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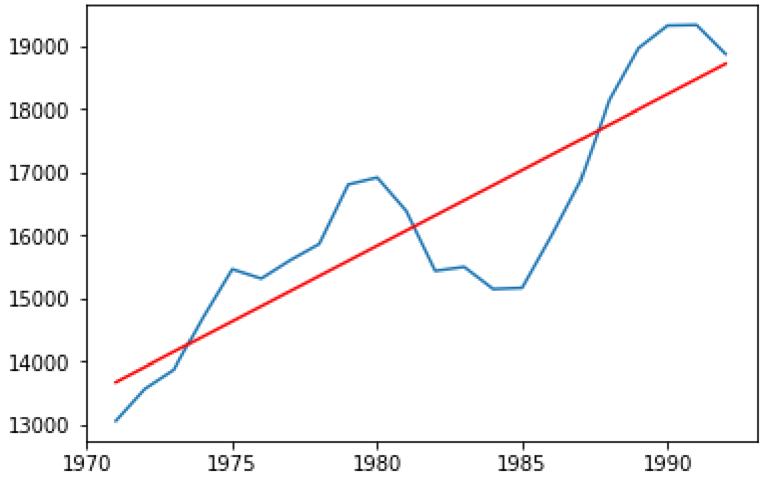
Pattern Recognition Computer Exercises 4

Task 1

In [3]:
```
import numpy as np
import matplotlib.pyplot as plt
% matplotlib inline

ALABAMA_DATA_PATH = './alabama.txt'
data = np.loadtxt(ALABAMA_DATA_PATH)
X, Y = data[:, 0], data[:, 1]
plt.plot(X, Y)


def plot_separating_line(w0, w1, bounds):
    x = np.linspace(bounds[0], bounds[1], 1000)
    y = w1 * x + w0
    plt.plot(x, y, '-r')


def linear_regression(X, Y):
    x_bar = np.mean(X)
    y_bar = np.mean(Y)
    w1 = np.sum(((X - x_bar) * (Y - y_bar))) / np.sum(np.square(X - x_bar))
    w0 = y_bar - w1 * x_bar
    return w0, w1


w0, w1 = linear_regression(X, Y)
plot_separating_line(w0, w1, [np.min(X), np.max(X)])
prediction_for2050 = w1 * 2050 + w0
print('Prediction for the year 2050 is {:.2f}'.format(prediction_for2050))
```

```
Prediction for the year 2050 is 32667.60
```



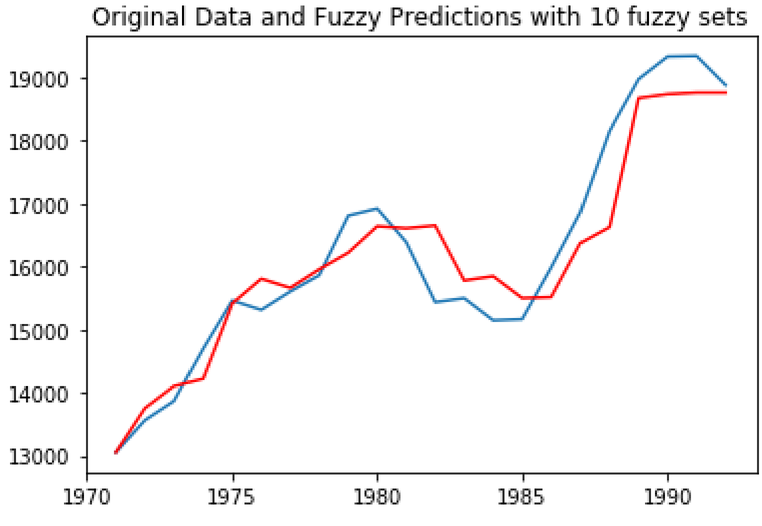
We see that the prediction is too high, so maybe it's not the best choice for time-series prediction.

Task 2

In [33]:
```
# Some util functions copied from exercises 2
def triangular(x, params):
    [a, b, c] = params
    return np.piecewise(x, [x < a, a <= x, b <= x, c <= x],
                        [0, lambda x: (x - a) / (b - a), lambda x: (c - x) / (
c - b), 0])


def min_implication(min, y):
    y[y > min] = min
    return y


def aggregate(Y):
    return np.max(Y, axis=0)


def coa(x, y):
    return np.sum(x * y) / np.sum(y)


def remove_duplicates(x):
    return list(dict.fromkeys(x))


def predict(x, y_bounds, fuzzy_sets, rules):
    lin_y_min, lin_y_max = y_bounds[0], y_bounds[1]
    lin_y = np.linspace(lin_y_min, lin_y_max, (lin_y_max - lin_y_min) * 100)
    Y = []
    for i in range(len(fuzzy_sets)):
        input_set = fuzzy_sets[i]
        output_sets = [fuzzy_sets[j] for j in rules[i]]
        if len(output_sets) == 0:
            continue
        calculated_input = triangular(x, input_set)
        y = np.array(
            [min_implication(calculated_input, triangular(lin_y, output_sets[j
])) for j in range(len(output_sets))])
        Y.append(aggregate(y))
    aggregated_Y = aggregate(np.array(Y))
    return coa(lin_y, aggregated_Y)


def fuzzy_prediction(num_fuzzy_sets, Y):
    [min_enrol, max_enrol] = [np.min(Y), np.max(Y)]
    fuzzy_edges = np.linspace(min_enrol, max_enrol, num_fuzzy_sets)
    fuzzy_edges = np.insert(fuzzy_edges, 0, min_enrol - 1000)
    fuzzy_edges = np.append(fuzzy_edges, max_enrol + 1000)
    fuzzy_sets = [fuzzy_edges[i: i + 3] for i in range(num_fuzzy_sets)]
    fuzzified_data = []
    for y in Y:
        memberships = [triangular(y, fuzzy_edges[i: i + 3]) for i in range(num
_fuzzy_sets)]
        fuzzified_data.append(np.argmax(memberships))

    rules = [[] for i in range(num_fuzzy_sets)]
    for i in range(len(fuzzified_data) - 1):
        rules[fuzzified_data[i]].append(fuzzified_data[i + 1])

    rules = [remove_duplicates(r) for r in rules]
    predicted_Y = [Y[0]]
    for y in Y[0:-1]:
```

```
        predicted_Y.append(predict(y, [min_enrol, max_enrol], fuzzy_sets, rule
s))
    return predicted_Y


def show_predicted_results(X, Y, Y_hat, num_fuzzy_sets):
    plt.plot(X, Y)
    plt.plot(X, Y_hat, c='r')
    plt.title('Original Data and Fuzzy Predictions with {} fuzzy sets'.format(
num_fuzzy_sets))
    plt.show()

NUM_FUZZY_SETS = 10
predicted_Y = fuzzy_prediction(NUM_FUZZY_SETS, Y)
show_predicted_results(X, Y, predicted_Y, NUM_FUZZY_SETS)
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/ipykernel_launcher.py:27: DeprecationWarning: object of type <class 'numpy.
float64'> cannot be safely interpreted as an integer.
```



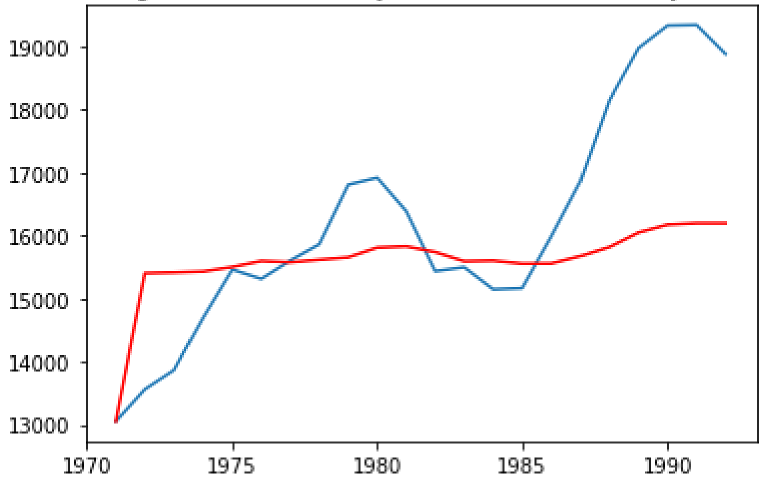
We can see that the predictions are pretty good. Now we're going to try different number of fuzzy sets to see which one works the best:

In [35]:

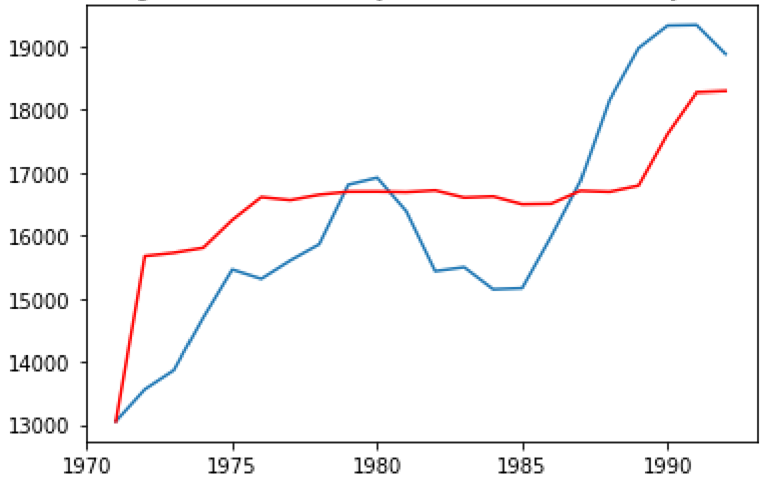
```
tests = [1, 3, 5, 10, 15, 20, 30]
for test in tests:
    predicted_Y = fuzzy_prediction(test, Y)
    show_predicted_results(X, Y, predicted_Y, test)
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/ipykernel_launcher.py:27: DeprecationWarning: object of type <class 'numpy.
float64'> cannot be safely interpreted as an integer.
```

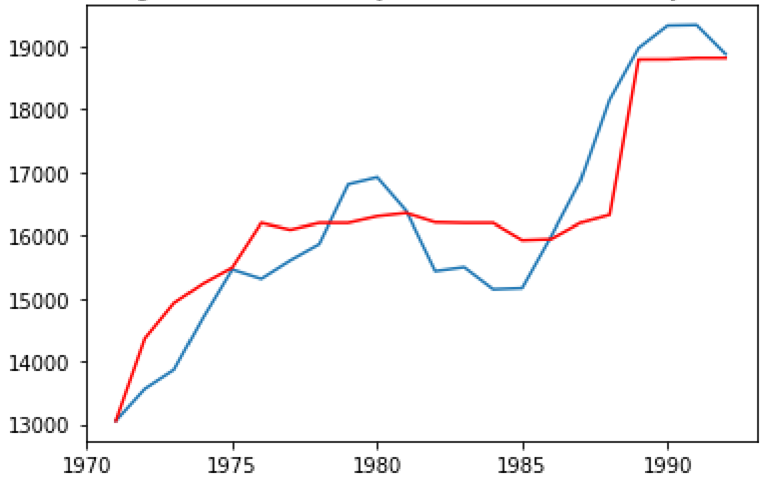
Original Data and Fuzzy Predictions with 1 fuzzy sets



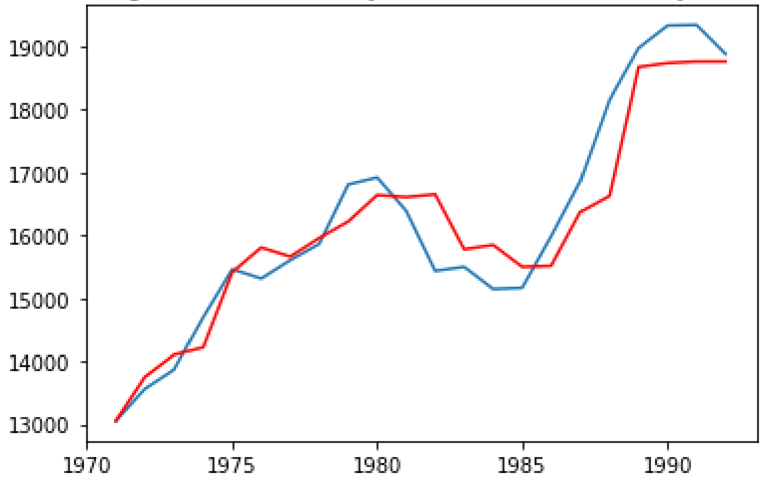
Original Data and Fuzzy Predictions with 3 fuzzy sets



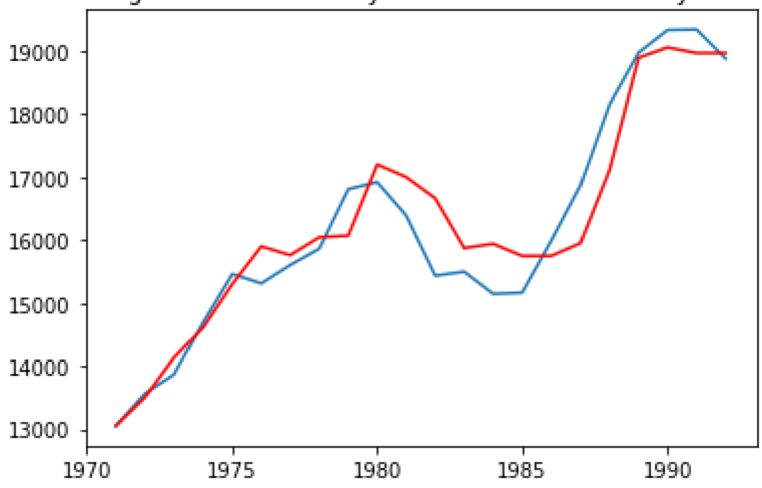
Original Data and Fuzzy Predictions with 5 fuzzy sets



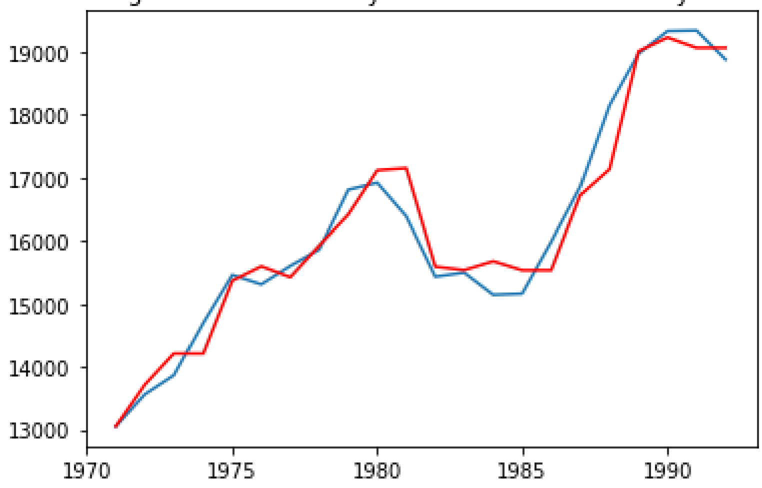
Original Data and Fuzzy Predictions with 10 fuzzy sets

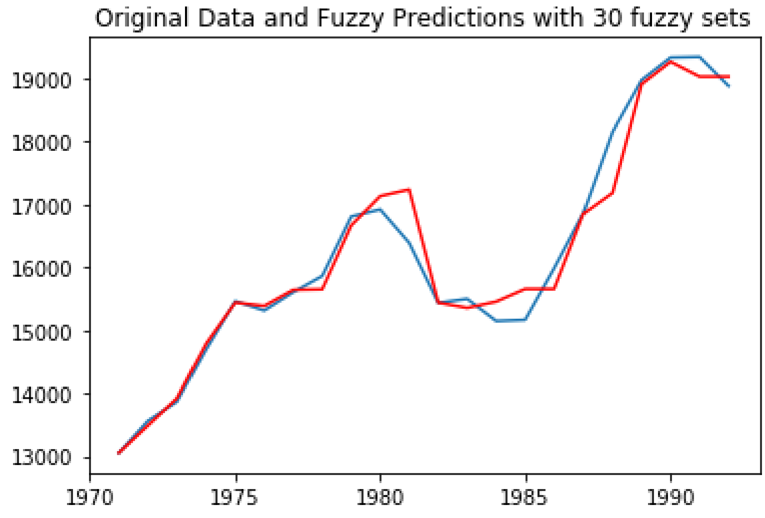


Original Data and Fuzzy Predictions with 15 fuzzy sets



Original Data and Fuzzy Predictions with 20 fuzzy sets





We can see that:

- IMHO, number of fuzzy sets between 10-15 work fine.
- If this number is too low, the model will underfit, the predictions, thus are not accurate.
- If this number is too high, the model will overfit, the predictions will follow closely to the true data, but will not generalize well. Also, the running time is significantly longer.