This project predicts/analyses the enrollment count of a fictitious University

Import Relevant Libraries ¶

In [34]:
```
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error as mae
from sklearn.metrics import r2_score
from sklearn.ensemble import RandomForestRegressor
import time
warnings.simplefilter(action="ignore", category=FutureWarning)
```

Load the Data

In [2]:
```
df=pd.read_csv('university_enrollment_2306.csv')
df.sample(10)
```

Out[2]:

	course_id	course_type	year	enrollment_count	pre_score	post_score	pre_requirement	d
1065	1066	online	2016	251	36.11	67.0	NaN	
624	625	online	2015	251	88.17	84.0	Beginner	
1333	1334	online	2018	246	42.63	76.0	Beginner	
1360	1361	online	2015	261	12.8	72.0	None	
7	8	online	2018	261	76.48	88.0	None	
1182	1183	classroom	2018	155	68.22	85.0	Intermediate	
1835	1836	online	2022	245	75.93	76.0	Beginner	
1410	1411	online	2014	256	94.86	98.0	None	
280	281	online	2020	261	17.48	76.0	None	
51	52	online	2019	261	7.74	61.0	None	

Perform Data Validation

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1850 entries, 0 to 1849
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   course_id         1850 non-null   int64  
 1   course_type       1850 non-null   object 
 2   year              1850 non-null   int64  
 3   enrollment_count  1850 non-null   int64  
 4   pre_score         1850 non-null   object 
 5   post_score        1665 non-null   float64
 6   pre_requirement   1761 non-null   object 
 7   department        1850 non-null   object 
dtypes: float64(1), int64(3), object(4)
memory usage: 115.8+ KB
```

In [4]:
```
# Check for null Values
post_score_na_count=df['post_score'].isna().sum()
pre_requirement_na_count=df['pre_requirement'].isna().sum()
print(f'The are {post_score_na_count} null values  in the post_score column')
print(f'The are {pre_requirement_na_count} null values in the pre_requirement
column')
```

```
The are 185 null values  in the post_score column
The are 89 null values in the pre_requirement column
```

In [5]:
```
# Replace null Values with appropriate values
df['post_score']=df.post_score.fillna(0)
df['pre_requirement']=df.pre_requirement.fillna('None')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1850 entries, 0 to 1849
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   course_id         1850 non-null   int64  
 1   course_type       1850 non-null   object 
 2   year              1850 non-null   int64  
 3   enrollment_count  1850 non-null   int64  
 4   pre_score         1850 non-null   object 
 5   post_score        1850 non-null   float64
 6   pre_requirement   1850 non-null   object 
 7   department        1850 non-null   object 
dtypes: float64(1), int64(3), object(4)
memory usage: 115.8+ KB
```

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

Out[7]:
```
course_id           1850
course_type            2
year                  12
enrollment_count      45
pre_score           1594
post_score            54
pre_requirement        3
department             5
dtype: int64
```

In [8]:
```
# Replace Mathemamatics with with since they mean same thing
df['department']=df['department'].replace({'Math':'Mathematics'})
```

In [9]:
```
# From inpection 'pre_score column has "- " in column'
#replace '_' with 0
df.loc[df['pre_score'] == '-', 'pre_score'] = 0
```

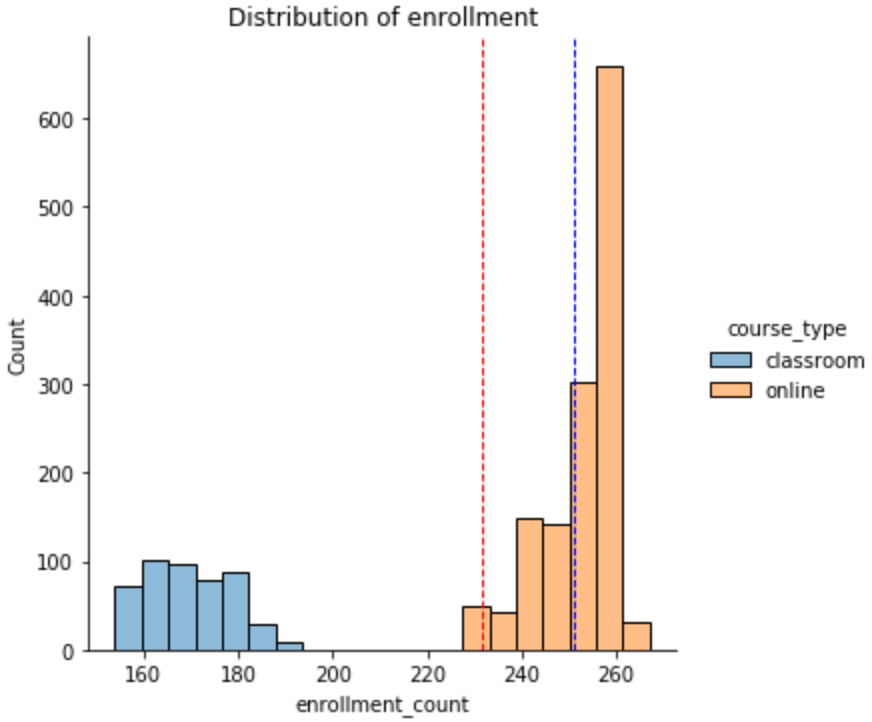
In [10]:
```
df.sample(10)
```

Out[10]:

	course_id	course_type	year	enrollment_count	pre_score	post_score	pre_requirement	c
1344	1345	online	2012	257	94.9	80.0	None	M
832	833	online	2020	261	65.34	72.0	None	
291	292	online	2021	241	51.62	75.0	Beginner	
46	47	online	2020	251	38.22	63.0	Beginner	
517	518	online	2013	255	56.13	85.0	None	M
1059	1060	classroom	2012	175	58.31	76.0	None	
1060	1061	online	2018	256	10.7	79.0	None	M
1334	1335	online	2015	256	16.38	57.0	Beginner	
423	424	online	2021	256	28.66	68.0	None	M
1201	1202	classroom	2014	170	45.14	80.0	Intermediate	

Perform Data Exploratory Analysis

In [11]:
```
# Distribution of enrollment_count'
sns.displot(x='enrollment_count', data=df, hue='course_type', bins=20)
plt.axvline(df.enrollment_count.mean(), color='r', linestyle='dashed', linewid
th=1)
plt.axvline(df.enrollment_count.median(), color='b', linestyle='dashed', linew
idth=1)
plt.title('Distribution of enrollment');
```



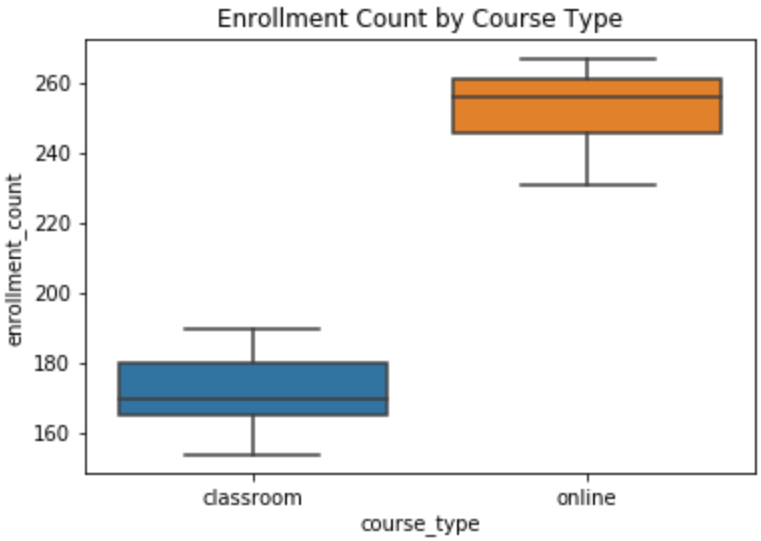
Analyzing the enrollment count, our graphical representation reveals an intriguing bimodal distribution. Notably, the peak enrollment numbers are attributed to online courses, suggesting a robust digital presence. However, the university's performance in classroom-based enrollments is less promising, with figures consistently below 200.

To elaborate further, classroom enrollments are registering below the 200 mark, while online enrollments hover slightly above 250. This discrepancy underscores the need for focused efforts to bridge this enrollment gap effectively.

In [12]:
```
#Visualize with boxplots
sns.boxplot(x='course_type', y='enrollment_count', data=df);
plt.title('Enrollment Count by Course Type')

# Print the mean enrollment for each course type
classroom = df[df['course_type'] == 'classroom']['enrollment_count'].mean()
online = df[df['course_type'] == 'online']['enrollment_count'].mean()
print(f" Average enrollment count for Online Courses: {online: .0f}")
print(f" Average enrollment count for Classroom Courses: {classroom: .0f}")
```

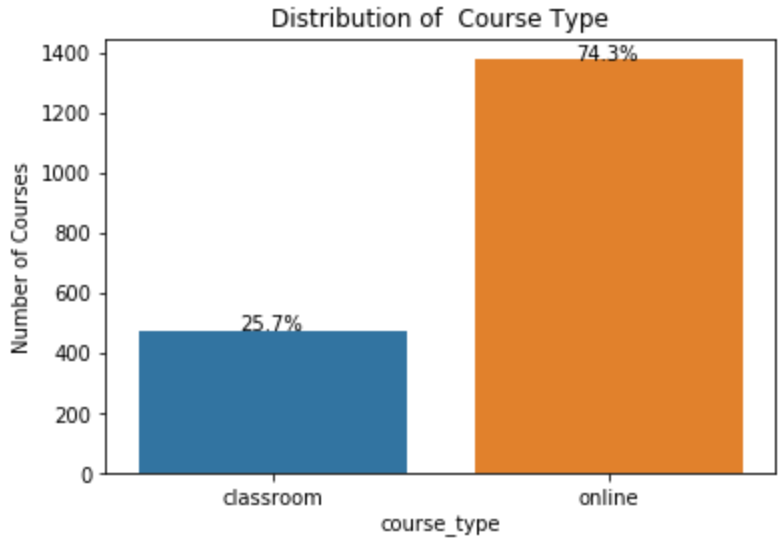
```
Average enrollment count for Online Courses:  253
Average enrollment count for Classroom Courses:  170
```



In [13]:
```
# Verify which course type has observation
ax=sns.countplot(data=df, x='course_type')
plt.title('Distribution of  Course Type')
plt.ylabel('Number of Courses')

total = len(df['course_type'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width()-0.5
        y = p.get_y() + p.get_height()
        ax.annotate(percentage, (x, y))

plt.show();
```



as shown in the graph, the online courses makes up about 74% of the total courses, leaving about 26% for classroom courses. Clearly there is an imbalance in the representation of the courses. This may affect the result of the model and an inaccurate conclusion may result. For future analyis , the observation should be balanced so obtain an accurate model. For our purpose the data is used 'as-is'.This observation may be due to the fact that the number of enrollment online classes are not retricted by a physical classroom size thus the univeristy created moreonline classes.

Predictive Modeling

Linear Regression

In [14]:
```
df.head()
```

Out[14]:

	course_id	course_type	year	enrollment_count	pre_score	post_score	pre_requirement	dep
0	1	classroom	2018	165	28.14	73.0	Beginner	
1	2	classroom	2020	175	79.68	86.0	None	
2	3	online	2016	257	57.24	80.0	None	Math
3	4	online	2013	251	97.67	75.0	Beginner	Tec
4	5	classroom	2019	165	39.75	76.0	Beginner	

In [15]:
```
#Encode Categorical features
df_encoded = pd.get_dummies(df, columns=['course_type', 'pre_requirement', 'department'])
```

In [16]:
```
# start time for the model exeution
reg_start_time=time.time()
```

In [17]:
```
# Separate features (X) and the target variable (y)
X=df_encoded.drop(columns=['enrollment_count','course_id'])
y=df_encoded['enrollment_count']
```

In [18]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [19]:
```
#instantiate a linear regression object
linear_model = LinearRegression()
```

In [20]:
```
# Train the model
linear_model.fit(X_train, y_train)
```

Out[20]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

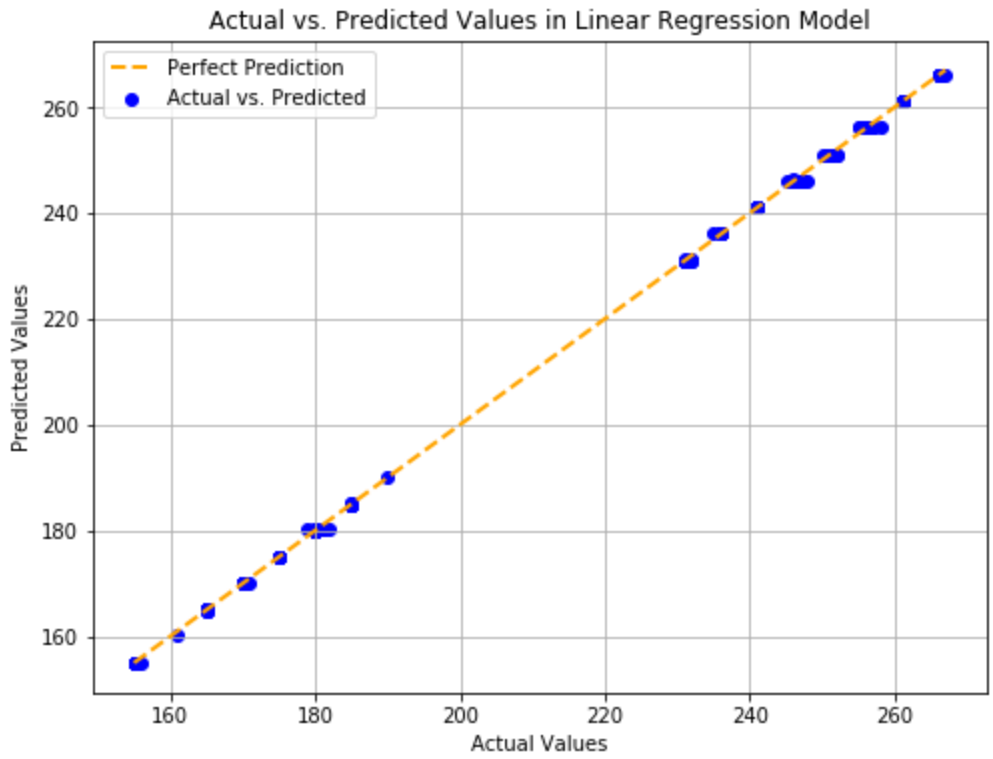
In [21]:
```
# Predict on the test set
y_pred =linear_model.predict(X_test)
y_pred[:5]
```

Out[21]:
```
array([240.97459333, 180.06724936, 250.96698407, 260.96869137,
       256.06810636])
```

In [22]:
```
## Check Performance Parameter
# stop time for model execution
reg_stop_time=time.time()
# get the time elapse
reg_elapse_time=reg_stop_time-reg_start_time
# print performance metrics
print(f" Time elaspse in seconds for Linear regression model execution: {reg_e
lapse_time}")
root_mean = np.sqrt(mae(y_test, y_pred))
print(f'Mean Absolute Error: {root_mean : .4f}')
r_squared = r2_score(y_test, y_pred)
print(f'The R-squared: {r_squared: .4f}')
```

```
 Time elaspse in seconds for Linear regression model execution: 3.12240099906
9214
Mean Absolute Error:  0.3149
The R-squared:  0.9999
```

In [23]:
```
# Visualize the performance
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, c='blue', label='Actual vs. Predicted', marker
='o')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--
', color='orange', linewidth=2, label='Perfect Prediction')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values in Linear Regression Model')
plt.legend()
plt.grid(True)
plt.show()
```



Random Forest Regressor Model

In [24]:
```
# start time for model execution
forest_start_time=time.time()
```

In [25]:
```
# Choose a more comparison model (e.g., Random Forest Regressor)
model_Forest = RandomForestRegressor(n_estimators=100, random_state=42)
```

In [26]:
```
# Train the model
model_Forest.fit(X_train, y_train)
```

Out[26]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=100,
                      n_jobs=None, oob_score=False, random_state=42, verbose=
0,
                      warm_start=False)
```

In [35]:
```
# Predict on the test set
y_pred_Forest = model_Forest.predict(X_test)
```

```
C:\Users\oladu\Anaconda3\lib\site-packages\sklearn\ensemble\base.py:158: Depr
ecationWarning: `np.int` is a deprecated alias for the builtin `int`. To sile
nce this warning, use `int` by itself. Doing this will not modify any behavio
r and is safe. When replacing `np.int`, you may wish to use e.g. `np.int64` o
r `np.int32` to specify the precision. If you wish to review your current us
e, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/de
vdocs/release/1.20.0-notes.html#deprecations
  dtype=np.int)
```

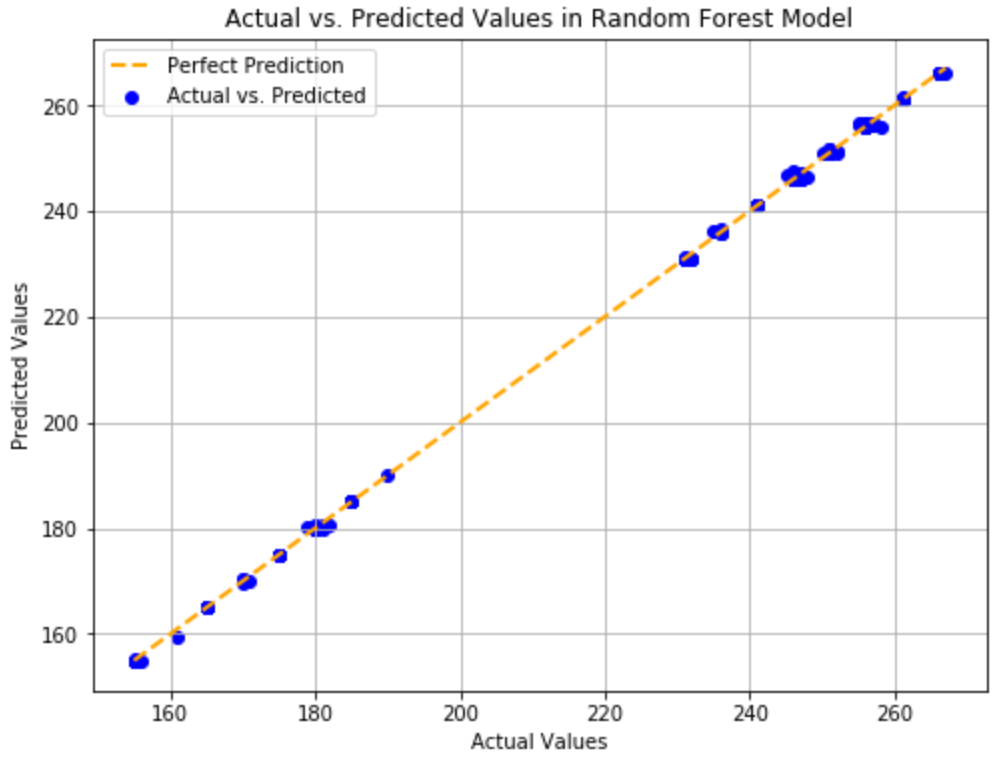
In [28]:
```
# stop time for model execution
forest_stop_time=time.time()
```

In [29]:
```
# get the time elapse
forest_elapse_time=forest_stop_time-forest_start_time
```

In [30]:
```
# print performance metrics
print(f" Time elaspse in seconds for Random Forest model execution: {forest_el
apse_time}")
rmse_Forest = np.sqrt(mae(y_test, y_pred_Forest))
print(f'Mean Absolute Error: {rmse_Forest}')
r_squared_Forest = r2_score(y_test, y_pred_Forest)
print(f'The R-squared: {r_squared_Forest: .4f}')
```

```
 Time elaspse in seconds for Random Forest model execution: 0.794255018234252
9
Mean Absolute Error: 0.3543238555256964
The R-squared:  0.9999
```

In [31]:
```
# Visualiza the performance of the model
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_Forest, c='blue', label='Actual vs. Predicted', mar
ker='o')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--
', color='orange', linewidth=2, label='Perfect Prediction')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values in Random Forest Model')
plt.legend()
plt.grid(True)
plt.show()
```



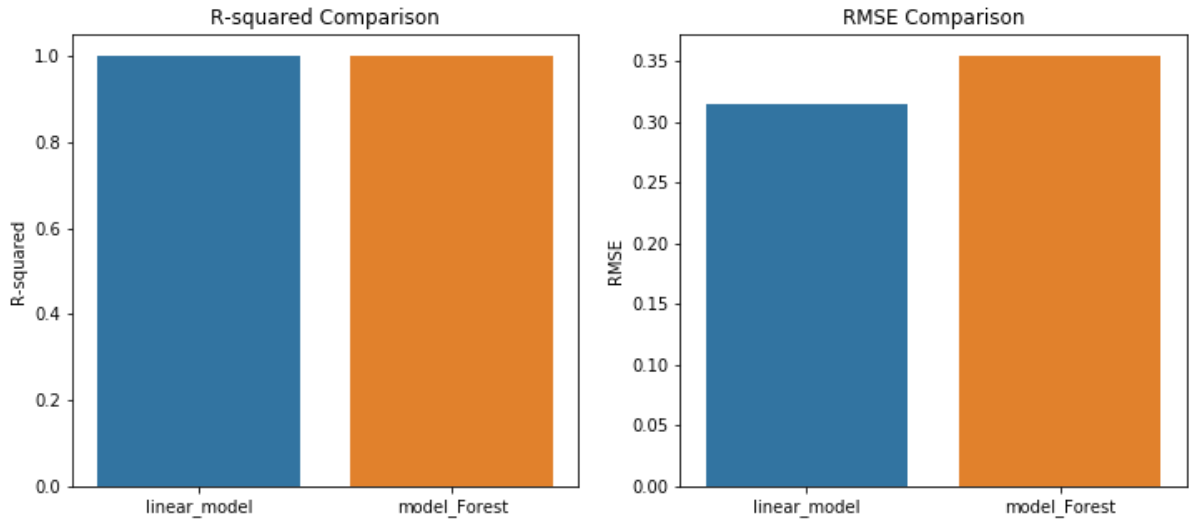
Compare the Performance of the Two Models

In [32]:
```
# Create visualizations
plt.figure(figsize=(12, 5))

# R-squared comparison
plt.subplot(1, 2, 1)
sns.barplot(x=['linear_model', 'model_Forest'], y=[ r_squared, r_squared_Fores
t])
plt.title('R-squared Comparison')
plt.ylabel('R-squared')

# RMSE comparison
plt.subplot(1, 2, 2)
sns.barplot(x=['linear_model', 'model_Forest'], y=[root_mean, rmse_Forest])
plt.title('RMSE Comparison')
plt.ylabel('RMSE')
```

Out[32]:
```
Text(0, 0.5, 'RMSE')
```



In [33]:
```
sns.barplot(x=['linear_model', 'model_Forest'], y=[reg_elapse_time, forest_ela
pse_time])
plt.title('Elapse Time Comparison')
plt.ylabel('Elapse Time')
```

Out[33]: Text(0, 0.5, 'Elapse Time')