Estimation of California Sea Otter's finite rate of growth

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The goal of this exercise is to estimate the finite growth rate of the sea otter population in the Monterey bay from the historical time series of population abundance. Specifically, wit this exercise, we will learn how:

- Read the data from a file
- Plot the data as a function of time in a natural and logarithmic scale
- Estimate the finite growth rate of this population
- Estimate how many years it takes for the population to double

Premise*

*excerpt from Ludina and Levin (1988)

The California sea otter has recovered only recently (and dramatically) from years of overharvesting, although the population is still considered vulnerable to significant pollution events (VanBlaricom and Jameson 1982). In the eastern Pacific Ocean, fur traders hunted the sea otter to near extinction in the early 1900s. When relict populations were protected in 1911 by international treaty, the California sea otter was thought to be extinct (Kenyon 1969; Wild and Ames 1974). However, in 1914, a small population of about 50 otters was discovered near Point Sur on the central California coast (Bryant 1915; Bolin 1938; Wild and Ames 1974). Since that time, the otters have increased their population size and expanded their range to reoccupy portions of the habitat from which they had been extirpated (fig. 1; Kenyon 1969; Peterson and Odemar 1969; Wild and Ames 1974).

In the original paper, the authors gathred data from published and unpublished information graciously provided by the California Department of Fish and Game (CFG), the U.S. Fish and Wildlife Service (USFWS), and the Institute of Marine Sciences at the University of California, Santa Cruz (Carlisle 1966; Peterson and Odemar 1969; Wild and Ames 1974; Geibel and Miller 1984; Riedman and Estes, MS; E. Ebert, pers. comm.). These data reflect the historical process of sea otter range expansion through 1984. The data are of three types:

- descriptions of the extent of the otters' range over time
- estimates of the total otter population size
- and CFG flight reports of aerial surveys containing distributional data.

For the sake of this exercise, we will use the data on population size from 1914 to 1974.

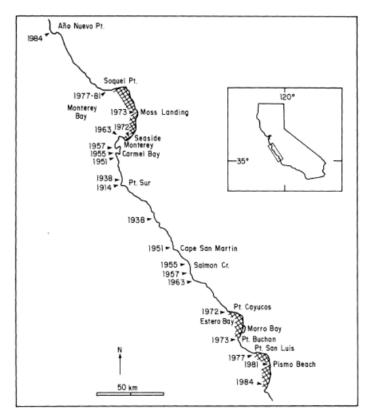


Fig. 1.—Expansion of the range of the California sea otter along the central California coast. Only representative locations of the position of the range boundaries are shown. Point Sur is the traditional location of the division of the range into northern and southern halves. Crosshatching, the approximate location of sandy or soft-bottom habitats. Data are taken from table 1. (Map after Wild and Ames 1974.)

Figure 1: from Ludina and Levin (1988)

Exercise

Let's read the file and, as it is a short one, just print screen its content:

```
df = as.data.frame(read.table("data/California_Sea_otters.csv", sep=",", header=T, na.string="-9.99"))
head(df)
```

year	abundance
1938	310
1947	530
1950	660
1955	800
1957	880
1959	1050

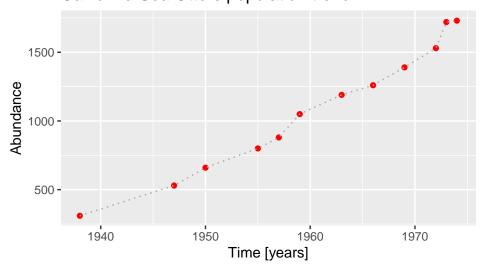
To plot the result, let's load the ggplot2() package

```
if (!require("ggplot2")) install.packages("ggplot2")
library(ggplot2)
```

and then "build up" the plot:

```
ggplot() +
geom_point(data=df, mapping=aes(x=year, y=abundance), color="red") + #the red points
geom_line( data=df, mapping=aes(x=year, y=abundance), color = "darkgrey", linetype=3) + # a dotted lin
    ggtitle("California Sea Otters population trend") + # the tite
    xlab("Time [years]") + ylab("Abundance") # the axis label
```

California Sea Otters population trend



To estimate average growth rate, we assume here Malthusian growth. Accordingly:

$$N_{t+1} = \lambda N_t$$

which lead to:

$$N_t = N_0 \lambda^t$$

Let's take the logarithm of both the righ and left hand sides:

$$\log N_t = \log N_0 \lambda^t = \log N_0 + \log \lambda^t = \log N_0 + t \cdot \log \lambda$$

which is the equation of a straight line:

$$y = a + b \cdot x$$

with $y \equiv \log N_t$, $a \equiv \log N_0$, $b \equiv \log \lambda$, and $x \equiv t$.

In R it is straightforward to estimate the finite growth rate through linear regression, namely:

```
LogModel=lm(data = df, log(abundance)~year);
summary(LogModel)
```

```
##
## Call:
## lm(formula = log(abundance) ~ year, data = df)
##
## Residuals:
##
         Min
                    1Q
                          Median
                                        3Q
                                                 Max
## -0.141000 -0.045938 -0.009272 0.049430 0.128191
##
## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -81.866017
                            4.085515 -20.04 2.11e-09 ***
                 0.045275
                            0.002084
                                       21.72 9.55e-10 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 0.0786 on 10 degrees of freedom
## Multiple R-squared: 0.9792, Adjusted R-squared: 0.9772
## F-statistic: 471.9 on 1 and 10 DF, p-value: 9.551e-10
```

We can extract intercept and slope

```
coef(LogModel)
```

```
## (Intercept) year
## -81.86601684 0.04527533
```

Now, assign the slope to a new parameter, say igr (instantaneous growth rate):

```
igr <- coef(LogModel)[2]; igr</pre>
```

```
## year
## 0.04527533
```

derive confident intervals

```
confint(LogModel, 'year', level=0.95)
```

```
## 2.5 % 97.5 %
## year 0.04063156 0.0499191
```

... and the the corresponding finite growth rate

```
lambda <- exp(igr); lambda</pre>
```

```
## year
## 1.046316
```

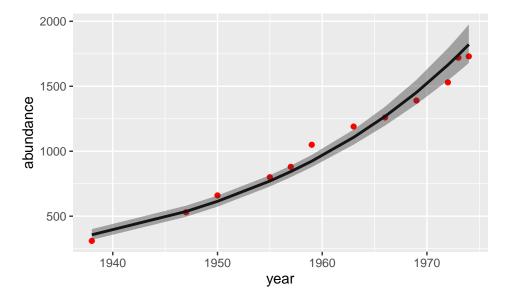
Here we create a new data frame to plot the results

temp.mat <- predict(LogModel, newdata = df, interval = "confidence"); as.data.frame(temp.mat)</pre>

fit	lwr	upr
5.877572	5.762543	5.992602
6.285050	6.205415	6.364686
6.420876	6.351439	6.490313
6.647253	6.591126	6.703380
6.737804	6.685043	6.790564
6.828354	6.777467	6.879242
7.009456	6.957312	7.061599
7.145282	7.088108	7.202455
7.281108	7.216247	7.345968
7.416934	7.342549	7.491319
7.462209	7.384354	7.540064
7.507484	7.426042	7.588927

abundance	fit	lwr	upr
310	356.9417	318.1565	400.4550
530	536.4913	495.4245	580.9622
660	614.5414	573.3174	658.7297
800	770.6644	728.6009	815.1564
880	843.7057	800.3455	889.4149
1050	923.6695	877.8421	971.8894
1190	1107.0517	1050.8054	1166.3087
1260	1268.1084	1197.6396	1342.7236
1390	1452.5961	1361.3703	1549.9350
1530	1663.9235	1544.6439	1792.4140
1720	1740.9896	1610.5864	1881.9511
1730	1821.6251	1679.1476	1976.1920
	310 530 660 800 880 1050 1190 1260 1390 1530 1720	310 356.9417 530 536.4913 660 614.5414 800 770.6644 880 843.7057 1050 923.6695 1190 1107.0517 1260 1268.1084 1390 1452.5961 1530 1663.9235 1720 1740.9896	310 356.9417 318.1565 530 536.4913 495.4245 660 614.5414 573.3174 800 770.6644 728.6009 880 843.7057 800.3455 1050 923.6695 877.8421 1190 1107.0517 1050.8054 1260 1268.1084 1197.6396 1390 1452.5961 1361.3703 1530 1663.9235 1544.6439 1720 1740.9896 1610.5864

```
ggplot(conf.int, aes(year,abundance)) + geom_point(color = 'red') +
geom_line(aes(year, fit), size = 1, linetype = 1) + # fitted lines
geom_ribbon(aes(ymin = lwr, ymax = upr), alpha=0.4) # confidence intervals
```



Now, compute the number of years this population took to double in size

```
# report the script and result here
```

Assignment

Estimate population growth rate for the grayseal puppy abundance in Sable island, use the following file in the "data" folder:

 $\bullet \ \ Grey_seal_puppy_production_Sable_Island_time_trend_data.csv$

Likewise for the loggerhead turtle population in the Great Barrier Reef in Australia, use the following file in the "data" folder:

 $\bullet \ \ australian_gbr_Loggerhead_sea_turtle_data.csv$