In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

```
/Users/kalyaniasthana/opt/anaconda3/lib/python3.7/importlib/_bootstrap.py:219: R
untimeWarning: numpy.ufunc size changed, may indicate binary incompatibility. Ex
pected 192 from C header, got 216 from PyObject
  return f(*args, **kwds)
/Users/kalyaniasthana/opt/anaconda3/lib/python3.7/importlib/_bootstrap.py:219: R
untimeWarning: numpy.ufunc size changed, may indicate binary incompatibility. Ex
pected 192 from C header, got 216 from PyObject
  return f(*args, **kwds)
```

Loading CSV files into pandas format and merging them together to create a training set similar to the test set:

In [2]:

```
df1 = pd.read_csv('dc_signal_strength.csv')
df2 = pd.read_csv('dc_ipads.csv')
df3 = pd.read_csv('dc_ap_locations.csv')
```

Since for iPad ID - '0452f3640b3e' there is no Access Point information, I removed it from the training set.

In [3]:

```
merge1 = pd.merge(df1, df2, how='inner', on='iPad ID')
merge2 = pd.merge(merge1, df3, how='inner', on='Access Point ID')
merge2.head()
```

Out[3]:

	iPad ID	Access Point ID	Signal Strength	iPad Name	iPad x	iPad y	Floor	Access Point x	Access Point y
0	0452f3638d1a	b45d50f656d0	43	Big Sur	3.0	49.2	3	2.725522	43.234657
1	0452f3638d1a	b45d50f656d0	43	Big Sur	3.0	49.2	3	2.725522	43.234657
2	0452f3638d1a	b45d50f656d0	43	Big Sur	3.0	49.2	3	2.725522	43.234657
3	0452f3638d1a	b45d50f656d0	43	Big Sur	3.0	49.2	3	2.725522	43.234657
4	0452f3638d1a	b45d50f656d0	43	Big Sur	3.0	49.2	3	2.725522	43.234657

Preparing merge2 for fitting ML models

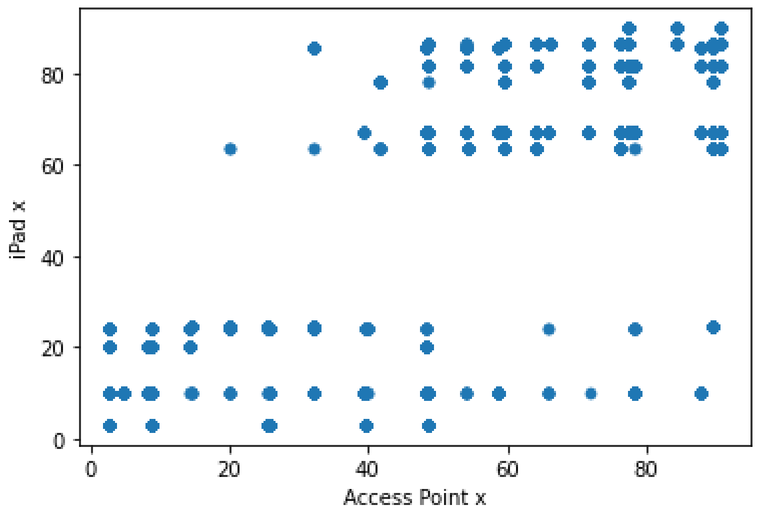
In [9]:

```
X = merge2[['Signal Strength', 'Access Point x', 'Access Point y']]
y1 = merge2[['iPad x']]
y2 = merge2[['iPad y']]
```

In [10]:

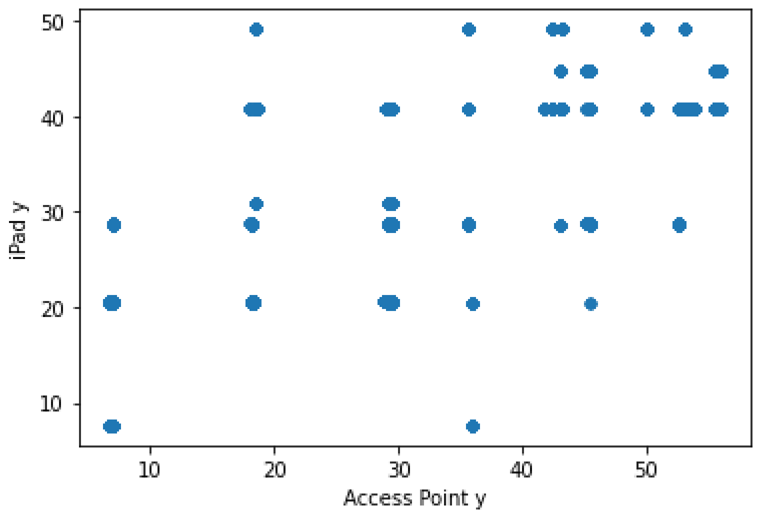
```
X_train, X_test, y1_train, y1_test = train_test_split(X, y1, test_size=0.2, rand
X_train, X_test, y2_train, y2_test = train_test_split(X, y2, test_size=0.2, rand
In [5]: merge2.plot.scatter('Access Point x', 'iPad x')
```

```
Out[5]: <AxesSubplot:xlabel='Access Point x', ylabel='iPad x'>
```



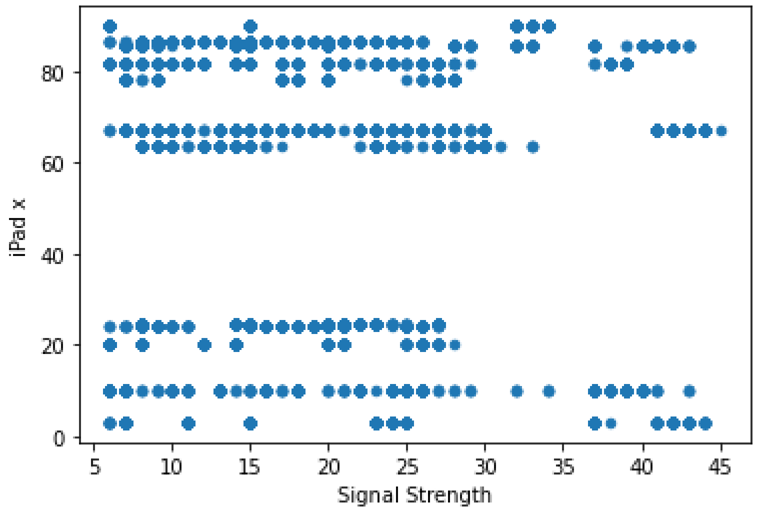
```
In [6]: merge2.plot.scatter('Access Point y', 'iPad y')
```

```
Out[6]: <AxesSubplot:xlabel='Access Point y', ylabel='iPad y'>
```



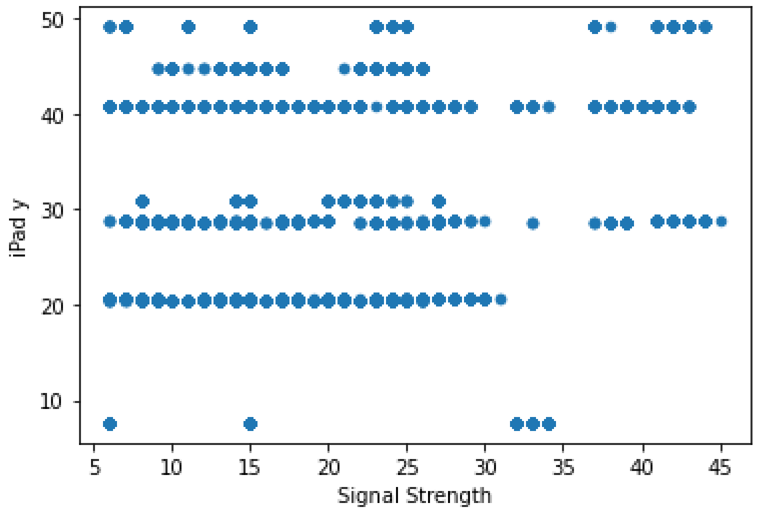
```
In [7]: merge2.plot.scatter('Signal Strength', 'iPad x')
```

```
Out[7]: <AxesSubplot:xlabel='Signal Strength', ylabel='iPad x'>
```



In [8]:
```
merge2.plot.scatter('Signal Strength', 'iPad y')
```

Out[8]:
```
<AxesSubplot:xlabel='Signal Strength', ylabel='iPad y'>
```



Since from the above plots we can see that there is no linear relation between the dependent and independent variables, we can assume that Linear Regression will not be able to fit the data well.

In [14]:
```
lr = LinearRegression()
lr.fit(X_train, y1_train)
y1_pred_lr = lr.predict(X_test)

lr.fit(X_train, y2_train)
y2_pred_lr = lr.predict(X_test)

print('Mean Squared error for iPad x:', mean_squared_error(y1_test, y1_pred_lr))
print('Mean Squared error for iPad y:', mean_squared_error(y2_test, y2_pred_lr))
```

```
Mean Squared error for iPad x: 367.700645442701
Mean Squared error for iPad y: 37.509941662531396
```

As expected, the mean squared error for linear regression is very high. We will try fitting a Decision Tree Regressor to the data instead.

In [23]:
```
dt_reg = DecisionTreeRegressor()
dt_reg.fit(X_train, y1_train)
y1_pred_dt = dt_reg.predict(X_test)

feature_importances_ipadx = dt_reg.feature_importances_

dt_reg.fit(X_train, y2_train)
y2_pred_dt = dt_reg.predict(X_test)

feature_importances_ipady = dt_reg.feature_importances_

print('Mean Squared error for iPad x:', mean_squared_error(y1_test, y1_pred_dt))
print('Mean Squared error for iPad y:', mean_squared_error(y2_test, y2_pred_dt))
```

```
Mean Squared error for iPad x: 22.69809889768927
Mean Squared error for iPad y: 1.957791574250314
```

In [18]:
```
print('Feature Importances for estimating ipad x: ', feature_importances_ipadx)
print('Feature Importances for estimating ipad y: ', feature_importances_ipady)
```

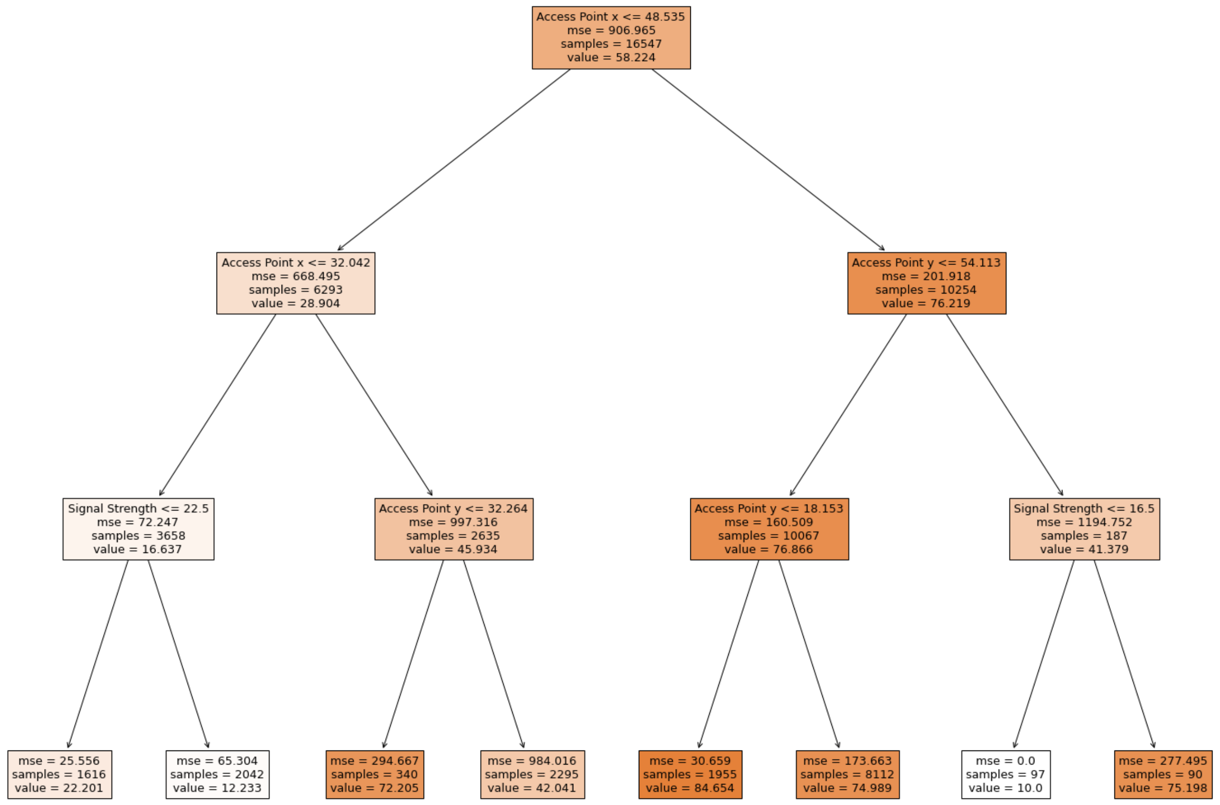
```
Feature Importances for estimating ipad x:  [0.17506705 0.75029452 0.07463843]
Feature Importances for estimating ipad y:  [0.17990229 0.21042237 0.60967534]
```

While predicting iPad x, the feature Access Point x has more importance. Whereas while predicting iPad y, the feature Access Point y has more importance.

We can see that there is a huge improvement in mean squared error from linear regression to decision tree.

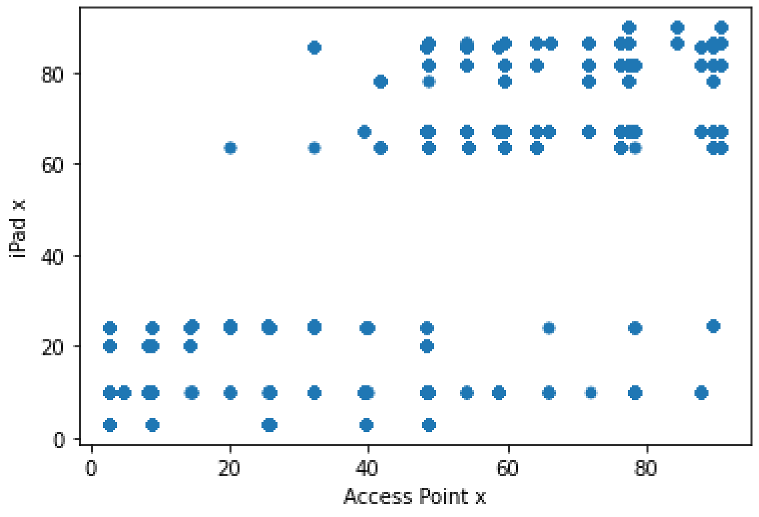
Visualizing the Decision Tree:

In [21]:
```
from sklearn import tree

dt_reg = DecisionTreeRegressor(max_depth=3)
dt_reg.fit(X_train, y1_train)

text_representation = tree.export_text(dt_reg)
fig = plt.figure(figsize=(25,20))
_ = tree.plot_tree(dt_reg,
                   feature_names=X_train.columns,
                   filled=True)
```



In [22]:
```python
merge2.plot.scatter('Access Point x', 'iPad x')
```

Out[22]:
```
<AxesSubplot:xlabel='Access Point x', ylabel='iPad x'>
```



The decision tree is first splitting based on Access point x by thresholding on ~48 which is very intuitive from the above plot.

Creating Final Prediction Data using a decision tree.

In [27]:
```python
df = pd.read_csv('dc_test_data.csv')
```

```
test_df = df[['Signal Strength', 'Access Point x', 'Access Point y']]
```

In [28]:

```
dt_reg = DecisionTreeRegressor()
dt_reg.fit(X_train, y1_train)
y1_pred_final = dt_reg.predict(test_df)

dt_reg.fit(X_train, y2_train)
y2_pred_final = dt_reg.predict(test_df)
```

In [30]:

```
final_df = pd.DataFrame()
final_df['iPad ID'] = df['iPad ID']
final_df['iPad x'] = y1_pred_final
final_df['iPad y'] = y2_pred_final
final_df.head()
```

Out[30]:

	iPad ID	iPad x	iPad y
0	0452f360ef9f	24.0	40.8
1	0452f360ef9f	10.0	40.8
2	0452f360ef9f	67.2	44.8
3	0452f36c3d9d	86.4	20.5
4	0452f36c3d9d	81.6	28.7

In [31]:

```
final_df.to_csv('FinalSubmission.csv', index=None)
```

I also tried Gradient Boosting, which is an ensemble method but did not see much improvement. This could be because the data is quite simple and more improvement couldn't be made after just once decision tree.

In [16]:

```
gb_reg = GradientBoostingRegressor(n_estimators=1000, max_depth=25)
gb_reg.fit(X_train, y1_train)
y1_pred_gb = gb_reg.predict(X_test)

gb_reg.fit(X_train, y2_train)
y2_pred_gb = gb_reg.predict(X_test)

print('Mean Squared error for iPad x:', mean_squared_error(y1_test, y1_pred_gb))
print('Mean Squared error for iPad y:', mean_squared_error(y2_test, y2_pred_gb))
```

```
/Users/kalyaniasthana/opt/anaconda3/lib/python3.7/site-packages/sklearn/utils/va
lidation.py:72: DataConversionWarning: A column-vector y was passed when a 1d ar
ray was expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  return f(**kwargs)
/Users/kalyaniasthana/opt/anaconda3/lib/python3.7/site-packages/sklearn/utils/va
lidation.py:72: DataConversionWarning: A column-vector y was passed when a 1d ar
ray was expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  return f(**kwargs)
Mean Squared error for iPad x: 22.6980988976638
Mean Squared error for iPad y: 1.9577915741950054
```