Analyzing Birth rate from World Bank Data using Agglomerative Clustering and Logistic Regression

In [1]:
```
import pandas as pd
import numpy as np
import missingno as ms
import scipy.optimize as opt
import sklearn.cluster as cluster

import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

Dataset Loading

In [2]:
```python
def function_transpose(file):
    '''
    this function will take a .csv file in the world bank format and transpose it into original
    format
    '''
    dataset=pd.read_csv(file)
    dataset=dataset.transpose()
    dataset.columns=dataset.iloc[0]
    dataset=dataset.iloc[:-1]
    dataset=dataset.reset_index()
    dataset=dataset.rename(columns={"index": "Year"})

    return dataset

file = 'countriesOfTheWorld-WDI.csv'
function_transpose(file)
```

Out[2]:

Country	Year	Afghanistan	Albania	Algeria	American Samoa	Andorra	Angola	Anguilla	Antigua & Barbuda	Argentina	...	Vanuatu	Venezuela
0	Country	Afghanistan	Albania	Algeria	American Samoa	Andorra	Angola	Anguilla	Antigua & Barbuda	Argentina	...	Vanuatu	Venezuela
1	Region	ASIA (EX. NEAR EAST)	EASTERN EUROPE	NORTHERN AFRICA	OCEANIA	WESTERN EUROPE	SUB-SAHARAN AFRICA	LATIN AMER. & CARIB	LATIN AMER. & CARIB	LATIN AMER. & CARIB	...	OCEANIA	LATIN AMER. & CARIB
2	Population	31056997	3581655	32930091	57794	71201	12127071	13477	69108	39921833	...	208869	25730435
3	Area (sq. mi.)	647500	28748	2381740	199	468	1246700	102	443	2766890	...	12200	912050
4	Pop. Density (per sq. mi.)	48,0	124,6	13,8	290,4	152,1	9,7	132,1	156,0	14,4	...	17,1	28,2
5	Coastline (coast/area ratio)	0,00	1,26	0,04	58,29	0,00	0,13	59,80	34,54	0,18	...	20,72	0,31
6	Net migration	23,06	-4,93	-0,39	-20,71	6,6	0	10,76	-6,15	0,61	...	0	-0,04
7	Infant mortality (per 1000 births)	163,07	21,52	31	9,27	4,05	191,19	21,03	19,46	15,18	...	55,16	22,2
8	GDP ($ per capita)	700	4500	6000	8000	19000	1900	8600	11000	11200	...	2900	4800
9	Literacy (%)	36,0	86,5	70,0	97,0	100,0	42,0	95,0	89,0	97,1	...	53,0	93,4
10	Phones (per 1000)	3,2	71,2	78,1	259,5	497,2	7,8	460,0	549,9	220,4	...	32,6	140,1
11	Arable (%)	12,13	21,09	3,22	10	2,22	2,41	0	18,18	12,31	...	2,46	2,95
12	Crops (%)	0,22	4,42	0,25	15	0	0,24	0	4,55	0,48	...	7,38	0,92
13	Other (%)	87,65	74,49	96,53	75	97,78	97,35	100	77,27	87,21	...	90,16	96,13
14	Climate	1	3	1	2	3	NaN	2	2	3	...	2	2
15	Birthrate	46,6	15,11	17,14	22,46	8,71	45,11	14,17	16,93	16,73	...	22,72	18,71
16	Deathrate	20,34	5,22	4,61	3,27	6,25	24,2	5,34	5,37	7,55	...	7,82	4,92
17	Agriculture	0,38	0,232	0,101	NaN	NaN	0,096	0,04	0,038	0,095	...	0,26	0,04
18	Industry	0,24	0,188	0,6	NaN	NaN	0,658	0,18	0,22	0,358	...	0,12	0,419

19 rows × 228 columns

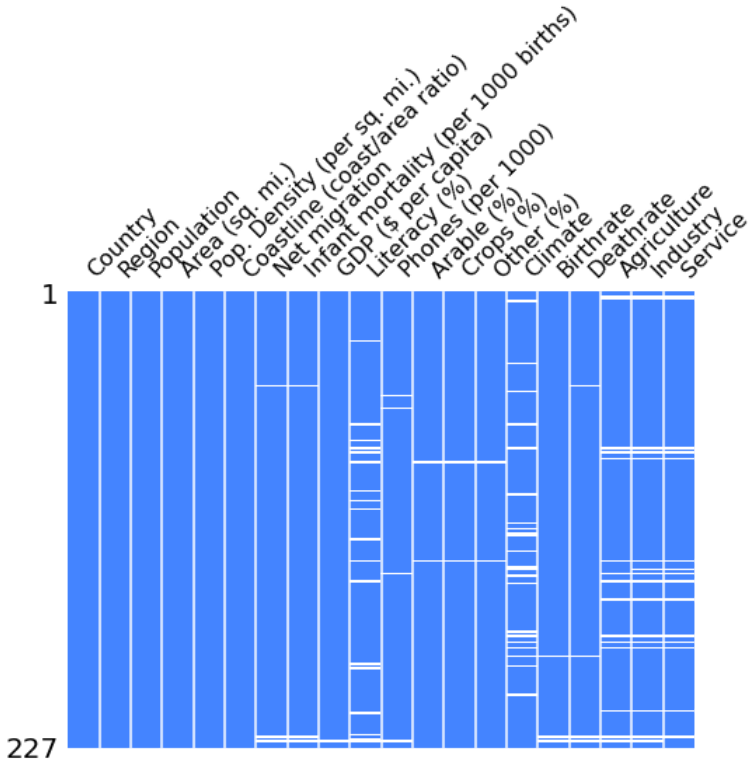
In [3]:
```python
dataset = pd.read_csv('countriesOfTheWorld-WDI.csv')
```

Data Pre-processing

Lets see the missing values first and then fix those outliers. This time I am using a library names "missingno", It will show the missing values in a viusal effects. We will then analyze the missing values in each features and then try to fix those.

```
In [4]: fig, ax = plt.subplots(figsize=(8,6))
        ms.matrix(dataset, ax=ax, sparkline=False, color=(0.27, 0.52, 1.0))
        plt.show
```

```
Out[4]: <function matplotlib.pyplot.show(*args, **kw)>
```



The matrix plot is showing the missing values trend in every feature. As it is visible that some of the features, For example Agriculture, Industry and Service; are showing missing values in the same country (the straight line). Let fill these missing feature values with the mean value of the respective column.

```
In [13]: dataset.fillna(dataset.mean(), inplace=True)
```

```
In [14]: dataset.isnull().sum()
```

```
Out[14]: Country                               0
         Region                                0
         Population                            0
         Area (sq. mi.)                        0
         Pop. Density (per sq. mi.)            0
         Coastline (coast/area ratio)          0
         Net migration                         0
         Infant mortality (per 1000 births)    0
         GDP ($ per capita)                    0
         Literacy (%)                          0
         Phones (per 1000)                     0
         Arable (%)                            0
         Crops (%)                             0
         Other (%)                             0
         Climate                               0
         Birthrate                             0
         Deathrate                             0
         Agriculture                           0
         Industry                              0
         Service                               0
         dtype: int64
```

```
In [15]: columns = dataset[['Net migration', 'Deathrate', 'Agriculture', 'Industry', 'Service',
                            'Infant mortality (per 1000 births)', 'Literacy (%)', 'Phones (per 1000)',
                            'Arable (%)', 'Crops (%)', 'Other (%)', 'Climate', 'Birthrate']]
         def changetype(columns):
             '''
             This function is used in the coversion of the feature column types as
             some are objects and some are floats. And replace all the , with the
             . in all numeric features for smooth visualizations.
             '''
             for i in columns:
                 dataset[i] = dataset[i].astype(str)
                 dataset1 = []
                 for j in dataset[i]:
                     j = j.replace(',','.')
                     j = float(j)
                     dataset1.append(j)
                 dataset[i] = dataset1
         changetype(columns)
```

```
In [16]: # trim the spaces after and before the text. It can be seen from the sample
         # data, there are some spaces in some countries names.

         dataset['Region'] = dataset.Region.str.strip()
         dataset['Country'] = dataset.Country.str.strip()
```

```
In [17]: df1 = dataset.copy() # copy dataset in df1
         df2 = df1.drop(columns= ['Pop. Density (per sq. mi.)', 'Coastline (coast/area ratio)'],
                        inplace = True ) # Drop the column Region as we will analysis the data with respect to country
```

Dataset Normalization

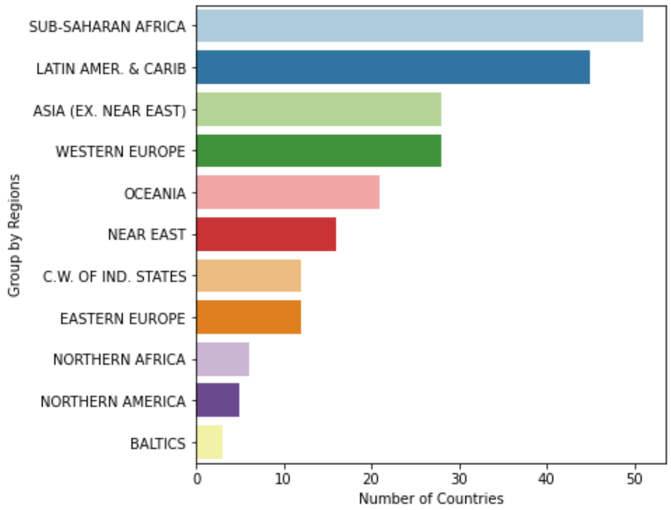
```
In [18]: def norm(array):
             """ Returns array normalised to [0,1]. Array can be a numpy array
             or a column of a dataframe"""

             min_val = np.min(array)
             max_val = np.max(array)

             scaled = (array-min_val) / (max_val-min_val)

             return scaled


         def norm_df(df):
             """
             Returns all columns of the dataframe normalised to [0,1] with the
             exception the first (containing the names)
             Calls function norm to do the normalisation of one column, but
             doing all in one function is also fine.
             """

             # iterate over all columns
             for col in df.columns[2:]:     # excluding the first column
                 df[col] = norm(df[col])

             return df
```

```
In [19]: df1 = norm_df(df1)
```

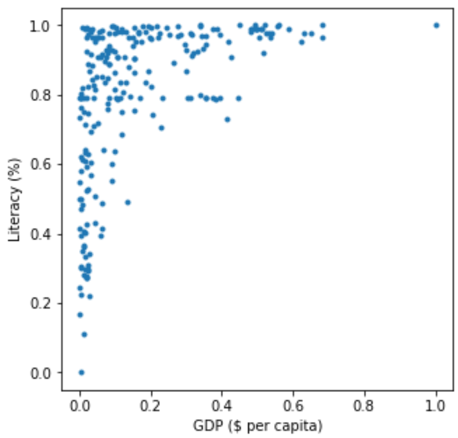
Number of countries in each region

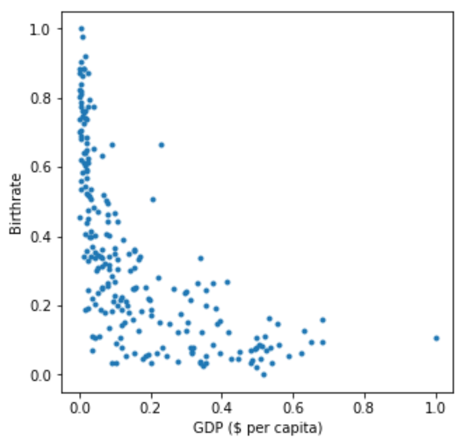
In [20]:

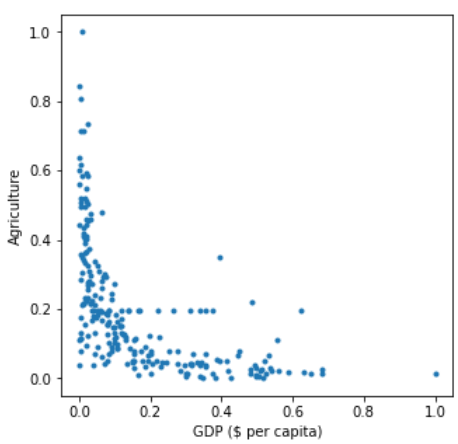
```
import seaborn as sns

country = df1['Region'].value_counts()
plt.figure(figsize=(6,6,))
sns.barplot(y=country.index,x=country.values, palette="Paired")
plt.xlabel('Number of Countries')
plt.ylabel('Group by Regions')
plt.show()
```



```
In [21]: def makeplot(df, col1, col2):
             """
             Produces a square plot of two columns of dataframe df using small circle
             symbols.
             """

             plt.figure(figsize=(5.0,5.0))
             plt.plot(df[col1], df[col2], "o", markersize=3)

             plt.xlabel(col1)
             plt.ylabel(col2)
             plt.show()


         # exploratory plots
         makeplot(df1, "GDP ($ per capita)", "Literacy (%)")
         makeplot(df1, "GDP ($ per capita)", "Birthrate")
         makeplot(df1, "GDP ($ per capita)", "Agriculture")
```



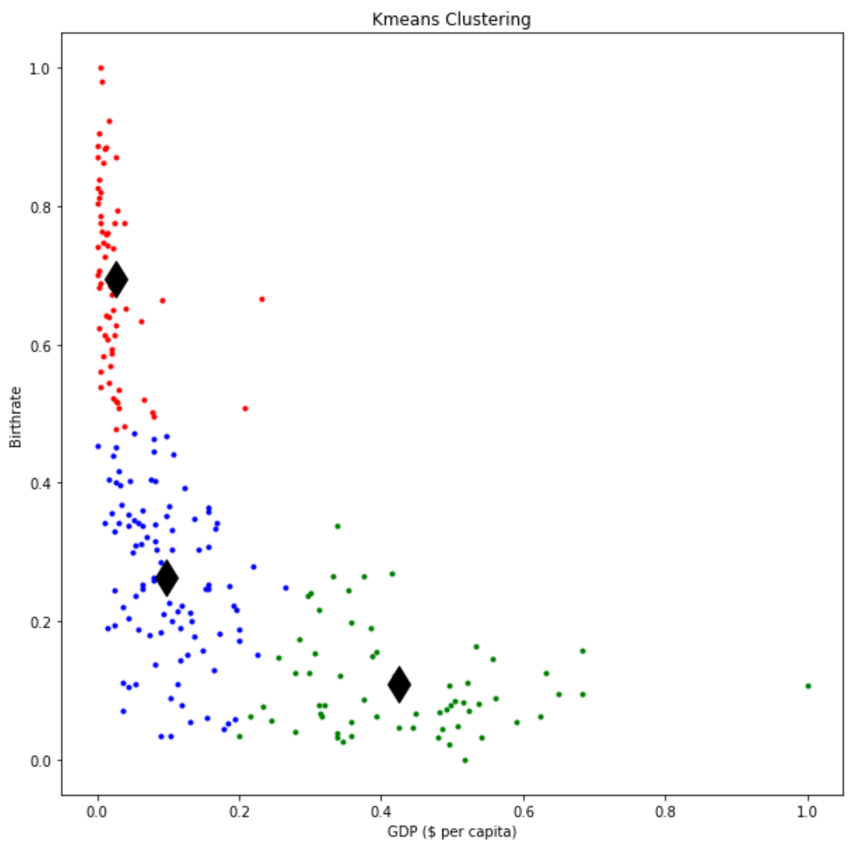




K-means Clustering

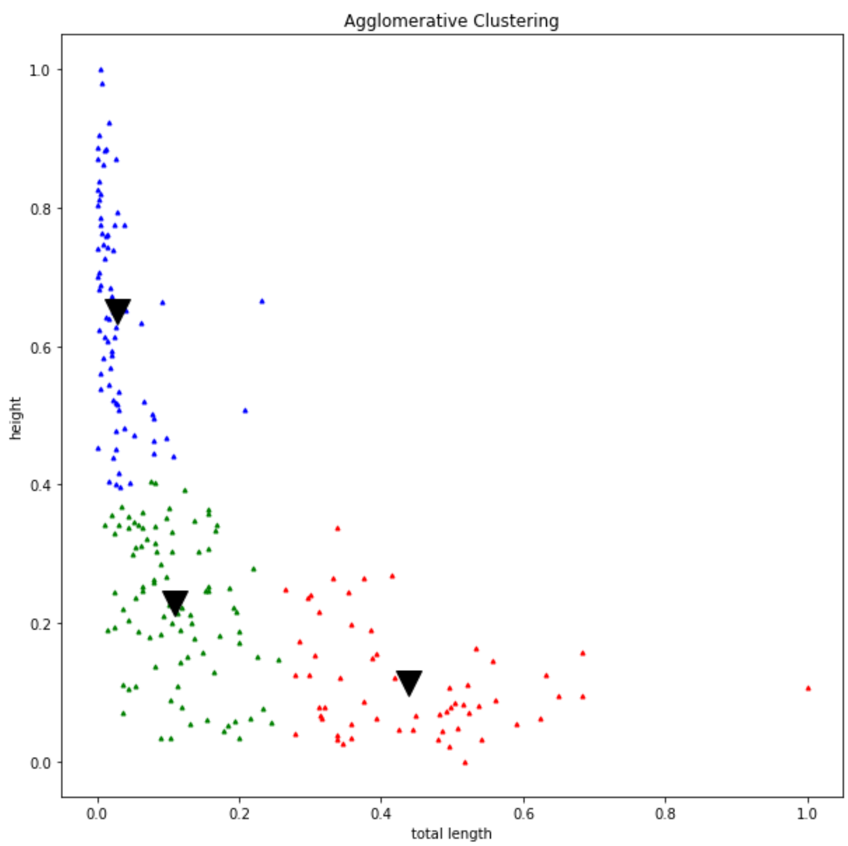
In [24]:

```
####### kmeans set up the clusterer, 4 expected clusters
kmeans = cluster.KMeans(n_clusters=3)

# extract columns for fitting
df_fit = df1[[ "GDP ($ per capita)", "Birthrate"]].copy()
kmeans.fit(df_fit)

# extract labels and cluster centres
labels = kmeans.labels_
cen = kmeans.cluster_centers_

# plot using the labels to select colour
plt.figure(figsize=(10,10))

col = ["blue", "red", "green", "magenta", "yellow", "red"]
for l in range(3):     # loop over the different labels
    plt.plot(df_fit["GDP ($ per capita)"][labels==l], df_fit["Birthrate"][labels==l], "o", markersize=3, color=col[l])

# show cluster centres
for ic in range(3):
    xc, yc = cen[ic,:]
    plt.plot(xc, yc, "dk", markersize=18)

plt.title("Kmeans Clustering")
plt.xlabel("GDP ($ per capita)")
plt.ylabel("Birthrate")
plt.show()
```



Agglomerative Clustering

In [25]:
```python
##### setting up agglomerative clustering for 6 clusters
ac = cluster.AgglomerativeClustering(n_clusters=3)

# carry out the fitting
df_fit = df1[[ "GDP ($ per capita)", "Birthrate"]].copy()
ac.fit(df_fit)

labels = ac.labels_

# The clusterer does not return cluster centres, but they are easily computed
xcen = []
ycen = []
for ic in range(3):
    xc = np.average(df_fit["GDP ($ per capita)"][labels==ic])
    yc = np.average(df_fit["Birthrate"][labels==ic])
    xcen.append(xc)
    ycen.append(yc)

# plot using the labels to select colour
plt.figure(figsize=(10,10))

col = ["blue", "red", "green", "magenta","yellow","aqua"]
for l in range(0,3):     # loop over the different labels
    plt.plot(df_fit["GDP ($ per capita)"][labels==l], df_fit["Birthrate"][labels==l], "^", markersize=3, color=col[l])

# show cluster centres
for ic in range(3):
    plt.plot(xcen[ic], ycen[ic], "vk", markersize=18, color = "k")

plt.title("Agglomerative Clustering")
plt.xlabel("total length")
plt.ylabel("height")
plt.show()


###### writing labels into df_fish, sorting and exporting as excel file
df1["labels"] = labels
df1 = df1.sort_values(["labels"], ignore_index=True)
#df.to_excel("fish_clusters.xlsx")
```



Data Fitting

In [26]:
```
from sklearn.linear_model import LinearRegression
data = pd.read_csv("WDI_country.csv")
data
```

Out[26]:

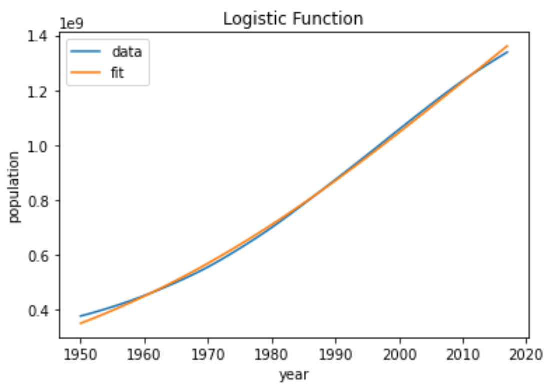
	year	Population	Birthrate % Change
0	1950	376325200	NaN
1	1951	382376948	1.61
2	1952	388799073	1.68
3	1953	395544369	1.73
4	1954	402578596	1.78
...	...	...	...
63	2013	1280842125	1.19
64	2014	1295600772	1.15
65	2015	1310152403	1.12
66	2016	1324517249	1.10
67	2017	1338676785	1.07

68 rows × 3 columns

In [27]:
```
"""
Define the logistics functions for fitting.
"""

def logistics(t, scale, growth, t0):
    """ Computes logistics function with scale, growth raat
    and time of the turning point as free parameters
    """

    f = scale / (1.0 + np.exp(-growth * (t - t0)))

    return f
```

In [28]:
```python
"""
fit the logistics function with some initial parameters such as p0. It will give us much better results
fit logistic growth and then calculate/ plot the result.
"""

# fit exponential growth
p, c = opt.curve_fit(logistics, data["year"], data["Population"], p0=(2e9, 0.05, 1990.0))
# much better
print("Fit parameter", p)

data["logistic"] = logistics(data["year"], *p)

plt.figure()
plt.plot(data["year"], data["Population"], label="data")
plt.plot(data["year"], data["logistic"], label="fit")

plt.legend()
plt.xlabel("year")
plt.ylabel("population")
plt.title("Logistic Function")
plt.show()
print()
```

```
Fit parameter [2.52480676e+09 2.96170675e-02 2.01171142e+03]
```

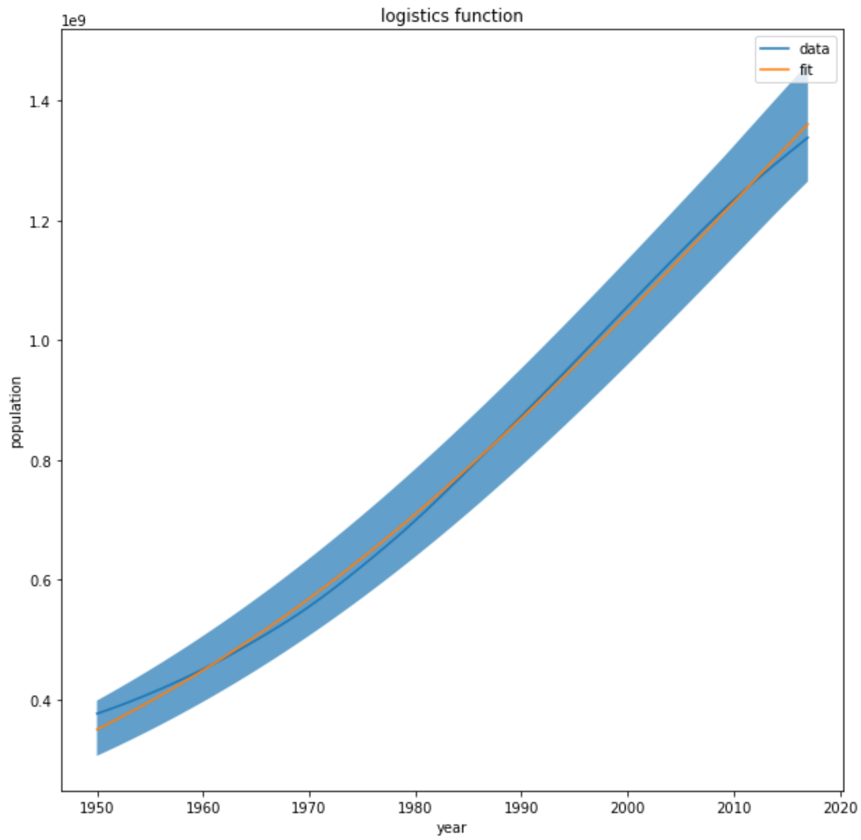


err_ranges()

In [29]:
```python
def err_ranges(x, func, param, sigma):
    """
    Calculates the upper and lower limits for the function, parameters and
    sigmas for single value or array x. Functions values are calculated for
    all combinations of +/- sigma and the minimum and maximum is determined.
    Can be used for all number of parameters and sigmas >=1.

    This routine can be used in assignment programs.
    """

    import itertools as iter

    # initiate arrays for lower and upper limits
    lower = func(x, *param)
    upper = lower

    uplow = []   # list to hold upper and lower limits for parameters
    for p,s in zip(param, sigma):
        pmin = p - s
        pmax = p + s
        uplow.append((pmin, pmax))

    pmix = list(iter.product(*uplow))

    for p in pmix:
        y = func(x, *p)
        lower = np.minimum(lower, y)
        upper = np.maximum(upper, y)

    return lower, upper
```

In [30]:
```
# extract the sigmas from the diagonal of the covariance matrix
sigma = np.sqrt(np.diag(c))
print(sigma)

low, up = err_ranges(data["year"], logistics, p, sigma)

plt.figure(figsize=(10,10))
plt.title("logistics function")
plt.plot(data["year"], data["Population"], label="data")
plt.plot(data["year"], data["logistic"], label="fit")

plt.fill_between(data["year"], low, up, alpha=0.7)
plt.legend()
plt.xlabel("year")
plt.ylabel("population")
plt.show()
```

```
[9.44349836e+07 6.01576537e-04 2.44923945e+00]
```



Prediction of the Population

In [31]:
```
# Give Ranges

print("Forcasted population")
low, up = err_ranges(2030, logistics, p, sigma)
print("2030 between ", low, "and", up)
low, up = err_ranges(2040, logistics, p, sigma)
print("2040 between ", low, "and", up)
low, up = err_ranges(2050, logistics, p, sigma)
print("2050 between ", low, "and", up)
```

```
Forcasted population
2030 between  1489613748.4262006 and 1707048163.5899236
2040 between  1650519621.8621323 and 1877585012.4929025
2050 between  1795631427.8485541 and 2027295272.1060772
```

In [32]:

```
print("Prediction of  population")
low, up = err_ranges(2030, logistics, p, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2030:", mean, "+/-", pm)

low, up = err_ranges(2040, logistics, p, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2040:", mean, "+/-", pm)

low, up = err_ranges(2050, logistics, p, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2050:", mean, "+/-", pm)
```

```
Prediction of  population
2030: 1598330956.0080621 +/- 108717207.5818615
2040: 1764052317.1775174 +/- 113532695.3153851
2050: 1911463349.9773157 +/- 115831922.12876153
```

In [ ]:

In [ ]: