_params['n_estimato
                                  n_jobs = -1).fit(X_train, y_train)
    yhat = model.predict(X_test)
    reg_scorer(y_test, yhat)
```

```
Explained Variance of this outer fold is:
-0.009776926651279272
The R2 of this outer fold is:
-28.117841915766085
Explained Variance of this outer fold is:
0.1439653102800994
The R2 of this outer fold is:
-15.600257786642462
Explained Variance of this outer fold is:
0.23656708868747967
The R2 of this outer fold is:
-4.634748590990988
Explained Variance of this outer fold is:
-0.31061217115911366
The R2 of this outer fold is:
-8.241972291902972
Explained Variance of this outer fold is:
0.03934795132908886
The R2 of this outer fold is:
-4.51701295332614
Explained Variance of this outer fold is:
-0.0016229637137128439
The R2 of this outer fold is:
-5.817129732839621
Explained Variance of this outer fold is:
-0.5337950481547977
The R2 of this outer fold is:
-8.474278877463993
Explained Variance of this outer fold is:
-0.167317359350851
The R2 of this outer fold is:
-4.684858732721283
Explained Variance of this outer fold is:
0.08334667248033123
The R2 of this outer fold is:
-45.417602208092646
Explained Variance of this outer fold is:
0.09426009303542482
The R2 of this outer fold is:
-7.603247013783932
Explained Variance of this outer fold is:
-0.2343135330761834
The R2 of this outer fold is:
-14.983129236552593
```

```
Explained Variance of this outer fold is:
-0.18468440249174933
The R2 of this outer fold is:
-5.150632953801281
Explained Variance of this outer fold is:
0.13426265089232847
The R2 of this outer fold is:
-5.613895408171319
Explained Variance of this outer fold is:
0.3699850131836424
The R2 of this outer fold is:
0.36085725743243025
Explained Variance of this outer fold is:
0.22368850020135567
The R2 of this outer fold is:
0.10475205322856007
Explained Variance of this outer fold is:
0.18954687603798392
The R2 of this outer fold is:
0.09795691467273915
Explained Variance of this outer fold is:
0.25253364603361395
The R2 of this outer fold is:
0.21402071988110338
Explained Variance of this outer fold is:
0.2396737311524786
The R2 of this outer fold is:
0.23689303316856936
```

Interestingly enough, the Random Forest Regression performed significantly worse on the TimeSeriesSplit data in comparison to the TrainTestSplit data. I would stick with normal TrainTestSplit if I were to use regression going forward.

Further Improvements / Next Steps

If I really wanted to make this model the best that it could possibly be, there are a number of further experiments that I could perform. I could perform some feature selection or PCA to see if a simpler input dataset can allow the model to achieve greater accuracy. I could also perform further hyperparameter optimization by both making the initial grid search larger and also including a second grid search to look over a range of hyperparameters surrounding the best ones from the original grid search. I would also compare a TimeSeriesSplit to TrainTestSplit for every single model rather than just the best ones with TrainTestSplit. Finally, I would also try to augment this dataset with more data from the last couple of seasons and just more data overall. The model could probably achieve a significant amount of improvement with all of these steps.