In [1]:

```
# -*- coding: utf-8 -*-

import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as img
from scipy import misc
from datetime import datetime
from tqdm import tqdm
import pandas as pd
import matplotlib.pyplot as plt
from tqdm import tqdm
from scipy.io import loadmat
from mpl_toolkits.mplot3d import axes3d
import matplotlib.pyplot as plt
import numpy as np
import copy
from matplotlib import cm
from matplotlib.animation import FuncAnimation
import scipy.optimize
import networkx as nx
import os
from sklearn import svm
from scipy.spatial.distance import cdist
from scipy.cluster.hierarchy import fcluster
from scipy.cluster import hierarchy
from scipy.spatial.distance import pdist
from scipy import stats
from sklearn.tree import *
from sklearn.ensemble import *


import math
from sklearn.model_selection import train_test_split
```

```
C:\Users\keipa\Anaconda2\lib\site-packages\sklearn\ensemble\weight_boosting.py:
29: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module and
should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [2]:

```

def rmse(predictions, targets):
    differences = predictions - targets                       #the DIFFERENCEs.
    differences_squared = differences ** 2                    #the SQUAREs of ^
    mean_of_differences_squared = differences_squared.mean()  #the MEAN of ^
    rmse_val = np.sqrt(mean_of_differences_squared)           #ROOT of ^
    return rmse_val                                           #get the ^

# remove random
np.random.seed(42)
```

In [3]:
```
# task 1
# Загрузите данные с помощью библиотеки sklearn.

from sklearn.datasets import load_boston
boston = load_boston()
x = boston["data"]
y = boston["target"]


def norm(x):
    m, n = x.shape
    for columnIndex in range(n):
        column = x[:, columnIndex]
        min_value, max_value = min(column), max(column)
        denominator = max_value - min_value if (max_value - min_value) != 0 else
        normalize_column = (column - min_value) / denominator
        x[:, columnIndex] = normalize_column
    return x
```

In [4]:
```
# task 2
# Разделите выборку на обучающую (75%) и контрольную (25%).

x_train, x_test, y_train, y_test = train_test_split(x, y,train_size=.75, test_siz
features = boston.feature_names
```

In [5]:
```
# task 4
# Заведите массив для объектов DecisionTreeRegressor (они будут использоваться в
DecisionTreeRegressors = []
alphas = []
tree_count = 50
max_depth = 5
random_state = 42
```

In [6]:
```
# task 5
# В цикле обучите последовательно 50 решающих деревьев с параметрами max_depth=5
y_shift = y_train.copy()
for i in range(tree_count):
    regressor = DecisionTreeRegressor(random_state=random_state, max_depth=max_de
    regressor.fit(x_train, y_shift)
    y_shift -= y_shift - regressor.predict(x_train)
    DecisionTreeRegressors.append(regressor)

print("Boosted Decision tree rmse: {}".format(rmse(DecisionTreeRegressors[-1].pre
```

```
Boosted Decision tree rmse: 3.32175540784
```

In [7]:

```
# task 6
# Попробуйте всегда брать коэффициент равным 0.9. Обычно оправдано выбирать коэф

DecisionTreeRegressors = []
tree_count = 50
max_depth = 5
random_state = 42

y_shift = y_train.copy()
for i in range(tree_count):
    regressor = DecisionTreeRegressor(random_state=random_state, max_depth=max_de
    regressor.fit(x_train, y_shift)
    y_shift -= (y_shift - 0.9*regressor.predict(x_train))
    DecisionTreeRegressors.append(regressor)

print("0.9 Boosted Decision tree rmse: {}".format(rmse(DecisionTreeRegressors[-1]
```

```
0.9 Boosted Decision tree rmse: 22.8619094779
```

In [ ]:

```
# task 7
# В процессе реализации обучения вам потребуется функция, которая будет вычислять

def rmse(predictions, targets):
    differences = predictions - targets                       #the DIFFERENCEs.
    differences_squared = differences ** 2                    #the SQUAREs of ^
    mean_of_differences_squared = differences_squared.mean()  #the MEAN of ^
    rmse_val = np.sqrt(mean_of_differences_squared)           #ROOT of ^
    return rmse_val                                           #get the ^
```

In [8]:
```
# task 8
# Попробуйте уменьшать вес перед каждым алгоритмом с каждой следующей итерацией п

DecisionTreeRegressors = []
tree_count = 50
max_depth = 5
random_state = 42

y_shift = y_train.copy()
for i in range(tree_count):
    regressor = DecisionTreeRegressor(random_state=random_state, max_depth=max_de
    regressor.fit(x_train, y_shift)
    y_shift -= (y_shift - 0.9/(1.+i)*regressor.predict(x_train))
    DecisionTreeRegressors.append(regressor)

print("Incremental Boosted Decision tree rmse: {}".format(rmse(DecisionTreeRegres


rtg_imp = GradientBoostingRegressor(random_state=random_state, max_depth=max_dept
rtg_imp.fit(x_train, y_train)
print("Ready to go Gradient Boosting Regressor rmse: {}".format(rmse(rtg_imp.prec

from sklearn.linear_model import LinearRegression
```

```
Incremental Boosted Decision tree rmse: 22.9904379302
Ready to go Gradient Boosting Regressor rmse: 3.0449243991
```

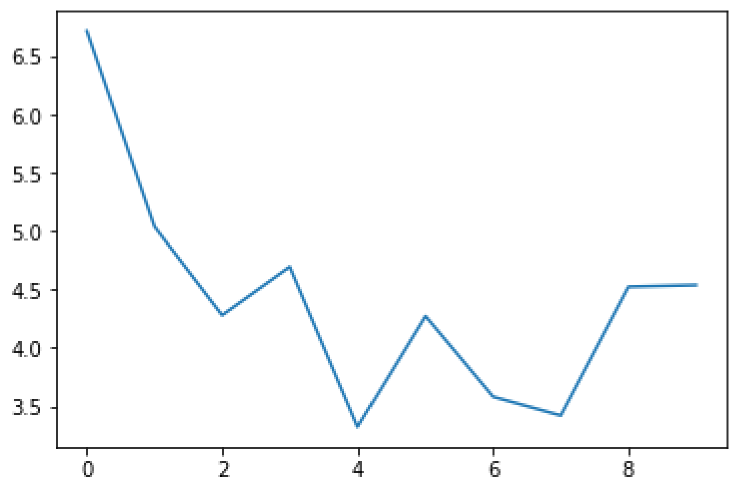
In [9]:
```
# task 9
# Исследуйте, переобучается ли градиентный бустинг с ростом числа итераций, а так


DecisionTreeRegressors = []
tree_count = 50
max_depth = 5
random_state = 42

error_rates = []

y_shift = y_train.copy()
for i in range(10):
    regressor = DecisionTreeRegressor(random_state=random_state, max_depth=i+1)
    regressor.fit(x_train, y_train)
    DecisionTreeRegressors.append(regressor)
    error_rates.append(rmse(regressor.predict(x_test), y_test))

plt.plot(error_rates)
plt.show()
# переобучение с ростом глубины деревьев
# нет
```



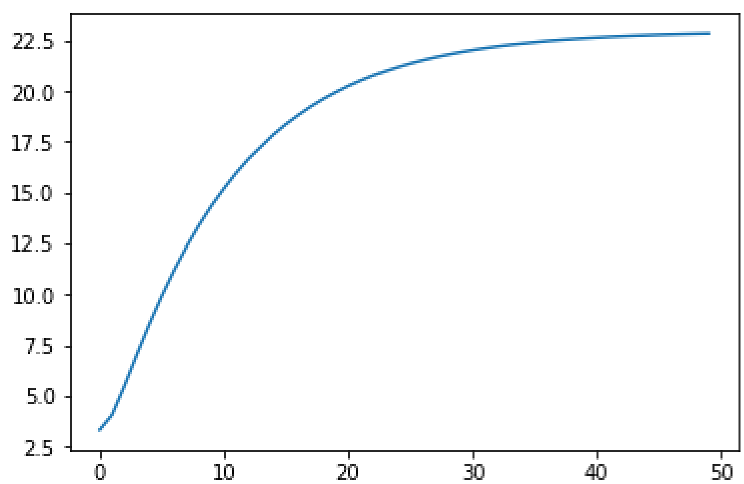
In [10]:
```
DecisionTreeRegressors = []
tree_count = 50
max_depth = 5
random_state = 42

error_rates = []

y_shift = y_train.copy()
for i in range(tree_count):
    regressor = DecisionTreeRegressor(random_state=random_state, max_depth=max_de
    regressor.fit(x_train, y_shift)
    y_shift -= (y_shift - 0.9*regressor.predict(x_train))
    DecisionTreeRegressors.append(regressor)
    error_rates.append(rmse(regressor.predict(x_test), y_test))

plt.plot(error_rates)
plt.show()

# переобучение ростом числа итераций,
# да
```



In [11]:

```
# task 10
# Сравните качество, получаемое с помощью градиентного бустинга с качеством работ

from sklearn.metrics import mean_squared_error
from math import sqrt

lin = LinearRegression().fit(x_train, y_train)
y_predicted = lin.predict(x_test)

rmse = rmse(y_predicted, y_test)
print("Linear regression rmse: {}".format(rmse))
```

```
Linear regression rmse: 4.70443172916
```