In [1]:
```
#Libraries
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, KFold, cross_val_score, cr
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, root_mean_squared_erro
```

In [2]:
```
#Reading the data
url = "https://raw.githubusercontent.com/angryolli/ML_Project/refs/heads/main/NB
df = pd.read_csv(url, sep=',', on_bad_lines='skip')
df.head(1)
```

Out[2]:

	Player	Salary	Year	Pos	Age	Team	G	GS	MP	FG	...	FT%	ORB	DRB
0	Kobe Bryant	23034375	2010	SG	31	LAL	73	73	38.8	9.8	...	0.811	1.1	4.3

1 rows × 31 columns

In [3]:
```
#Filtering for the last three season
#Couple of nan are in the dataset
df = df.query("Year >= 2023")
```

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 1449 entries, 5849 to 7297
Data columns (total 31 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Player  1449 non-null   object 
 1   Salary  1449 non-null   int64  
 2   Year    1449 non-null   int64  
 3   Pos     1449 non-null   object 
 4   Age     1449 non-null   int64  
 5   Team    1449 non-null   object 
 6   G       1449 non-null   int64  
 7   GS      1449 non-null   int64  
 8   MP      1449 non-null   float64
 9   FG      1449 non-null   float64
 10  FGA     1449 non-null   float64
 11  FG%     1447 non-null   float64
 12  3P      1449 non-null   float64
 13  3PA     1449 non-null   float64
 14  3P%     1429 non-null   float64
 15  2P      1449 non-null   float64
 16  2PA     1449 non-null   float64
 17  2P%     1445 non-null   float64
 18  eFG%    1447 non-null   float64
 19  FT      1449 non-null   float64
 20  FTA     1449 non-null   float64
 21  FT%     1440 non-null   float64
 22  ORB     1449 non-null   float64
 23  DRB     1449 non-null   float64
 24  TRB     1449 non-null   float64
 25  AST     1449 non-null   float64
 26  STL     1449 non-null   float64
 27  BLK     1449 non-null   float64
 28  TOV     1449 non-null   float64
 29  PF      1449 non-null   float64
 30  PTS     1449 non-null   float64
dtypes: float64(23), int64(5), object(3)
memory usage: 362.2+ KB
```

In [5]:
```
#columns including nan values
#delete players without throws
arr = ["FG%", "3P%", "2P%", "eFG%", "FT%"]
for a in arr:
    print("Null values " + a)
    print(df.loc[(df[a].isna()), ["Player", "FG", "FGA", "2P", "2PA", "3P", "3PA
    df[[a]] = df[[a]].fillna(0)
df = df.drop([7267, 7275], axis=0)
```

```
Null values FG%
                Player   FG  FGA   2P  2PA   3P  3PA   FT  FTA
7267  Jalen McDaniels  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
7275    Jahlil Okafor  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
Null values 3P%
                  Player   FG   FGA   2P   2PA   3P  3PA   FT  FTA
6824         Rudy Gobert  4.7   7.1  4.7   7.1  0.0  0.0  2.6  3.8
6920  Mitchell Robinson  2.2   3.3  2.2   3.3  0.0  0.0  0.8  1.1
6925      Daniel Gafford  5.0   7.1  5.0   7.1  0.0  0.0  2.4  3.4
6948         Ivica Zubac  7.4  11.8  7.4  11.8  0.0  0.0  2.0  3.0
7048     Dereck Lively II  3.7   5.3  3.7   5.3  0.0  0.0  1.3  2.0
7059         Jalen Duren  4.8   7.0  4.8   7.0  0.0  0.0  2.1  3.1
7063      Isaiah Jackson  2.8   4.6  2.8   4.6  0.0  0.0  1.4  2.8
7150        Jericho Sims  0.8   1.3  0.8   1.3  0.0  0.0  0.2  0.2
7155      Charles Bassey  1.9   3.3  1.9   3.3  0.0  0.0  0.6  0.9
7177      DeAndre Jordan  1.6   2.5  1.6   2.5  0.0  0.0  0.5  1.1
7230      Bruno Fernando  1.5   2.9  1.5   2.9  0.0  0.0  0.4  0.5
7231      Ariel Hukporti  0.8   1.2  0.8   1.2  0.0  0.0  0.2  0.5
7239         Ben Simmons  2.3   4.4  2.3   4.4  0.0  0.0  0.5  0.6
7259     Bismack Biyombo  2.4   4.1  2.4   4.1  0.0  0.0  0.4  0.9
7267     Jalen McDaniels  0.0   0.0  0.0   0.0  0.0  0.0  0.0  0.0
7269        Terry Taylor  0.0   0.3  0.0   0.3  0.0  0.0  0.0  0.0
7275       Jahlil Okafor  0.0   0.0  0.0   0.0  0.0  0.0  0.0  0.0
7276         Moses Brown  2.6   3.8  2.6   3.8  0.0  0.0  0.6  0.8
7286        Yuri Collins  0.5   1.5  0.5   1.5  0.0  0.0  0.0  0.0
7296        Kylor Kelley  1.3   2.0  1.3   2.0  0.0  0.0  0.5  0.9
Null values 2P%
                Player   FG  FGA   2P  2PA   3P  3PA   FT  FTA
7232         PJ Dozier  0.2  0.3  0.0  0.0  0.2  0.3  0.1  0.7
7267  Jalen McDaniels  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
7271       Daishen Nix  0.0  0.3  0.0  0.0  0.0  0.3  0.3  0.7
7275    Jahlil Okafor  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
Null values eFG%
                Player   FG  FGA   2P  2PA   3P  3PA   FT  FTA
7267  Jalen McDaniels  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
7275    Jahlil Okafor  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
Null values FT%
                Player   FG  FGA   2P  2PA   3P  3PA   FT  FTA
7169        Joe Ingles  0.3  1.2  0.2  0.4  0.2  0.8  0.0  0.0
7178     Vlatko Cancar  0.8  2.0  0.5  0.8  0.3  1.2  0.0  0.0
7266       P.J. Tucker  1.0  2.3  0.0  0.3  1.0  2.0  0.0  0.0
7267  Jalen McDaniels  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
7269     Terry Taylor  0.0  0.3  0.0  0.3  0.0  0.0  0.0  0.0
7270  Skal Labissiere  0.5  1.0  0.3  0.8  0.3  0.3  0.0  0.0
7275    Jahlil Okafor  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
7286     Yuri Collins  0.5  1.5  0.5  1.5  0.0  0.0  0.0  0.0
7289    Terence Davis  0.0  2.0  0.0  1.0  0.0  1.0  0.0  0.0
```

In [6]:
```
#0 nan values
df.info()
```

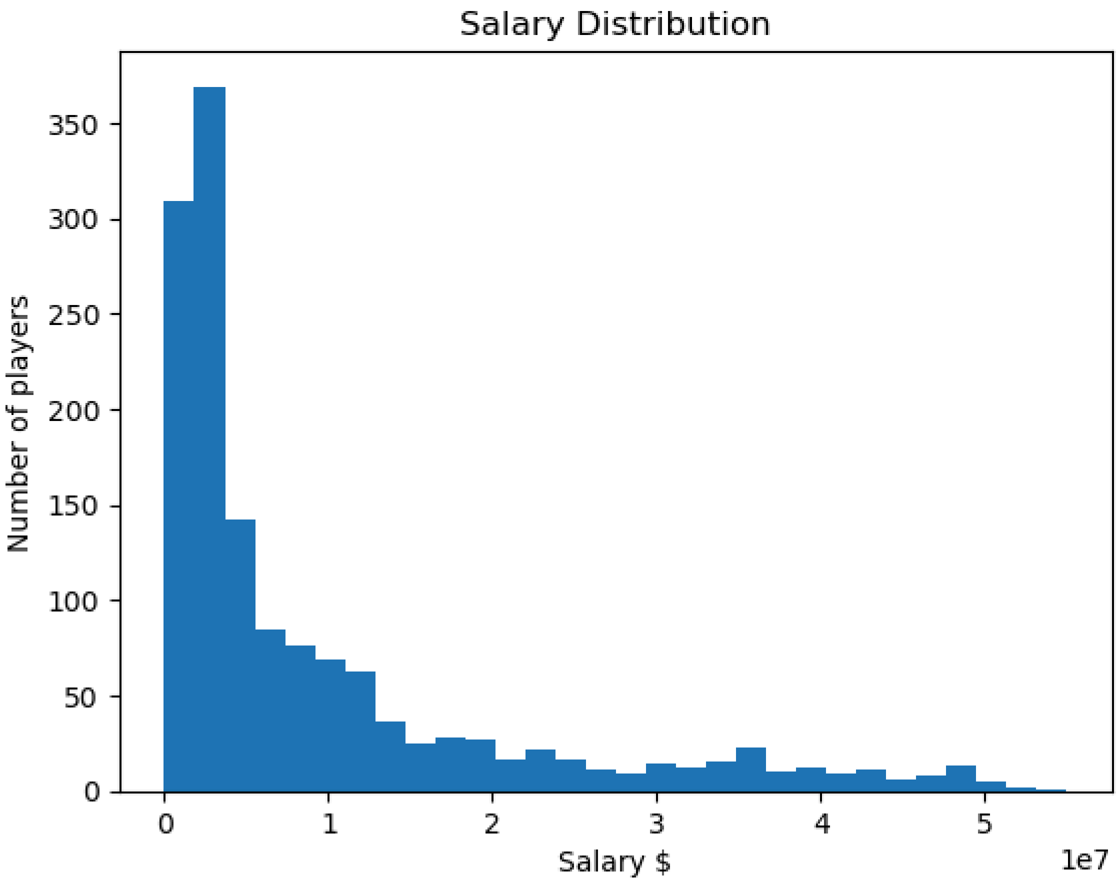
```
<class 'pandas.core.frame.DataFrame'>
Index: 1447 entries, 5849 to 7297
Data columns (total 31 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Player  1447 non-null   object 
 1   Salary  1447 non-null   int64  
 2   Year    1447 non-null   int64  
 3   Pos     1447 non-null   object 
 4   Age     1447 non-null   int64  
 5   Team    1447 non-null   object 
 6   G       1447 non-null   int64  
 7   GS      1447 non-null   int64  
 8   MP      1447 non-null   float64
 9   FG      1447 non-null   float64
 10  FGA     1447 non-null   float64
 11  FG%     1447 non-null   float64
 12  3P      1447 non-null   float64
 13  3PA     1447 non-null   float64
 14  3P%     1447 non-null   float64
 15  2P      1447 non-null   float64
 16  2PA     1447 non-null   float64
 17  2P%     1447 non-null   float64
 18  eFG%    1447 non-null   float64
 19  FT      1447 non-null   float64
 20  FTA     1447 non-null   float64
 21  FT%     1447 non-null   float64
 22  ORB     1447 non-null   float64
 23  DRB     1447 non-null   float64
 24  TRB     1447 non-null   float64
 25  AST     1447 non-null   float64
 26  STL     1447 non-null   float64
 27  BLK     1447 non-null   float64
 28  TOV     1447 non-null   float64
 29  PF      1447 non-null   float64
 30  PTS     1447 non-null   float64
dtypes: float64(23), int64(5), object(3)
memory usage: 361.8+ KB
```

In [7]:

```
#Salary distribution
plt.hist(df.Salary, bins=30, range=(0, 55_000_000))
plt.xlabel("Salary $")
plt.ylabel("Number of players")
plt.title("Salary Distribution")
```

Out[7]:

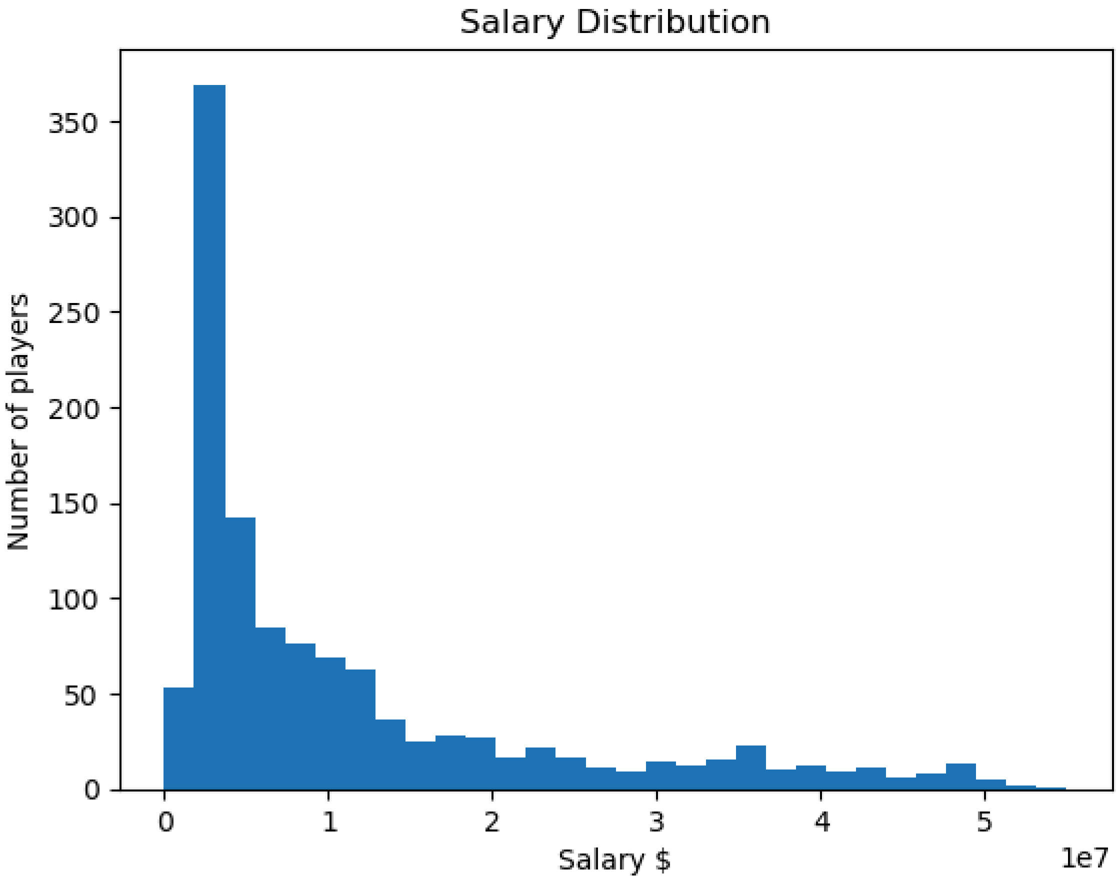
```
Text(0.5, 1.0, 'Salary Distribution')
```



In [8]:
```
#Drop below the rookie salary players
df = df[df["Salary"] >= 1157153]
```

In [9]:
```
#Salary distribution
plt.hist(df.Salary, bins=30, range=(0, 55_000_000))
plt.xlabel("Salary $")
plt.ylabel("Number of players")
plt.title("Salary Distribution")
```

Out[9]:
```
Text(0.5, 1.0, 'Salary Distribution')
```


Salary Distribution
Number of players
350
300
250
200
150
100
50
0
0
1
2
3
4
5
1e7
Salary $

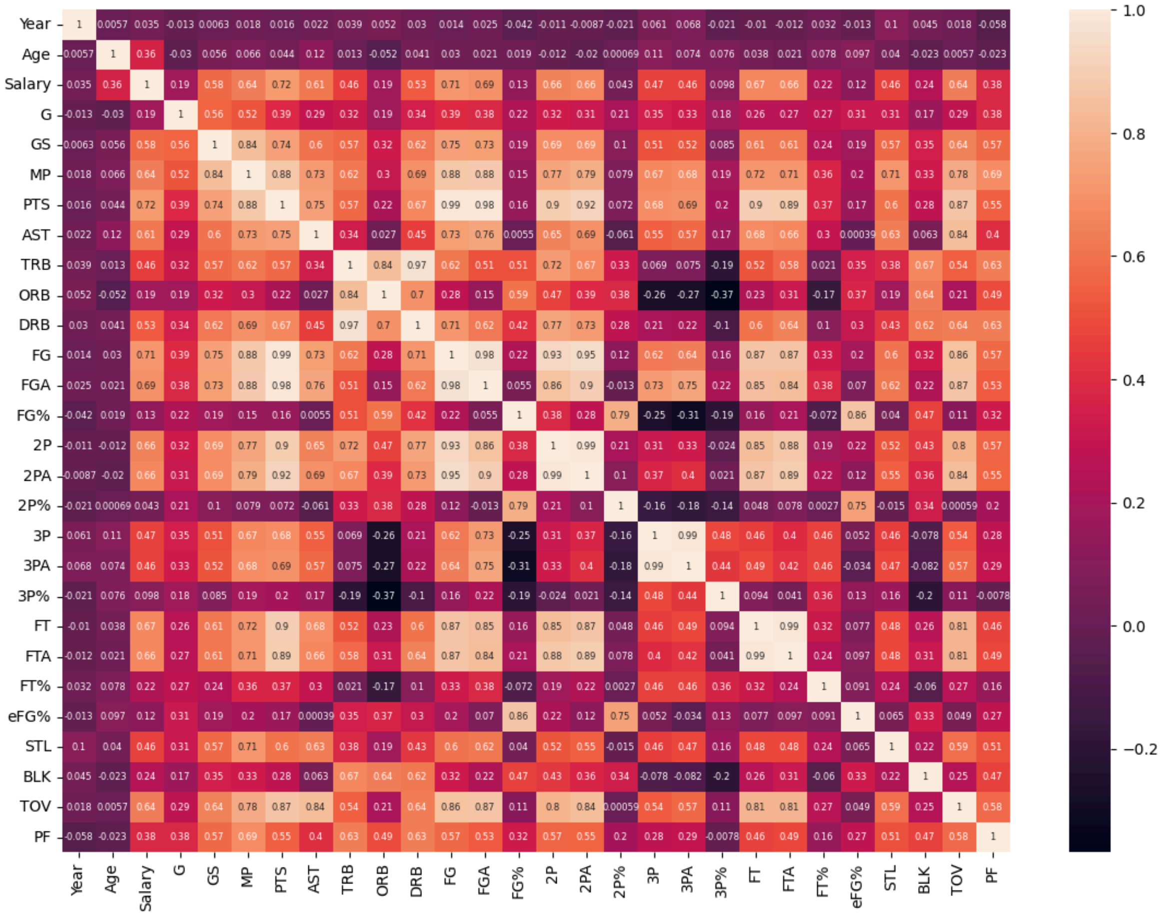
In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1191 entries, 5849 to 7274
Data columns (total 31 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Player  1191 non-null   object
 1   Salary  1191 non-null   int64
 2   Year    1191 non-null   int64
 3   Pos     1191 non-null   object
 4   Age     1191 non-null   int64
 5   Team    1191 non-null   object
 6   G       1191 non-null   int64
 7   GS      1191 non-null   int64
 8   MP      1191 non-null   float64
 9   FG      1191 non-null   float64
 10  FGA     1191 non-null   float64
 11  FG%     1191 non-null   float64
 12  3P      1191 non-null   float64
 13  3PA     1191 non-null   float64
 14  3P%     1191 non-null   float64
 15  2P      1191 non-null   float64
 16  2PA     1191 non-null   float64
 17  2P%     1191 non-null   float64
 18  eFG%    1191 non-null   float64
 19  FT      1191 non-null   float64
 20  FTA     1191 non-null   float64
 21  FT%     1191 non-null   float64
 22  ORB     1191 non-null   float64
 23  DRB     1191 non-null   float64
 24  TRB     1191 non-null   float64
 25  AST     1191 non-null   float64
 26  STL     1191 non-null   float64
 27  BLK     1191 non-null   float64
 28  TOV     1191 non-null   float64
 29  PF      1191 non-null   float64
 30  PTS     1191 non-null   float64
dtypes: float64(23), int64(5), object(3)
memory usage: 297.8+ KB
```

In [11]:

```
#Pearson correlation matrix
heat_salary= df[['Year', 'Age', 'Salary', 'G', 'GS', 'MP','PTS','AST','TRB','ORB
'FG','FGA', 'FG%','2P','2PA','2P%','3P', '3PA', '3P%','FT', 'FTA','FT%','eFG%','
plt.figure(figsize=(14, 10))
dfData = heat_salary.corr()
sns.heatmap(dfData, annot=True, annot_kws={"size":6})
```

Out[11]: <Axes: >



In [12]:
```
playerdb = df[["Salary",'Age', 'G', 'GS', 'MP','PTS','AST','TRB','ORB', 'DRB',
'FG','FGA', 'FG%','2P','2PA','2P%','3P', '3PA', '3P%','FT', 'FTA','FT%','eFG%','

X = playerdb.drop(columns=["Salary"])
y = playerdb["Salary"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=49
)
```

In [13]:
```
feature_sets = {
    "F1_important": ["PTS", "3PA", "DRB"],

    "F2_core": ["PTS", "MP", "TOV", "AST", "TRB", "STL", "BLK", "Age"],

    "F3_scoring": ["PTS", "3PA", "DRB", "STL", "MP", "FG"],

    "F4_all": [
        'Age', 'G', 'GS', 'MP', 'PTS', 'AST', 'TRB', 'ORB', 'DRB',
        'FG', 'FGA', 'FG%', '2P', '2PA', '2P%', '3P', '3PA', '3P%',
        'FT', 'FTA', 'FT%', 'eFG%', 'STL', 'BLK', 'TOV', 'PF'
    ]
}
```

In [14]:
```
linreg_results = []

cv = KFold(n_splits=5, shuffle=True, random_state=49)

for name, features in feature_sets.items():
    X_tr = X_train[features]
    linreg = LinearRegression()
```

```python
    scores = cross_validate(
        linreg,
        X_tr,
        y_train,
        cv=cv,
        scoring={
            "rmse": "neg_root_mean_squared_error",
            "r2": "r2"
        }
    )

    linreg_results.append({
        "Model": "Linear Regression",
        "Feature_Set": name,
        "RMSE": -scores["test_rmse"].mean(),
        "R2": scores["test_r2"].mean()
    })
```

In [15]:

```python
ranfor_results = []

for name, features in feature_sets.items():
    X_tr = X_train[features]

    rf = RandomForestRegressor(
        n_estimators=300,
        max_depth=None,
        random_state=49,
        n_jobs=-1
    )

    scores = cross_validate(
        rf,
        X_tr,
        y_train,
        cv=cv,
        scoring={
            "rmse": "neg_root_mean_squared_error",
            "r2": "r2"
        }
    )

    ranfor_results.append({
        "Model": "Random Forest",
        "Feature_Set": name,
        "RMSE": -scores["test_rmse"].mean(),
        "R2": scores["test_r2"].mean()
    })

ranfor_results
```

Out[15]:
```
[{'Model': 'Random Forest',
  'Feature_Set': 'F1_important',
  'RMSE': np.float64(8752335.068202568),
  'R2': np.float64(0.4796757551175661)},
 {'Model': 'Random Forest',
  'Feature_Set': 'F2_core',
  'RMSE': np.float64(6430518.963598682),
  'R2': np.float64(0.7221287812470895)},
 {'Model': 'Random Forest',
  'Feature_Set': 'F3_scoring',
  'RMSE': np.float64(8596308.319644738),
  'R2': np.float64(0.5024185227541278)},
 {'Model': 'Random Forest',
  'Feature_Set': 'F4_all',
  'RMSE': np.float64(6200264.348918025),
  'R2': np.float64(0.7421415110614864)}]
```

In [16]:
```
results_df = pd.DataFrame(linreg_results + ranfor_results)
results_df["RMSE_mil"] = results_df["RMSE"] / 1e6
results_df.sort_values(by="RMSE")
#Best feature subset is F4_all for both models
```

Out[16]:

	Model	Feature_Set	RMSE	R2	RMSE_mil
7	Random Forest	F4_all	6.200264e+06	0.742142	6.200264
5	Random Forest	F2_core	6.430519e+06	0.722129	6.430519
3	Linear Regression	F4_all	7.342383e+06	0.635035	7.342383
1	Linear Regression	F2_core	7.434146e+06	0.626774	7.434146
0	Linear Regression	F1_important	8.398112e+06	0.524606	8.398112
2	Linear Regression	F3_scoring	8.426318e+06	0.520983	8.426318
6	Random Forest	F3_scoring	8.596308e+06	0.502419	8.596308
4	Random Forest	F1_important	8.752335e+06	0.479676	8.752335

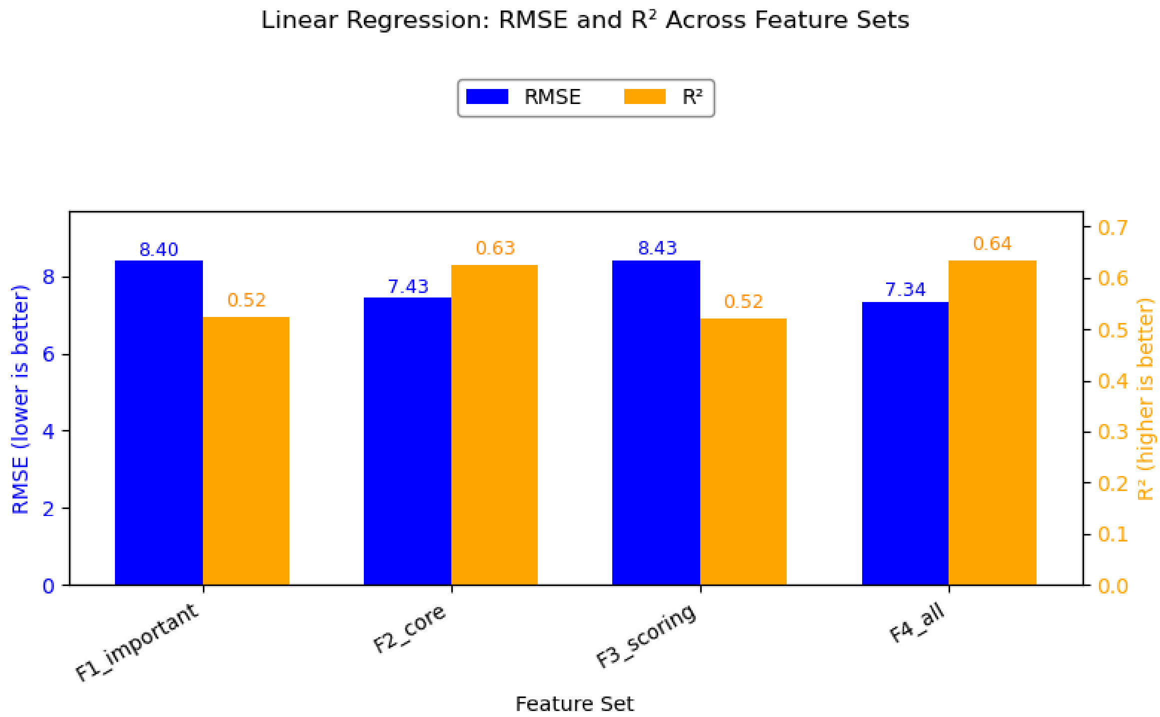
In [17]:
```
wide_rmse = results_df.pivot(index="Feature_Set", columns="Model", values="RMSE_
wide_r2   = results_df.pivot(index="Feature_Set", columns="Model", values="R2")
wide_rmse
```

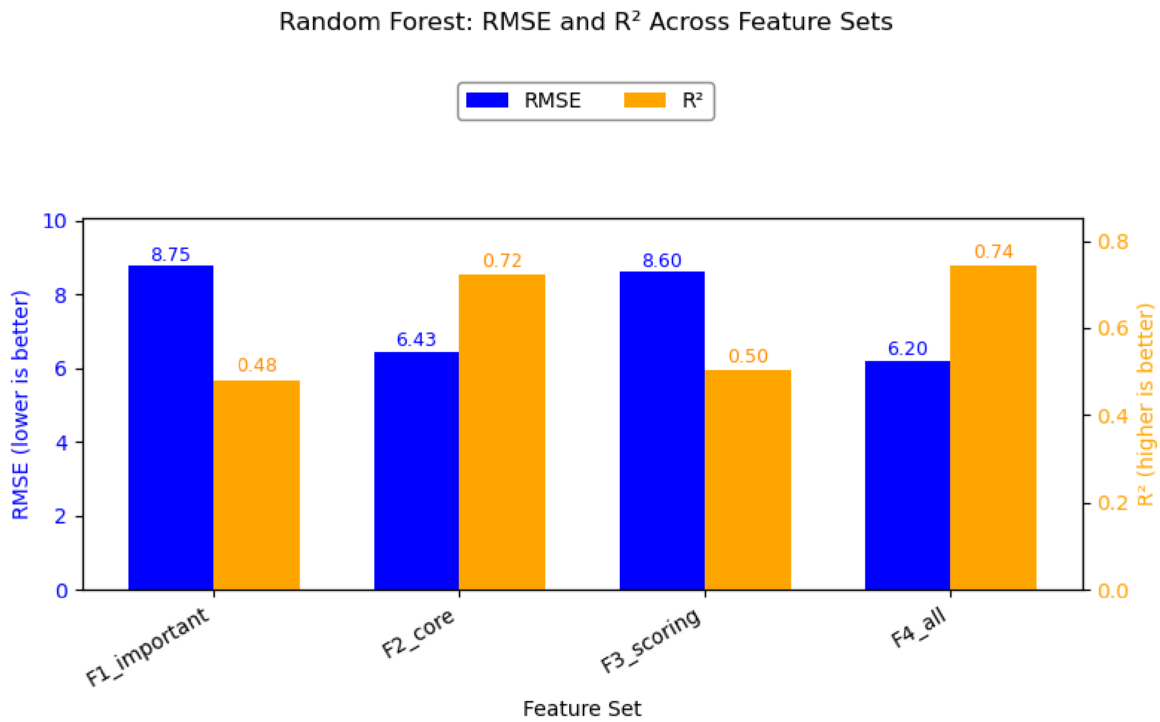
Out[17]:

Model	**Linear Regression**	**Random Forest**
Feature_Set		
F1_important	8.398112	8.752335
F2_core	7.434146	6.430519
F3_scoring	8.426318	8.596308
F4_all	7.342383	6.200264

In [18]:
```
data = {
    "Model":   wide_rmse.index.tolist(),        # feature sets
    "LR_RMSE": wide_rmse["Linear Regression"].tolist(),        # change "LR" to
    "LR_R2":   wide_r2["Linear Regression"].tolist(),
```

```
    "RF_RMSE": wide_rmse["Random Forest"].tolist(),        # change "RF" to actu
    "RF_R2":   wide_r2["Random Forest"].tolist(),
}


ddf = pd.DataFrame(data)
x = np.arange(len(ddf["Model"]))
width = 0.35

def plot_model(title, rmse_values, r2_values):
    fig, ax1 = plt.subplots(figsize=(8,5))

    # RMSE bars
    bars1 = ax1.bar(x - width/2, rmse_values, width, color='blue', label='RMSE')
    ax1.set_ylabel("RMSE (lower is better)", color='blue')
    ax1.tick_params(axis='y', labelcolor='blue')

    # R^2 bars
    ax2 = ax1.twinx()       #second y-axis, same x-axis
    bars2 = ax2.bar(x + width/2, r2_values, width, color='orange', label='R²')
    ax2.set_ylabel("R² (higher is better)", color='orange')
    ax2.tick_params(axis='y', labelcolor='orange')

    # X-axis labels
    ax1.set_xticks(x)
    ax1.set_xticklabels(ddf["Model"], rotation=30, ha='right')
    ax1.set_xlabel("Feature Set")

    # Add value labels
    for bar in bars1:
        ax1.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.15,
                 f"{bar.get_height():.2f}", ha='center', color='blue', fontsize=
    for bar in bars2:
        ax2.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.02,
                 f"{bar.get_height():.2f}", ha='center', color='darkorange', fon

    # Adjust Y-axis upper limits for padding
    ax1.set_ylim(0, max(rmse_values) * 1.15)
    ax2.set_ylim(0, max(r2_values) * 1.15)

    # Get legend handles/labels from both axes
    handles1, labels1 = ax1.get_legend_handles_labels()
    handles2, labels2 = ax2.get_legend_handles_labels()

    # Title at the very top
    fig.suptitle(title, y=0.98)

    # Legend centered just under the title
    fig.legend(handles1 + handles2, labels1 + labels2,
               loc='upper center', bbox_to_anchor=(0.5, 0.90),
               ncol=2, frameon=True, framealpha=0.9, edgecolor='gray')

    # Leave room at the top for title + legend
    fig.tight_layout(rect=[0, 0, 1, 0.80])
    plt.show()

# Plot both charts
plot_model("Linear Regression: RMSE and R² Across Feature Sets", ddf["LR_RMSE"],
plot_model("Random Forest: RMSE and R² Across Feature Sets", ddf["RF_RMSE"], ddf
```





In [19]:

```
best_features = feature_sets["F4_all"]
X_tr = X_train[best_features]
X_te = X_test[best_features]

rf = RandomForestRegressor(
        n_estimators=300,
        max_depth=None,
        random_state=49,
        n_jobs=-1
    )
```

In [20]:

```
rf.fit(X_tr, y_train)
y_pred = rf.predict(X_te)

test_rmse = root_mean_squared_error(y_test, y_pred)
```

```
test_r2 = r2_score(y_test, y_pred)

print("FINAL TEST RMSE:", test_rmse)
print("FINAL TEST R2:", test_r2)
```

```
FINAL TEST RMSE: 5685640.858484306
FINAL TEST R2: 0.7392993303249291
```