Football Transfers Seasons 2000 - 2019

This is the project EDA created for demonstration of different analysis and visualisation techniques.

Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
params = {'axes.facecolor': '#F8F7E9',
  'axes.edgecolor': 'black',
  'axes.labelcolor': 'black',
  'figure.facecolor': '#F8F7E9',
  'grid.color': '#b0b0b0',
  'grid.linestyle': '-',
  'text.color': 'black',
  'xtick.color': 'black',
  'ytick.color': 'black',
  'xtick.direction': 'out',
  'ytick.direction': 'out',
  'axes.titlesize': 'Large',
  'axes.labelsize': 'Large',
  'patch.edgecolor': 'white',
  'patch.force_edgecolor': True,
  'xtick.bottom': True,
  'xtick.top': False,
  'ytick.left': True,
  'ytick.right': False,
  'axes.spines.right': False,
  'axes.spines.top': False}

sns.set_theme(style = 'whitegrid',rc = params)
sns.color_palette("colorblind")
```

Out[2]:

Importing data

In [3]:
```
df = pd.read_csv("fotbal_prestupy_2000_2019.csv")
```

In [4]:
```
df.head()
```

Out[4]:

	Jméno	Pozice	Věk	Původní tým	Původní liga	Nový tým	Nová Liga	Sezóna	Odhadovaná hodnota	Pi
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 [5]:
```
df.shape
```

Out[5]:
```
(4700, 10)
```

Data consists of 10 columns and 4700 rows. Let's check type of the values and missing values

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4700 entries, 0 to 4699
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Jméno                4700 non-null   object 
 1   Pozice               4700 non-null   object 
 2   Věk                  4700 non-null   int64  
 3   Původní tým          4700 non-null   object 
 4   Původní liga         4700 non-null   object 
 5   Nový tým             4700 non-null   object 
 6   Nová  Liga           4700 non-null   object 
 7   Sezóna               4700 non-null   object 
 8   Odhadovaná hodnota   3440 non-null   float64
 9   Přestupová částka    4700 non-null   int64  
dtypes: float64(1), int64(2), object(7)
memory usage: 367.3+ KB
```

We have only 3 parameters with numerical values and one of them (Odhadovaná hodnota) has 1260 missing values. Before we start extracting information let's check if there are hiding some zero or wrong values.

Data cleaning

Before cleaning let's check number of unique values for the dataframe.

In [7]:
```
df.nunique()
```

Out[7]:
```
Jméno                   3104
Pozice                    17
Věk                       22
Původní tým              570
Původní liga             118
Nový tým                 325
Nová  Liga                65
Sezóna                    19
Odhadovaná hodnota       180
Přestupová částka        507
dtype: int64
```

We can see that most of the unique values have parameter "Jméno". Because the number of names is lesser than total number of rows we can assume that several players have had transfered more than once during seasons. Number of original leagues and clubs is bigger than new ones which is logical: players transferes to more prestige leagues/clubs from lesser ones.

Let's check "Jméno" parameter.

In [8]:
```
for name in df["Jméno"]:
    if len(name) <= 1:
        print(name)
```

All names have at least 2 characters. We can conclude that there are no zero values.

In [9]:
```
df["Pozice"].unique()
```

Out[9]:
```
array(['Right Winger', 'Centre-Forward', 'Left Winger', 'Centre-Ba
ck',
       'Central Midfield', 'Attacking Midfield', 'Defensive Midfie
ld',
       'Second Striker', 'Goalkeeper', 'Right-Back', 'Left Midfiel
d',
       'Left-Back', 'Right Midfield', 'Forward', 'Sweeper', 'Defen
der',
       'Midfielder'], dtype=object)
```

Pozice looks okay.

In [10]:
```
df["Věk"].unique()
```

Out[10]:
```
array([27, 25, 31, 21, 22, 26, 28, 23, 19, 24, 30, 20, 29, 35, 18,
32,  0,
       33, 34, 17, 16, 15])
```

we have zero value. Let's check how many players have this value.

In [11]:
```
df[df["Věk"]==0]
```

Out[11]:

	Jméno	Pozice	Věk	Původní tým	Původní liga	Nový tým	Nová Liga	Sezóna	Odhadovaná hodnota	Přestu č
236	Marzouq Al-Otaibi	Centre-Forward	0	Shabab	Saudi Arabia	Ittihad	Saudi Arabia	2000-2001	NaN	20

Only one player have this value. We can find his age from the internet or fill it with mean value.

In [12]:
```
df["Věk"].mean()
```

Out[12]:
```
24.33872340425532
```

From the internet we found that Marzouq Al-Otaibi was 26 years old in the season 2000-2001. We will replase zero value.

In [13]:
```
df["Věk"] = df["Věk"].replace([0], 26)
```

In [14]:
```
for team in df["Původní tým"].unique():
    if len(team) <= 3:
        print(team)
```

```
QPR
Rad
```

Original team has no wrong values.

In [15]:
```
for team in df["Původní liga"].unique():
    if len(team) <= 3:
        print(team)
```

```
MLS
```

In [16]:
```
for team in df["Nová  Liga"].unique():
    if len(team) <= 3:
        print(team)
```

```
MLS
```

We can conclude that teams and leagues have not wrong values

In [17]:
```
df["Sezóna"].unique()
```

Out[17]:
```
array(['2000-2001', '2001-2002', '2002-2003', '2003-2004', '2004-2
005',
       '2005-2006', '2006-2007', '2007-2008', '2008-2009', '2009-2
010',
       '2010-2011', '2011-2012', '2012-2013', '2013-2014', '2014-2
015',
       '2015-2016', '2016-2017', '2017-2018', '2018-2019'], dtype=
object)
```

Season looks good. Now, before we will observe "Odhadovaná hodnota", let's check the "Přestupová částka"

In [18]:
```
print(df["Přestupová částka"].min())
print(df["Přestupová částka"].max())
```

```
825000
222000000
```

Everything looks good. Now we can observe the "Odhadovaná hodnota" parameter. It has 1260 missing values. Let's find out how can we fill it.

In [19]:

```
print(df["Odhadovaná hodnota"].min())
print(df["Odhadovaná hodnota"].max())
```

```
50000.0
120000000.0
```

There is no zero in non-missing values.

As it was mentioned earlier, there only 3 columns with numerical values. To create the correlation map, we need to transform our categorical parameters into numerical ones.
We will use label encoder for this purpose.
First, let's mark all the columns we want to encode.

In [20]:

```
columns = df.columns[:-2]
columns
```

Out[20]:

```
Index(['Jméno', 'Pozice', 'Věk', 'Původní tým', 'Původní liga', 'N
ový tým',
       'Nová  Liga', 'Sezóna'],
      dtype='object')
```

In [21]:

```
columns = list(columns)
```

In [22]:

```
columns.pop(2)
columns
```

Out[22]:

```
['Jméno',
 'Pozice',
 'Původní tým',
 'Původní liga',
 'Nový tým',
 'Nová  Liga',
 'Sezóna']
```

Importing label enocder and encoding the columns.

In [23]:

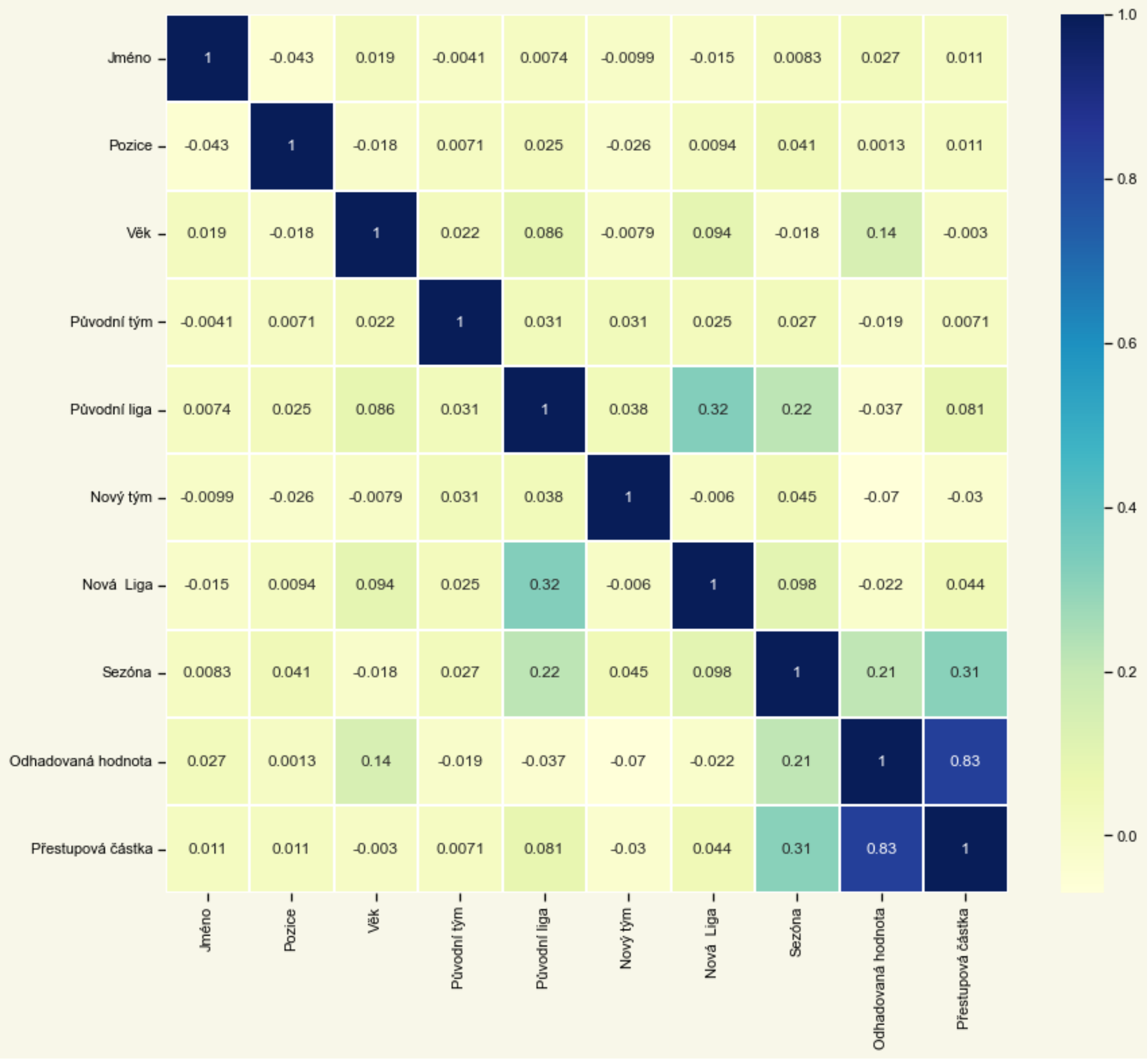
```
df_encode = df.copy()
```

In [24]:

```
from sklearn.preprocessing import LabelEncoder
labelencoder=LabelEncoder()
for column in columns:
    df_encode[column] = labelencoder.fit_transform(df_encode[column
```

Creating heatmap of correlations.

In [25]:
```
plt.figure(figsize=(14,12))
sns.heatmap(df_encode.corr(),linewidths=.1,cmap="YlGnBu", annot=Tru
plt.yticks(rotation=0);
```



As we can see, the "Odhadovaná hodnota" parameter is most correlated with "Přestupová částka", which is no surprise. Next close parameter is 'Sezóna' (0,21) and then 'Věk' (0,14). All other parameters are have almost zero correlation. Even 'Sezóna' and 'Věk' have quite poor values of coefficient. Predictions based only on one parameter will lead to errors, so we will not fill the "Odhadovaná hodnota" parameter and will use its non-missing values in our further steps.

Extraction of information

First, let's start with values "of all time".

From earlier EDA we already know that maximum price for the player is 222 000 000, let's find out this player.

In [26]:
```
df[df["Přestupová částka"] == 222000000]
```

Out[26]:

	Jméno	Pozice	Věk	Původní tým	Původní liga	Nový tým	Nová Liga	Sezóna	Odhadovaná hodnota	Přestu čá
4211	Neymar	Left Winger	25	FC Barcelona	LaLiga	Paris SG	Ligue 1	2017-2018	100000000.0	22200

Neymar is the most priciest player of all seasons. Next is the player with least price, which is 825 000

In [27]:
```
df[df["Přestupová částka"] == 825000]
```

Out[27]:

	Jméno	Pozice	Věk	Původní tým	Původní liga	Nový tým	Nová Liga	Sezóna	Odhadovaná hodnota
741	Rémo Meyer	Centre-Back	21	Lausanne-Sport	Challenge League	1860 Munich	1.Bundesliga	2002-2003	NaN

Let's check the ratio between prices of these two players.

In [28]:
```
df["Přestupová částka"].max()/df["Přestupová částka"].min()
```

Out[28]:
```
269.09090909090907
```

The ratio between minimum price and maximum one is 269. Pretty impressive.

Now, let's check top 5 players.

In [29]:
```
df_top5 = df.copy()
df_top5 = df_top5.groupby(["Sezóna", "Jméno", "Pozice", "Věk"])["Př
df_top5 = df_top5.sort_values(by=["Přestupová částka"],ascending =
df_top5.head(5)
```

Out[29]:

	Sezóna	Jméno	Pozice	Věk	Přestupová částka
4346	2017-2018	Neymar	Left Winger	25	222000000
4553	2018-2019	Kylian Mbappé	Right Winger	19	135000000
4362	2017-2018	Philippe Coutinho	Attacking Midfield	25	125000000
4468	2018-2019	Cristiano Ronaldo	Centre-Forward	33	117000000
4356	2017-2018	Ousmane Dembélé	Right Winger	20	115000000

```
As we can see, all top 5 are from last two seasons and 4 of 5
positions are forward's positions. 4 of 5 players are in the age
below 30.
```

Now, let's check top 5 clubs, who spent the most.

In [30]:
```
df_top5buy = df.copy()
df_top5buy = df_top5buy.groupby(["Nový tým"])["Přestupová částka"].
df_top5buy = df_top5buy.sort_values(by=["Přestupová částka"],ascend
df_top5buy.head(5)
```

Out[30]:

	Nový tým	Přestupová částka
83	Chelsea	1820650000
192	Man City	1800520000
243	Real Madrid	1680650000
110	FC Barcelona	1673040000
194	Man Utd	1497360000

Chelsea is the club wich spent the most with value of 1 820 650 000. Out of curiosity let's check the club with the least spent and compare it to Chelsea.

In [31]:
```
df_top5buy["Přestupová částka"].min()
```

Out[31]:
```
900000
```

In [32]:
```
df_top5buy[df_top5buy["Přestupová částka"] == 900000]
```

Out[32]:

	Nový tým	Přestupová částka
33	Ascoli	900000

In [33]:
```
df_top5buy["Přestupová částka"].max()/df_top5buy["Přestupová částka
```

Out[33]:
```
2022.9444444444443
```

The team with the least spent is Ascoli and compare to Chelsea it spent almost 2023 times less money!

Now it is time for the top 5 clubs, who receive the most.

In [34]:
```
df_top5sell = df.copy()
df_top5sell = df_top5sell.groupby(["Původní tým"])["Přestupová část
df_top5sell = df_top5sell.sort_values(by=["Přestupová částka"],asce
df_top5sell.head(5)
```

Out[34]:

	Původní tým	Přestupová částka
348	Monaco	948170000
197	FC Porto	917550000
426	Real Madrid	891400000
124	Chelsea	839530000
321	Liverpool	798410000

Chelsea is in the both top 5.

We have total value of fee spent by teams and total value of fee recieved by teams. What if we find the difference between these values and create top 5 of clubs with the biggest profit?

In [35]:

```
df_top5buy = df_top5buy.rename(columns={"Nový tým":"Původní tým"})
data_profit = pd.merge(df_top5sell, df_top5buy, on = "Původní tým")
data_profit["Result"] = data_profit["Přestupová částka_x"] - data_p
data_profit = data_profit.sort_values(by=["Result"],ascending = Fal
data_profit
```

Out[35]:

	Původní tým	Přestupová částka_x	Přestupová částka_y	Result
1	FC Porto	917550000	360810000	556740000
6	Benfica	785750000	334700000	451050000
21	Udinese Calcio	472500000	130000000	342500000
34	River Plate	348230000	23600000	324630000
15	Parma	554320000	290530000	263790000
...	...	...	...	...
29	Paris SG	394630000	1274780000	-880150000
8	FC Barcelona	752100000	1673040000	-920940000
18	Man Utd	527570000	1497360000	-969790000
3	Chelsea	839530000	1820650000	-981120000
27	Man City	419250000	1800520000	-1381270000

280 rows × 4 columns

In [36]:

```
data_profit_top5 = data_profit.copy()
data_profit_top5 = data_profit_top5.head(5)
data_profit_tail5 = data_profit.copy()
data_profit_tail5 = data_profit_tail5.tail(5)

data_profit_tops = pd.concat([data_profit_top5, data_profit_tail5])
data_profit_tops
```

Out[36]:

	Původní tým	Přestupová částka_x	Přestupová částka_y	Result
1	FC Porto	917550000	360810000	556740000
6	Benfica	785750000	334700000	451050000
21	Udinese Calcio	472500000	130000000	342500000
34	River Plate	348230000	23600000	324630000
15	Parma	554320000	290530000	263790000
29	Paris SG	394630000	1274780000	-880150000
8	FC Barcelona	752100000	1673040000	-920940000
18	Man Utd	527570000	1497360000	-969790000
3	Chelsea	839530000	1820650000	-981120000
27	Man City	419250000	1800520000	-1381270000

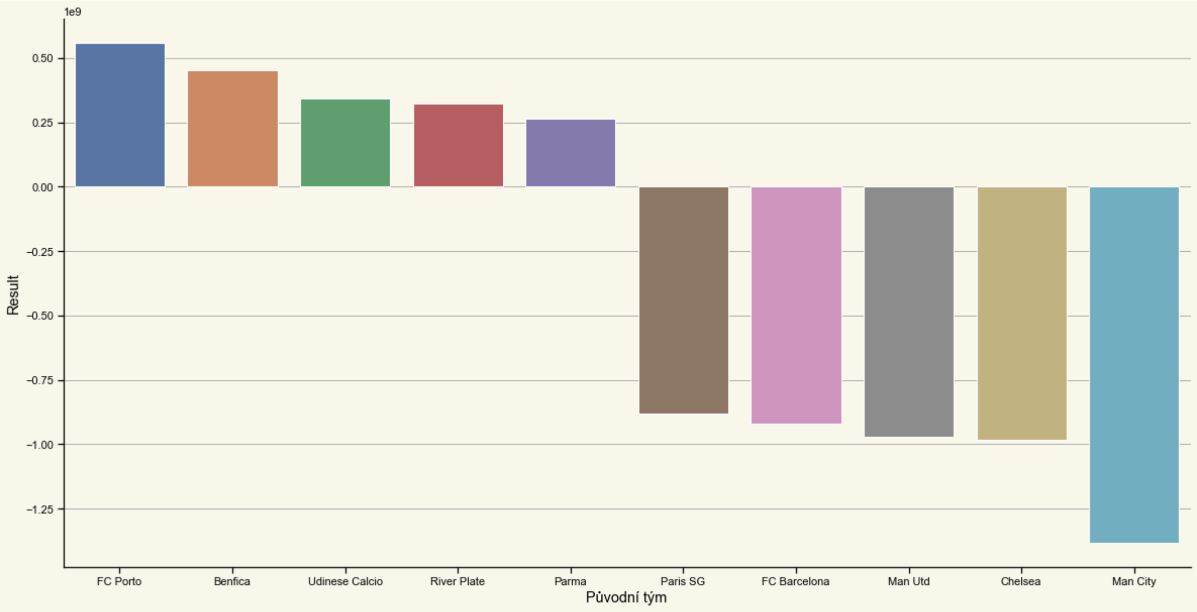
Now let's check leagues.

In [37]:

```
plt.figure(figsize=(20,10))
sns.barplot(data = data_profit_tops, x = "Původní tým", y = "Result
```

Out[37]:

```
<AxesSubplot:xlabel='Původní tým', ylabel='Result'>
```



Team with the biggest "pure" profit is FC Porto with value 556 740 000. Man City has a "pure" losses 1 381 270 000 and is a winner in this category.

In [38]:

```
df_top5l = df.copy()
df_top5l = df_top5l.groupby(["Nová  Liga"])["Přestupová částka"].su
df_top5l = df_top5l.sort_values(by=["Přestupová částka"],ascending
df_top5l.head(5)
```

Out[38]:

	Nová Liga	Přestupová částka
46	Premier League	14695400000
54	Serie A	7535220000
36	LaLiga	6680360000
43	Ligue 1	3682720000
24	1.Bundesliga	3599645000

Top 5 leagues are European leagues. England on the first place, Italy on the second and Spain on the third. This means that European football market is the largest one.

In [39]:

```
df_top5l = df.copy()
df_top5l = df_top5l.groupby(["Původní liga"])["Přestupová částka"].
df_top5l = df_top5l.sort_values(by=["Přestupová částka"],ascending
df_top5l.head(5)
```

Out[39]:

	Původní liga	Přestupová částka
84	Premier League	7248510000
97	Serie A	7083980000
68	LaLiga	5533860000
78	Ligue 1	4396890000
40	1.Bundesliga	3062960000

Again top 5 are European leagues with the same order.

Now it is time to check seasons.

In [40]:

```
df_top5s = df.copy()
df_top5s = df_top5s.groupby(["Sezóna"])["Přestupová částka"].sum().
df_top5s = df_top5s.sort_values(by=["Přestupová částka"],ascending
df_top5s.head(5)
```

Out[40]:

	Sezóna	Přestupová částka
17	2017-2018	4748180000
16	2016-2017	3979920000
18	2018-2019	3435670000
15	2015-2016	3415910000
13	2013-2014	2878720000

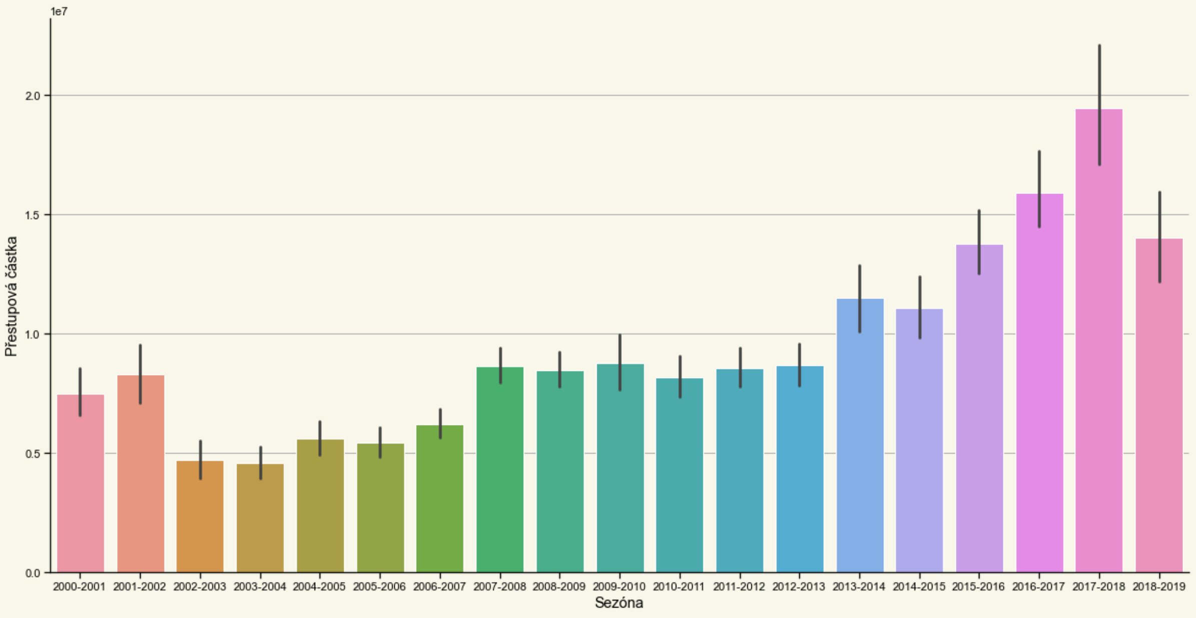
We can also make visualisation of seasons.

In [41]:

```
plt.figure(figsize=(20,10))
sns.barplot(data = df, x = "Sezóna", y = "Přestupová částka")
```

Out[41]:

```
<AxesSubplot:xlabel='Sezóna', ylabel='Přestupová částka'>
```



Unsurprisingly in top 5 are the last 5 season. The last season is only on the third place. From the graph above we can observe stagnation in seasons 2007-2013 (possibly due to World Economical Crysis) and decrease in fee value for the last season (reason is unknown).

Another interesting parameter is the "Pozice". Let's find out the most transferring positions.

In [42]:

```
df_top5_pozice = df.copy()
df_top5_pozice = df_top5_pozice.groupby(["Pozice"])["Přestupová čás
df_top5_pozice = df_top5_pozice.sort_values(by=["Přestupová částka"
df_top5_pozice.head(5)
```

Out[42]:

	Pozice	Přestupová částka
9	Left Winger	1.290464e+07
13	Right Winger	1.193036e+07
1	Central Midfield	1.009624e+07
0	Attacking Midfield	9.824178e+06
3	Centre-Forward	9.590271e+06

If we look on the mean values for each position, we will see that the most priceable position is Left Winger followed by Right winger and Central Midfield. This can be explained by top 5 of player where on the first three places are players with dame positions.

In [43]:

```
df_top5_pozice_sum = df.copy()
df_top5_pozice_sum = df_top5_pozice_sum.groupby(["Pozice"])["Přestu
df_top5_pozice_sum = df_top5_pozice_sum.sort_values(by=["Přestupová
df_top5_pozice_sum.head(5)
```

Out[43]:

	Pozice	Přestupová částka
3	Centre-Forward	11680950000
2	Centre-Back	6032295000
1	Central Midfield	4916870000
0	Attacking Midfield	4185100000
5	Defensive Midfield	3695720000

For the total sum on position Centre-Forward goes up on the first place while previous top 2 not even in the top 5 now. It can be explained by the count of transfer fo each position. Let's check it.

In [44]:
```
df_pozice_count = df.copy()
df_pozice_count = df_pozice_count.groupby(["Pozice"])["Původní tým"
df_pozice_count = df_pozice_count.sort_values(by=["Původní tým"],as
df_pozice_count.head(5)
```

Out[44]:

	Pozice	Původní tým
3	Centre-Forward	1218
2	Centre-Back	714
1	Central Midfield	487
0	Attacking Midfield	426
5	Defensive Midfield	411

In [45]:
```
data_diff = pd.merge(df_top5_pozice, df_pozice_count, on = "Pozice"
data_diff.head(5)
```

Out[45]:

	Pozice	Přestupová částka	Původní tým
0	Left Winger	1.290464e+07	267
1	Right Winger	1.193036e+07	305
2	Central Midfield	1.009624e+07	487
3	Attacking Midfield	9.824178e+06	426
4	Centre-Forward	9.590271e+06	1218

In [46]:
```
data_diff.corr()['Přestupová částka']
```

Out[46]:
```
Přestupová částka    1.000000
Původní tým          0.541621
Name: Přestupová částka, dtype: float64
```

As we can see, correlation between number of transfer and total amount of fee is almos 1. Let' return to the mean values.

In [47]:

```
df_top5_pozice.head(5)
```

Out[47]:

	Pozice	Přestupová částka
9	Left Winger	1.290464e+07
13	Right Winger	1.193036e+07
1	Central Midfield	1.009624e+07
0	Attacking Midfield	9.824178e+06
3	Centre-Forward	9.590271e+06

What if we drop top 5 players of all time from the initial dataframe and compare top 5 mean fee with this one?

In [48]:

```
df_top5_pozice_without = df.copy()
top = [4346, 4553, 4362, 4468, 4356]
for i in top:
    df_top5_pozice_without.drop(i, axis = 0, inplace = True)
df_top5_pozice_without = df_top5_pozice_without.groupby(["Pozice"])
df_top5_pozice_without = df_top5_pozice_without.sort_values(by=["Př
df_top5_pozice_without.head(5)
```

Out[48]:

	Pozice	Přestupová částka
9	Left Winger	1.280579e+07
13	Right Winger	1.193342e+07
1	Central Midfield	1.009624e+07
0	Attacking Midfield	9.824178e+06
3	Centre-Forward	9.590271e+06

Looks like top 5 player doesnt change order of positions, which means that position are the most expensive.

Now let's check top 5 teams, whith highest number of bought/selled players

In [49]:

```
df_top5_playernumber_buy = df.copy()
df_top5_playernumber_buy = df_top5_playernumber_buy.groupby(["Nový
df_top5_playernumber_buy = df_top5_playernumber_buy.sort_values(by=
df_top5_playernumber_buy.head(5)
```

Out[49]:

	Nový tým	Jméno
159	Inter	97
83	Chelsea	96
192	Man City	94
282	Spurs	93
165	Juventus	87

In [50]:

```
df_top5_playernumber_sell = df.copy()
df_top5_playernumber_sell = df_top5_playernumber_sell.groupby(["Pův
df_top5_playernumber_sell = df_top5_playernumber_sell.sort_values(b
df_top5_playernumber_sell.head(5)
```

Out[50]:

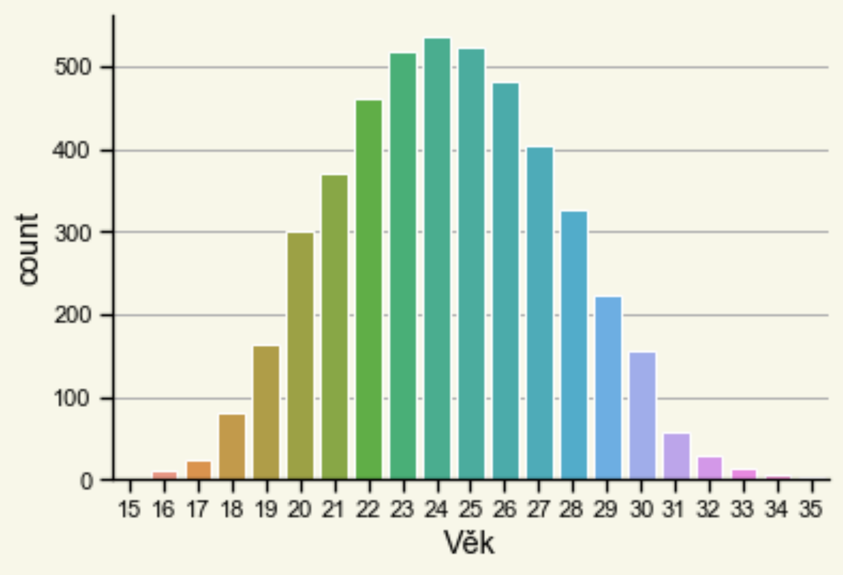
	Původní tým	Jméno
263	Inter	68
487	Spurs	63
277	Juventus	59
124	Chelsea	57
197	FC Porto	56

Inter has the biggest transfer of players in all seasons summary.

The last one before we move to seasonality is the "Věk" parameter. Let's check its distribution.

```
In [51]: sns.countplot(x = df["Věk"], data = df)
```

```
Out[51]: <AxesSubplot:xlabel='Věk', ylabel='count'>
```



We can observe beautiful Gaussian distribution here. The most popular age for a transfer is 24. What if we check mean value of age for every position?

In [52]:

```
df_age_position = df.copy()
df_age_position = df_age_position.groupby(["Pozice"])["Věk"].mean()
df_age_position = df_age_position.sort_values(by=["Věk"],ascending
df_age_position
```

Out[52]:

```
                Pozice        Věk
 6             Forward  27.000000
11          Midfielder  27.000000
 7          Goalkeeper  26.022222
16             Sweeper  26.000000
 8        Left Midfield  25.356322
12       Right Midfield  24.904762
 5   Defensive Midfield  24.610706
 3       Centre-Forward  24.523810
15       Second Striker  24.446154
 2          Centre-Back  24.431373
 0   Attacking Midfield  24.197183
14           Right-Back  24.154696
10            Left-Back  24.128889
 1     Central Midfield  23.845996
13         Right Winger  23.645902
 9          Left Winger  23.471910
 4             Defender  17.000000
```

Looks like some position have a few values and need correction. Let's return to the count of position and check how many positions have less than 10 values.

In [53]:

```
df_pozice_count
```

Out[53]:

	Pozice	Původní tým
3	Centre-Forward	1218
2	Centre-Back	714
1	Central Midfield	487
0	Attacking Midfield	426
5	Defensive Midfield	411
13	Right Winger	305
9	Left Winger	267
10	Left-Back	225
14	Right-Back	181
7	Goalkeeper	180
15	Second Striker	130
8	Left Midfield	87
12	Right Midfield	63
6	Forward	3
11	Midfielder	1
4	Defender	1
16	Sweeper	1

Last 4 position should be removed from our dataframe for better results.

In [54]:
```
positions = ["Forward", "Midfielder", "Defender", "Sweeper"]
for pos in positions:
    df_age_position.drop(df_age_position.loc[df_age_position['Pozic
df_age_position
```

Out[54]:

	Pozice	Věk
7	Goalkeeper	26.022222
8	Left Midfield	25.356322
12	Right Midfield	24.904762
5	Defensive Midfield	24.610706
3	Centre-Forward	24.523810
15	Second Striker	24.446154
2	Centre-Back	24.431373
0	Attacking Midfield	24.197183
14	Right-Back	24.154696
10	Left-Back	24.128889
1	Central Midfield	23.845996
13	Right Winger	23.645902
9	Left Winger	23.471910

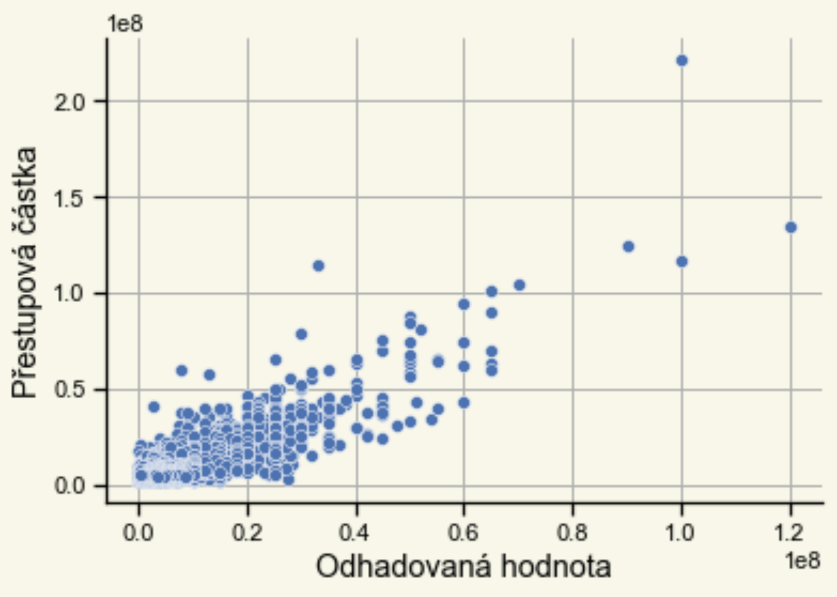
Goalkeeper is the most aged position while wingers are younger ones.

In [63]:
```
df_pred = df.copy()
df_pred = df_pred[df_pred["Odhadovaná hodnota"].isnull() == False]
```

In [65]:
```
df_pred["Difference"] = df_pred["Odhadovaná hodnota"] - df_pred["Př
```

In [66]:
```
sns.scatterplot(data = df_pred, x = "Odhadovaná hodnota", y = "Přes
```

Out[66]:
```
<AxesSubplot:xlabel='Odhadovaná hodnota', ylabel='Přestupová částk
a'>
```



```
Scatter plot shows linear dependence of "Přestupová částka" on
"Odhadovaná hodnota" with some outliers.
```

In [78]:
```
print("Minimal difference: ", df_pred["Difference"].abs().min())
print("Max negative difference: ", df_pred["Difference"].min())
print("Max positive difference: ", df_pred["Difference"].max())
print("Number of precise predictions: ", df_pred[df_pred["Differenc
print("Percent of precise predictions: ", df_pred[df_pred["Differen
```

```
Minimal difference:  0.0
Max negative difference:  -122000000.0
Max positive difference:  24500000.0
Number of precise predictions:  210
Percent of precise predictions:  6.104651162790697
```

In [ ]:

Seasonality

Let's start with top 5 most expencive players for each season.

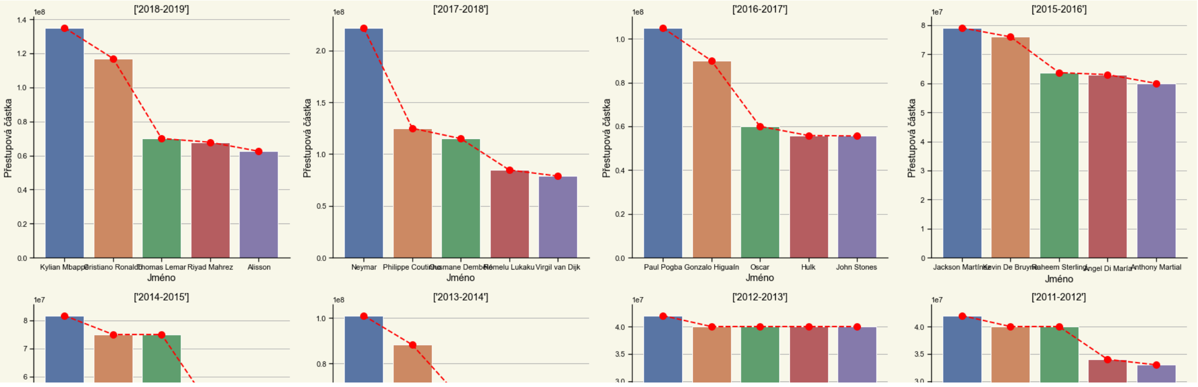
In [55]:
```
df_top5_season_p = df.copy()
df_top5_season_p = df_top5_season_p.groupby(["Sezóna", "Jméno"])["P
df_top5_season_p = df_top5_season_p.sort_values(by=["Sezóna","Přest
df_top5_season_p = df_top5_season_p.groupby("Sezóna").head(5).reset
df_top5_season_p
```

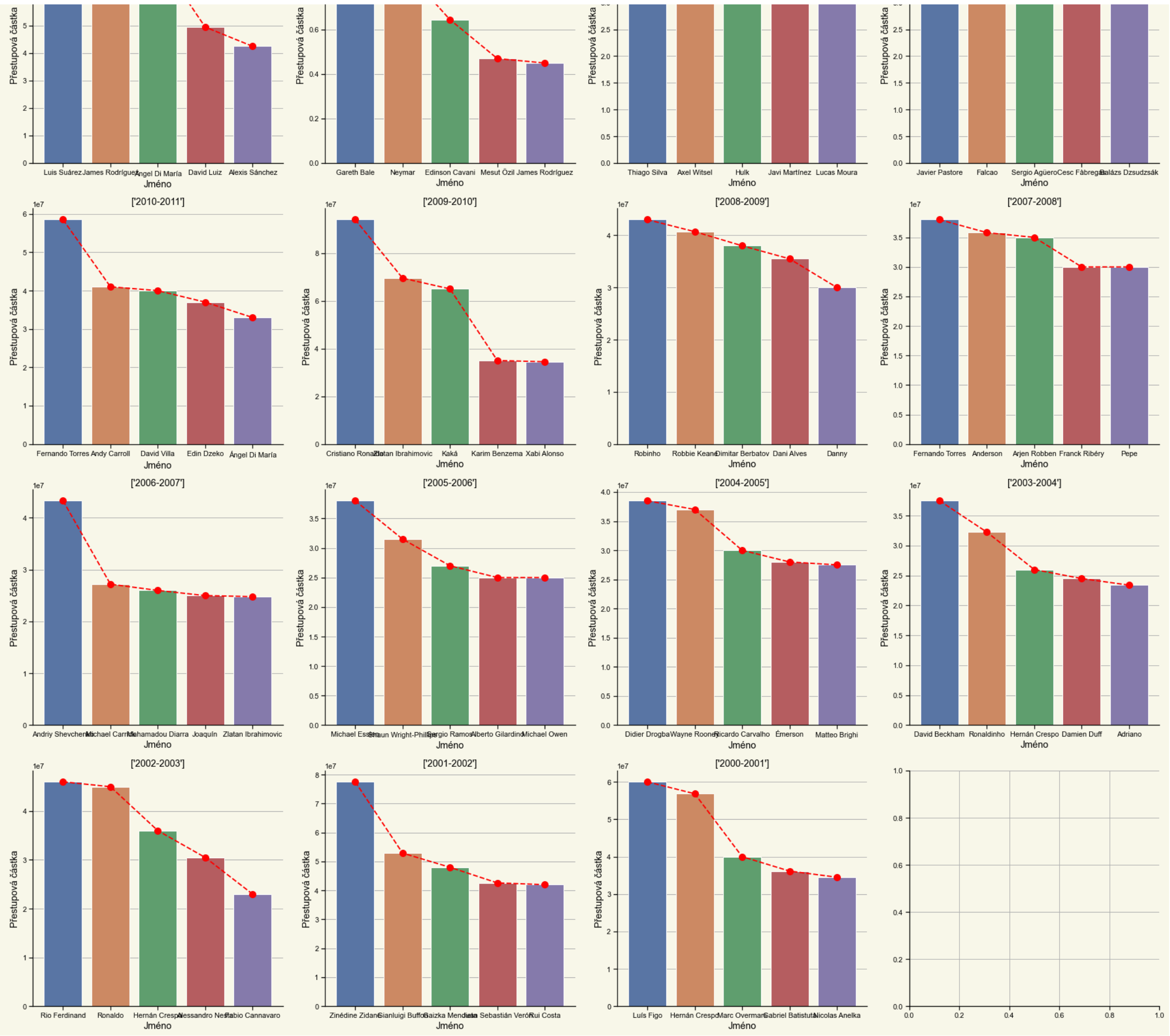
Out[55]:

	index	Sezóna	Jméno	Přestupová částka
0	4522	2018-2019	Kylian Mbappé	135000000
1	4437	2018-2019	Cristiano Ronaldo	117000000
2	4611	2018-2019	Thomas Lemar	70000000
3	4582	2018-2019	Riyad Mahrez	67800000
4	4405	2018-2019	Alisson	62500000
...	...	...	...	...
90	149	2000-2001	Luís Figo	60000000
91	108	2000-2001	Hernán Crespo	56810000
92	151	2000-2001	Marc Overmars	40000000
93	92	2000-2001	Gabriel Batistuta	36150000
94	168	2000-2001	Nicolas Anelka	34500000

95 rows × 4 columns

In [56]:
```
list_df = np.array_split(df_top5_season_p, 19)
fig, ax = plt.subplots(5,4,figsize=(25,30))
ax = ax.flatten()
for i in range(0,19):
    sns.barplot(data = list_df[i] , x = "Jméno", y = "Přestupová čá
    ax[i].plot(
        ax[i].get_xticks(), list_df[i]["Přestupová částka"],
        color='red', linestyle='--', marker='.',
        markersize=20, linewidth=2
    )
    lims = ax[i].get_ylim()
    ax[i].set_title(list_df[i]["Sezóna"].unique())
plt.tight_layout()
```





Now top 5 team with biggest spences for each season.

In [57]:

```
df_top5_season_t = df.copy()
df_top5_season_t = df_top5_season_t.groupby(["Sezóna", "Nový tým"])
df_top5_season_t = df_top5_season_t.sort_values(by=["Sezóna","Přest
df_top5_season_t = df_top5_season_t.groupby("Sezóna").head(5).reset
df_top5_season_t
```

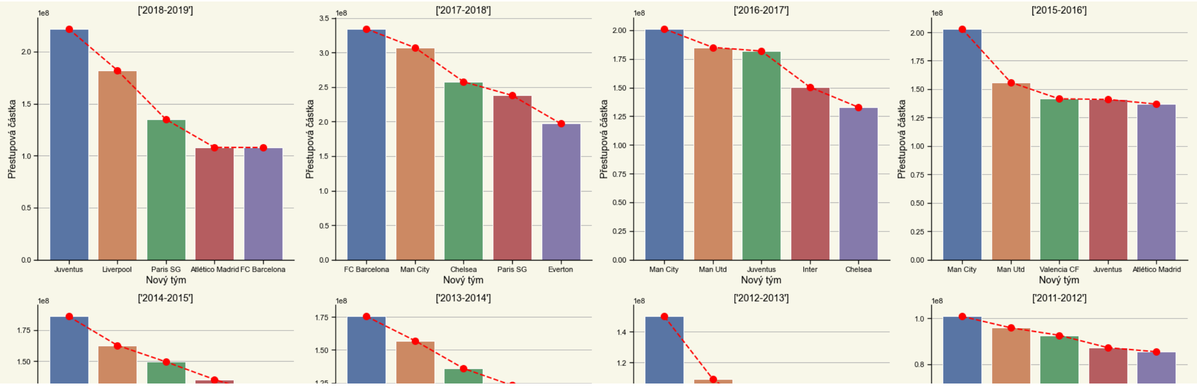
Out[57]:

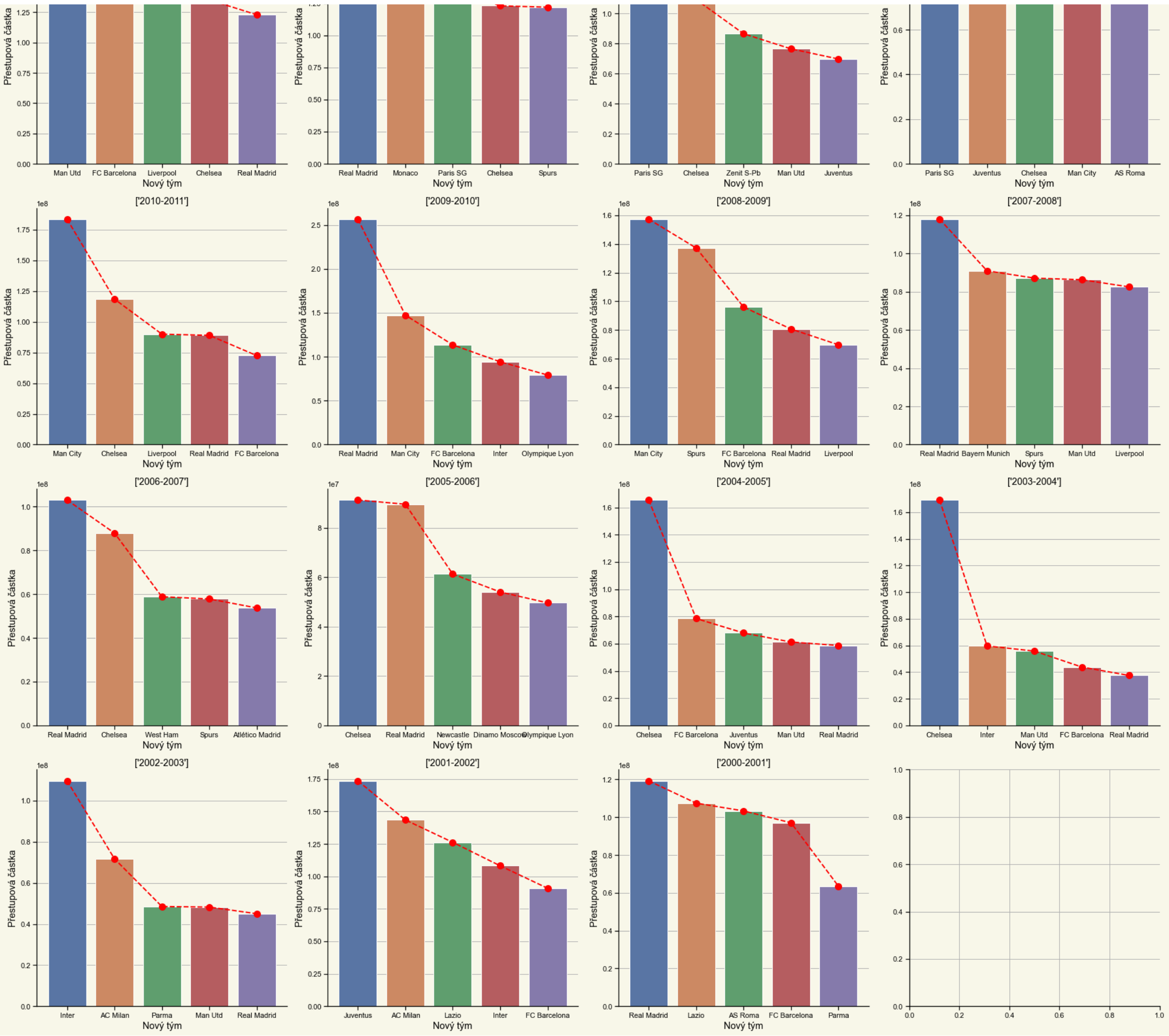
	index	Sezóna	Nový tým	Přestupová částka
0	1831	2018-2019	Juventus	221900000
1	1837	2018-2019	Liverpool	182200000
2	1852	2018-2019	Paris SG	135000000
3	1790	2018-2019	Atlético Madrid	108000000
4	1814	2018-2019	FC Barcelona	107900000
...	...	...	...	...
90	76	2000-2001	Real Madrid	119250000
91	49	2000-2001	Lazio	107460000
92	4	2000-2001	AS Roma	103350000
93	31	2000-2001	FC Barcelona	97100000
94	69	2000-2001	Parma	63550000

95 rows × 4 columns

In [58]:

```
list_df = np.array_split(df_top5_season_t, 19)
fig, ax = plt.subplots(5,4,figsize=(25,30))
ax = ax.flatten()
for i in range(0,19):
    sns.barplot(data = list_df[i] , x = "Nový tým", y = "Přestupová
    ax[i].plot(
        ax[i].get_xticks(), list_df[i]["Přestupová částka"],
        color='red', linestyle='--', marker='.',
        markersize=20, linewidth=2
    )
    lims = ax[i].get_ylim()
    ax[i].set_title(list_df[i]["Sezóna"].unique())
plt.tight_layout()
```





And, finally, top 5 leagues with the biggest spences for each season.

In [59]:

```
df_top5_season_l = df.copy()
df_top5_season_l = df_top5_season_l.groupby(["Sezóna", "Nová  Liga"
df_top5_season_l = df_top5_season_l.sort_values(by=["Sezóna","Přest
df_top5_season_l = df_top5_season_l.groupby("Sezóna").head(5).reset_
df_top5_season_l
```

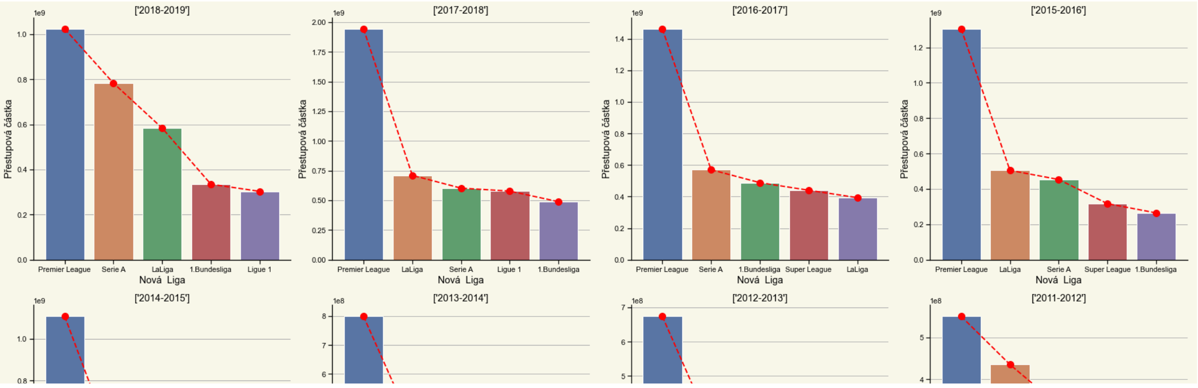
Out[59]:

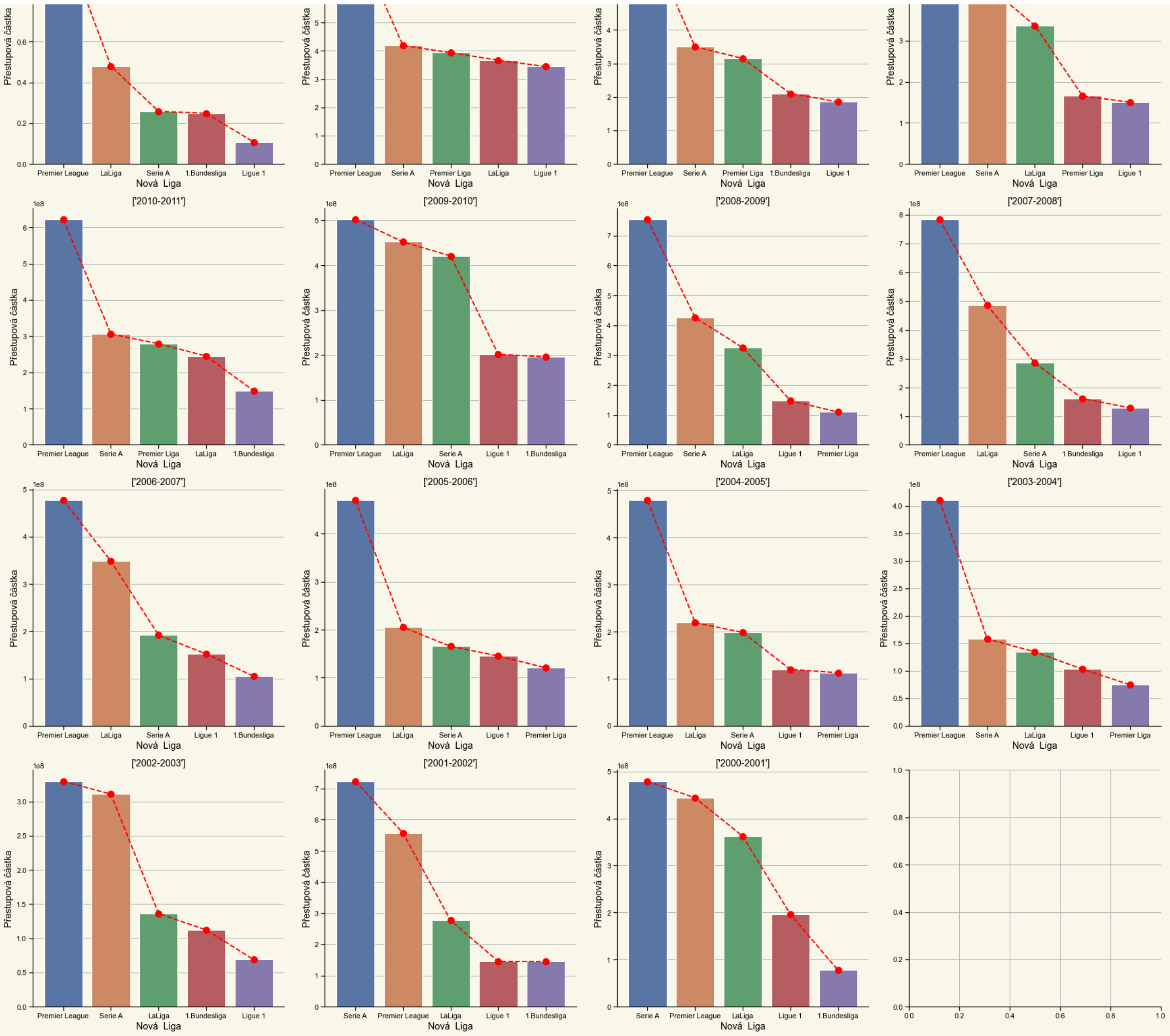
	index	Sezóna	Nová Liga	Přestupová částka
0	380	2018-2019	Premier League	1023200000
1	385	2018-2019	Serie A	782700000
2	374	2018-2019	LaLiga	583300000
3	370	2018-2019	1.Bundesliga	334500000
4	378	2018-2019	Ligue 1	303000000
...	...	...	...	...
90	14	2000-2001	Serie A	479100000
91	12	2000-2001	Premier League	443700000
92	9	2000-2001	LaLiga	362270000
93	11	2000-2001	Ligue 1	196650000
94	4	2000-2001	1.Bundesliga	77780000

95 rows × 4 columns

In [60]:

```
list_df = np.array_split(df_top5_season_l, 19)
fig, ax = plt.subplots(5,4,figsize=(25,30))
ax = ax.flatten()
for i in range(0,19):
    sns.barplot(data = list_df[i] , x = "Nová  Liga", y = "Přestupo
    ax[i].plot(
        ax[i].get_xticks(), list_df[i]["Přestupová částka"],
        color='red', linestyle='--', marker='.',
        markersize=20, linewidth=2
    )
    lims = ax[i].get_ylim()
    ax[i].set_title(list_df[i]["Sezóna"].unique())
plt.tight_layout()
```





I would like to thank you for your time. I hope you'll enjoy results of my work!

Alexandr Kolomijec

```
In [ ]:
```