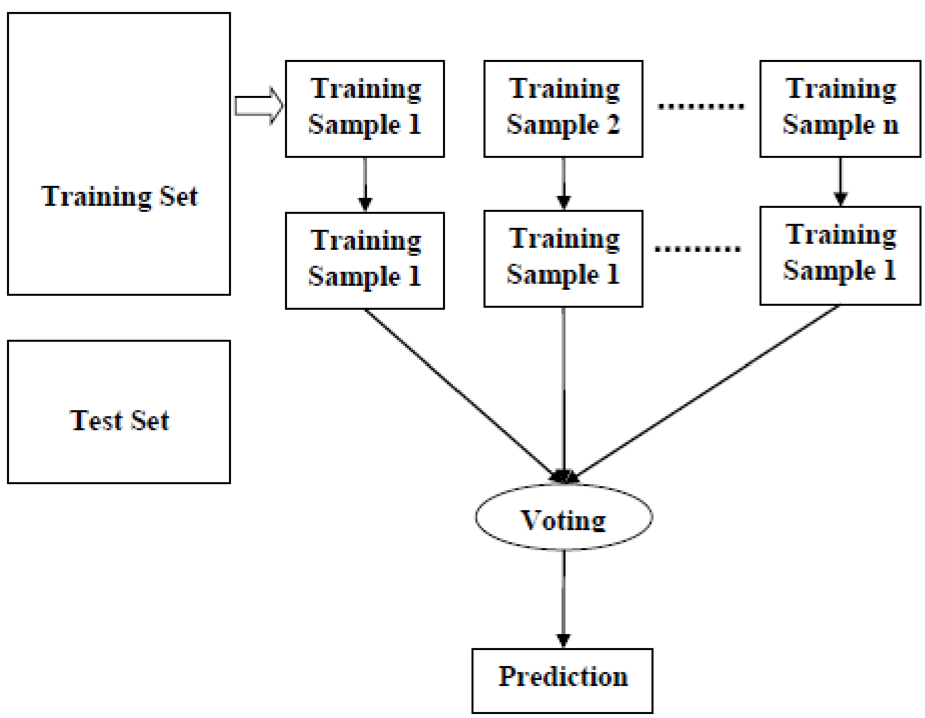
# Random Forest

- Random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting.
- It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

### Steps Involved:

- Step 1 − First, start with the selection of random samples from a given dataset.
- Step 2 − Next, this algorithm will construct a decision tree for every sample. Then it will get the prediction result from every decision tree.
- Step 3 − In this step, voting will be performed for every predicted result.
- Step 4 − At last, select the most voted prediction result as the final prediction result.




# Pros and Cons of Random Forest Algorithm:

### Pros:

- It overcomes the problem of overfitting by averaging or combining the results of different decision trees.
- Random forests work well for a large range of data items than a single decision tree does.

- Random forest has less variance then single decision tree.
- Random forests are very flexible and possess very high accuracy.
- Random Forest algorithms maintains good accuracy even a large proportion of the data is missing.

***Scaling of data does not require in random forest algorithm. It maintains good accuracy even after providing data without scaling.***

## Cons:

- Complexity is the main disadvantage of Random forest algorithms.
- Construction of Random forests are much harder and time-consuming than decision trees.
- More computational resources are required to implement Random Forest algorithm.
- It is less intuitive in case when we have a large collection of decision trees.
- The prediction process using random forests is very time-consuming in comparison with other algorithms.

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

In [2]:
```
dataset = pd.read_csv('Position_Salaries.csv')
```

In [3]:
```
X = dataset.iloc[:,1:2].values
y = dataset.iloc[:,2].values
```

## Building a regressor model.

In [4]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [5]:
```
def r_forest(n, objective):
    '''
    n = Number of estimators.
    objective = X_value whose y_value has to be predicted.
    '''
    regressor = RandomForestRegressor(n_estimators = n, random_state = 0)
    regressor.fit(X,y)
    return regressor.predict(np.array(objective).reshape(-1,1))
```

In [6]:
```
# Creating a list of tuples containing varyig values of n_estimators & correspond
mylist = []
for ii in range(10,500+1,10):
    mylist.append((ii,r_forest(ii,6.5)[0]))
```

In [7]:
```
mylist[:5]
```

Out[7]:
```
[(10, 167000.0),
 (20, 166000.0),
 (30, 164333.33333333334),
 (40, 161250.0),
 (50, 161200.0)]
```

In [8]:
```
# Separation for plot.
x_grid,y_grid = np.array(mylist).T
```

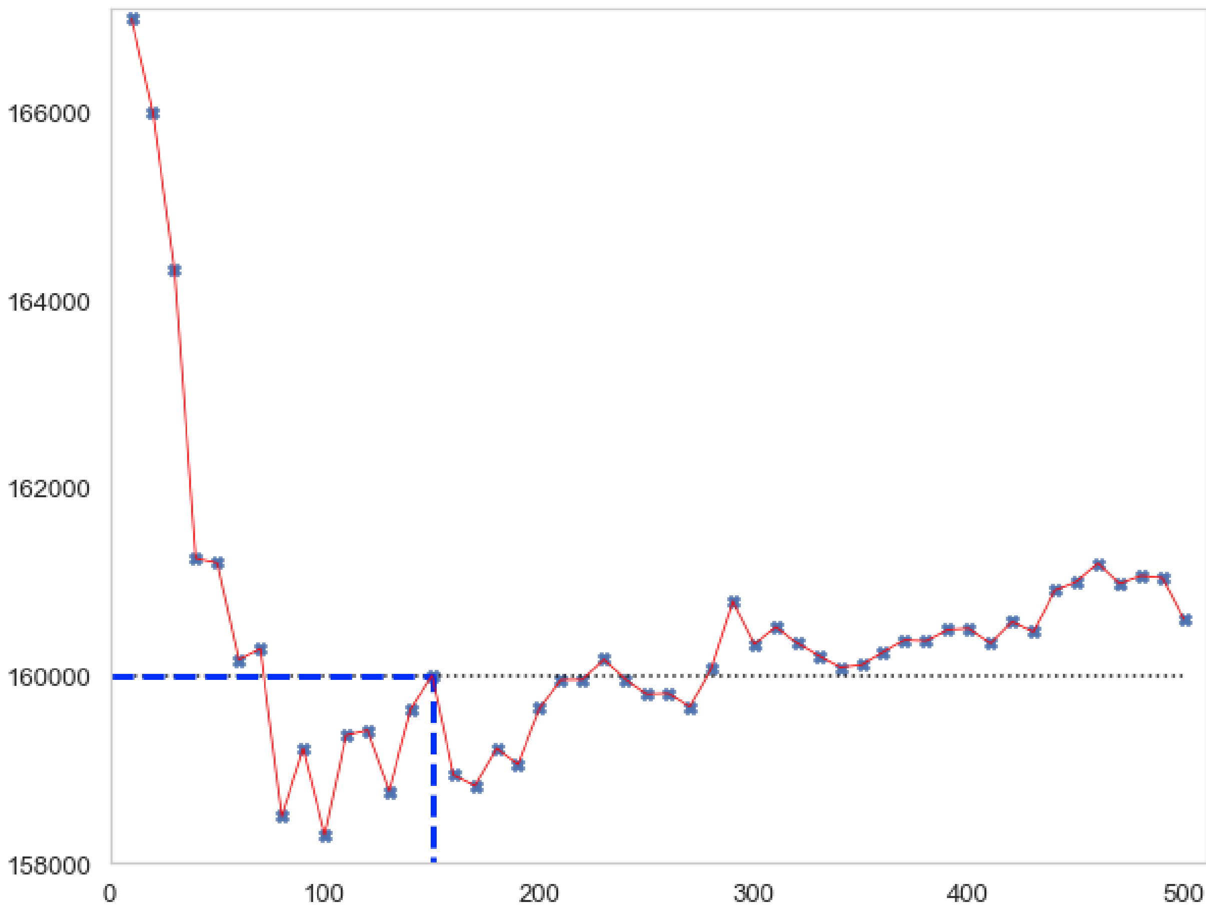
In [9]:
```
# Getting the index for which the predicted value is the closest to 160k.
epsilon = np.abs(y_grid-(np.ones(len(y_grid))*160000))
min_index = np.where(epsilon == min(epsilon))[0]
min_index
```

Out[9]:
```
array([14], dtype=int64)
```

### Visualization using plot:

- Here, we see for what value of 'n_estimators', the predicted value of the salary will be the closest to 160k.

In [10]:
```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

plt.scatter(x_grid, y_grid, marker = 'X')
plt.plot(x_grid, y_grid, color = 'red', linewidth = 0.8)
plt.hlines(160000, 0,501, linestyles = 'dotted')
plt.hlines(y_grid[min_index], 0, x_grid[min_index]+1, linestyle = 'dashed',
           linewidth = 3, color = '#002ffa')
plt.vlines(x_grid[min_index], 157500, y_grid[min_index]+1, linestyle = 'dashed',
           linewidth = 3, color = '#002ffa')


plt.xlim(0,510)
plt.ylim(158000, max(y_grid)+100)
plt.grid(0)
plt.show()
```




In [11]:
```
print('The best predicted salary for level 6.5 is ', y_grid[min_index][0], '.\n'
     'For this, we use n_estimators = ',int( x_grid[min_index][0]), '.')
```

```
The best predicted salary for level 6.5 is  160000.0 .
 For this, we use n_estimators =  150 .
```

## Testing for level = 9.

In [13]:
```
r_forest(150, 9)[0].round(2)
```

Out[13]:
```
480666.67
```

In [14]:
```
dataset.iloc[-2,:]
```

Out[14]:
```
Position    C-level
Level             9
Salary       500000
Name: 8, dtype: object
```

**Checking whether we can do any better prediction than this.**

In [15]:
```
def minimum_index(objective,truevalue):
    # Creating a list of tuples containing varyig values of n_estimators & corre
    mylist = []
    for ii in range(10,500+1,10):
        mylist.append((ii,r_forest(ii,objective)[0]))

    # Separation for plot.
    x_grid,y_grid = np.array(mylist).T

    # Getting the index for which the predicted value is the closest to 160k.
    epsilon = np.abs(y_grid-(np.ones(len(y_grid))*truevalue))
    min_index = np.where(epsilon == min(epsilon))[0]
    return (min_index, x_grid[min_index], y_grid[min_index])
```

In [31]:
```
minimum_index(9,500000)
```

Out[31]:
```
(array([3], dtype=int64), array([40.]), array([502500.]))
```

***This means, for determining the best predicted value for level 9, we set n_estimators = 40 and doing so, we get the optimal predicted salary as 502500.***

## Determining the optimal number of estimators for all the levels.

In [17]:
```
true_values = dataset.iloc[:,2].values
objectives = dataset.iloc[:,1].values

optimal_estimators = []
for ii in range(len(objectives)):
    optimal_estimators.append(minimum_index(objectives[ii], true_values[ii])[1]

optimal_estimators
```

Out[17]:
```
[array([10.]),
 array([150.]),
 array([240.]),
 array([70.]),
 array([60.]),
 array([480.]),
 array([20.]),
 array([ 10., 200.]),
 array([40.]),
 array([10.])]
```

**Adding optimal estimators into the original dataset.**

In [68]:
```
dataset['opt_estimators'] = [optimal_estimators[ii][0] for ii in range(len(optim
dataset['opt_estimators'].values
```

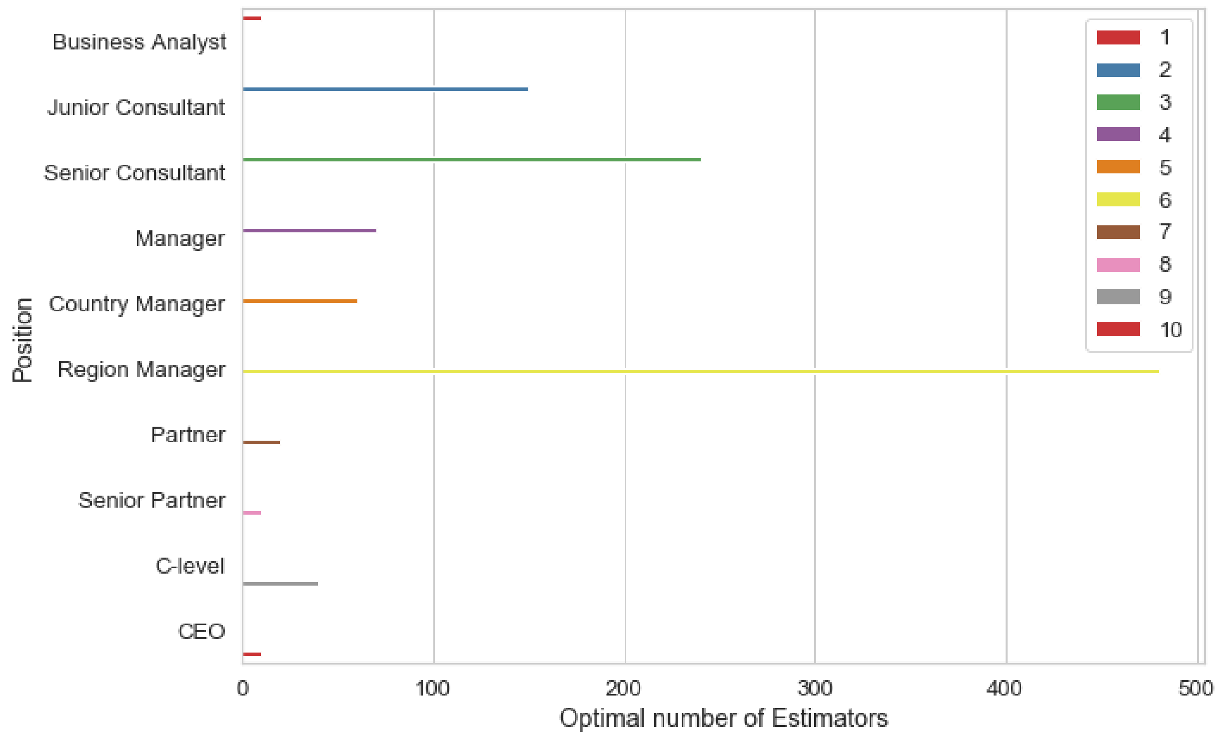
Out[68]:
```
array([ 10., 150., 240.,  70.,  60., 480.,  20.,  10.,  40.,  10.])
```

**Adding the best estimates into the original dataset.**

In [35]:
```
best_prediction = []
objectives = dataset.iloc[:,1].values

for ii in range(len(dataset['opt_estimators'].values)):
    regressor1 = RandomForestRegressor(n_estimators = int(dataset['opt_estimator
                                       random_state = 0)
    regressor1.fit(X,y)
    best_prediction.append(regressor1.predict(np.array(objectives[ii]).reshape(-

dataset['best_prediction'] = [best_prediction[ii][0].round(2) for ii in range(le
```

**Optimal number of estimators for each level visualized in a bar plot.**

In [67]:
```
plt.figure(figsize = (10,7))
labels = [str(ii) for ii in np.arange(1,11)]
ax = sns.barplot(x = [optimal_estimators[ii][0] for ii in range(len(optimal_esti
            y = dataset['Position'], hue = dataset.Level, palette = 'Set1')

#h,l = ax.get_legend_handles_labels()

plt.xlabel('Optimal number of Estimators')
plt.legend(loc = 'upper right')
plt.show()
```



In [41]:
```
dataset['Difference'] = -dataset['Salary'] + dataset['best_prediction']
dataset
```

Out[41]:

| | Position | Level | Salary | opt_estimators | best_prediction | Difference |
|---|---|---|---|---|---|---|
| **0** | Business Analyst | 1 | 45000 | 10.0 | 46000.00 | 1000.00 |
| **1** | Junior Consultant | 2 | 50000 | 150.0 | 50066.67 | 66.67 |
| **2** | Senior Consultant | 3 | 60000 | 240.0 | 59875.00 | -125.00 |
| **3** | Manager | 4 | 80000 | 70.0 | 80142.86 | 142.86 |
| **4** | Country Manager | 5 | 110000 | 60.0 | 109833.33 | -166.67 |
| **5** | Region Manager | 6 | 150000 | 480.0 | 143895.83 | -6104.17 |
| **6** | Partner | 7 | 200000 | 20.0 | 200000.00 | 0.00 |
| **7** | Senior Partner | 8 | 300000 | 10.0 | 305000.00 | 5000.00 |
| **8** | C-level | 9 | 500000 | 40.0 | 502500.00 | 2500.00 |
| **9** | CEO | 10 | 1000000 | 10.0 | 850000.00 | -150000.00 |

# The End.