

MATH 3610 – 02

Single population growth models

Introduction to modelling

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The University of Manitoba campuses are located on original lands of Anishinaabeg, Ininew, Anisininew, Dakota and Dene peoples, and on the National Homeland of the Red River Métis. We respect the Treaties that were made on these territories, we acknowledge the harms and mistakes of the past, and we dedicate ourselves to move forward in partnership with Indigenous communities in a spirit of Reconciliation and collaboration.

Outline

The data – US census

Fitting a curve to the data

Least squares problems

Population growth – The logistic equation & friends

The continuous-time Markov chain logistic “equation”

The delayed logistic equation

The logistic map

Objective of this part

In this set of slides, we introduce some of the basic concepts of population growth models

We introduce some of the basic concepts of mathematical modelling and some of the questions that will be considered during the course

The data – US census

Fitting a curve to the data

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The logistic map

Objective

We are given a table with the population census at different time intervals between a date a and a date b , and want to get an expression for the population. This allows us to:

- ▶ compute a value for the population at any time between the date a and the date b (**interpolation**)
- ▶ predict a value for the population at a date before a or after b (**extrapolation**)

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*ON THE RATE OF GROWTH OF THE POPULATION OF THE
UNITED STATES SINCE 1790 AND ITS MATHEMATICAL
REPRESENTATION¹*

BY RAYMOND PEARL AND LOWELL J. REED

DEPARTMENT OF BIOMETRY AND VITAL STATISTICS, JOHNS HOPKINS UNIVERSITY

Read before the Academy, April 26, 1920

SHOWING THE DATES OF THE TAKING OF THE CENSUS AND THE RECORDED POPULATIONS
FROM 1790 TO 1910

Year	DATE OF CENSUS	RECORDED POPULATION (REVISED FIGURES FROM STATISTICAL ABST., 1918)
	Month and Day	
1790	First Monday in August	3,929,214
1800	First Monday in August	5,308,483
1810	First Monday in August	7,239,881
1820	First Monday in August	9,638,453
1830	June 1	12,866,020
1840	June 1	17,069,453
1850	June 1	23,191,876
1860	June 1	31,443,321
1870	June 1	38,558,371
1880	June 1	50,155,783
1890	June 1	62,947,714
1900	June 1	75,994,575
1910	April 15	91,972,266

USA census from 1790 to 1910

Although we have data up to 2020, we use the data up to 1910 like Pearl & Reed (note that there were some corrections to the census since the paper of Pearl & Reed)

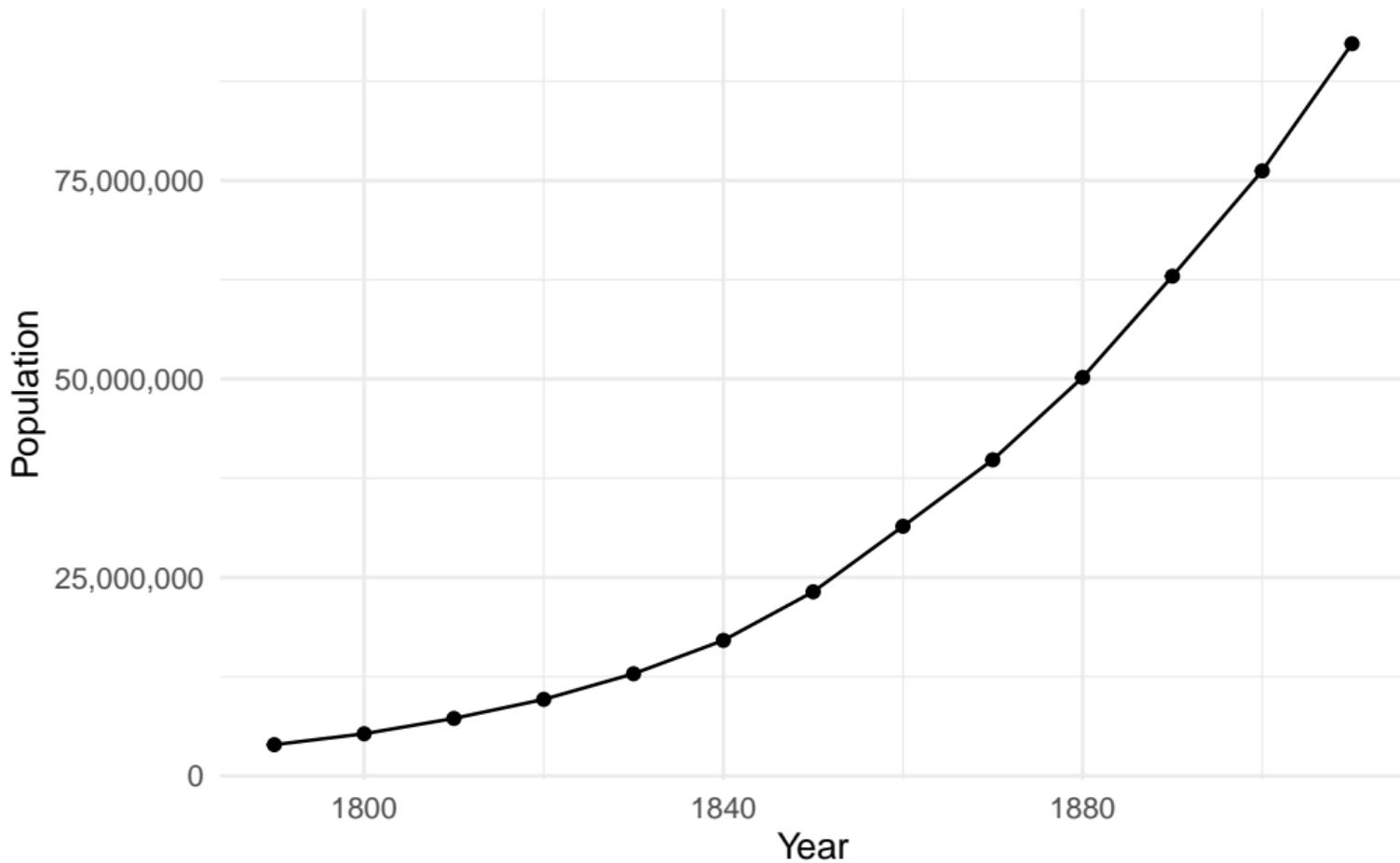
Year	Population	Year	Population	Year	Population
1790	3,929,326	1840	17,069,458	1890	62,947,714
1800	5,308,483	1850	23,191,876	1900	76,212,168
1810	7,239,881	1860	31,443,321	1910	92,228,496
1820	9,638,453	1870	39,818,449		
1830	12,866,020	1880	50,189,209		

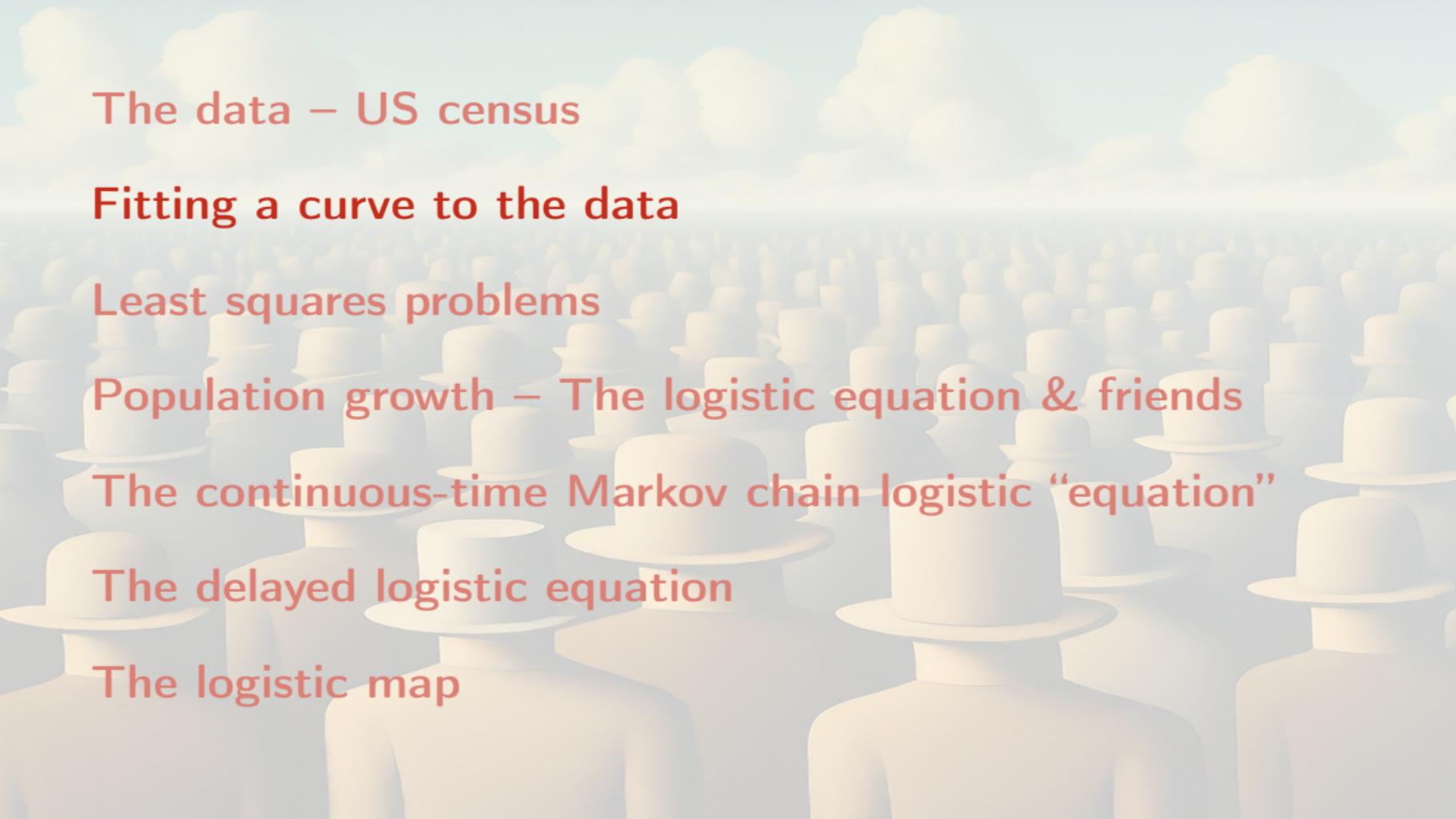
Plot the data !!!

It is always a good idea to plot the data before trying to do anything with it

```
plot_USA_census_to_1910 =  
  ggplot(USA_census_to_1910, aes(x=Year, y=Population)) +  
    geom_line() +  
    geom_point() +  
    labs(title="US population from 1790 to 1910",  
         x="Year",  
         y="Population") +  
    theme_minimal()  
  print(plot_USA_census_to_1910)
```

US population from 1790 to 1910





The data – US census

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Fitting a curve to the data

Fitting a quadratic curve to the data

Some similar curves

Population curves – Gompertz

First idea – This looks quadratic!

The curve looks like a piece of a parabola. So let us “fit” a curve of the form

$$P(t) = a + bt + ct^2$$

This means we want to find coefficients a, b, c such that the curve $P(t)$ is as close as possible to the data points

The data points

Year	Population	Year	Population	Year	Population
1790	3,929,326	1840	17,069,458	1890	62,947,714
1800	5,308,483	1850	23,191,876	1900	76,212,168
1810	7,239,881	1860	31,443,321	1910	92,228,496
1820	9,638,453	1870	39,818,449		
1830	12,866,020	1880	50,189,209		

We have 13 data points (t_k, P_k) , $k = 1, \dots, 13$, e.g., $(t_1, P_1) = (1790, 3929214)$, $(t_2, P_2) = (1800, 5308483)$, etc.

Some of you are familiar with this problem

If you have taken MATH 2740 (Math of Data Science), you have seen this before!

See the notes on the course website for a refresher on this problem [here](#) and the corresponding videos [here](#), [here](#), [here](#), [here](#) and [here](#)

(Sorry about the number of videos, I need to reorganize them!)

To do this, we want to minimize

$$S = \sum_{k=1}^{13} (P(t_k) - P_k)^2$$

where t_k are the known dates, P_k are the known populations, and $P(t_k) = a + bt_k + ct_k^2$

The t_k and P_k are known, a, b, c are to be found, so we write S as a function of a, b, c :
 $S(a, b, c)$

Recall your multivariable calculus:

$$S = S(a, b, c) = \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)^2$$

is maximal if (necessary condition) $\partial S / \partial a = \partial S / \partial b = \partial S / \partial c = 0$

We have

$$\frac{\partial S}{\partial a} = 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)$$

$$\frac{\partial S}{\partial b} = 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) t_k$$

$$\frac{\partial S}{\partial c} = 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) t_k^2$$

Thus, we want

$$\frac{\partial S}{\partial a} = 0 \iff 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) = 0$$

$$\frac{\partial S}{\partial b} = 0 \iff 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)t_k = 0$$

$$\frac{\partial S}{\partial c} = 0 \iff 2 \sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)t_k^2 = 0$$

that is

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) = 0$$

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)t_k = 0$$

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k)t_k^2 = 0$$

Rearranging the system

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) = 0$$

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) t_k = 0$$

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2 - P_k) t_k^2 = 0$$

we get

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2) = \sum_{k=1}^{13} P_k$$

$$\sum_{k=1}^{13} (at_k + bt_k^2 + ct_k^3) = \sum_{k=1}^{13} P_k t_k$$

$$\sum_{k=1}^{13} (at_k^2 + bt_k^3 + ct_k^4) = \sum_{k=1}^{13} P_k t_k^2$$

$$\sum_{k=1}^{13} (a + bt_k + ct_k^2) = \sum_{k=1}^{13} P_k$$

$$\sum_{k=1}^{13} (at_k + bt_k^2 + ct_k^3) = \sum_{k=1}^{13} P_k t_k$$

$$\sum_{k=1}^{13} (at_k^2 + bt_k^3 + ct_k^4) = \sum_{k=1}^{13} P_k t_k^2$$

after a bit of tidying up, takes the form

$$\left(\sum_{k=1}^{13} 1 \right) a + \left(\sum_{k=1}^{13} t_k \right) b + \left(\sum_{k=1}^{13} t_k^2 \right) c = \sum_{k=1}^{13} P_k$$

$$\left(\sum_{k=1}^{13} t_k \right) a + \left(\sum_{k=1}^{13} t_k^2 \right) b + \left(\sum_{k=1}^{13} t_k^3 \right) c = \sum_{k=1}^{13} P_k t_k$$

$$\left(\sum_{k=1}^{13} t_k^2 \right) a + \left(\sum_{k=1}^{13} t_k^3 \right) b + \left(\sum_{k=1}^{13} t_k^4 \right) c = \sum_{k=1}^{13} P_k t_k^2$$

So the aim is to solve the linear system

$$\begin{pmatrix} 13 & \sum_{k=1}^{13} t_k & \sum_{k=1}^{13} t_k^2 \\ \sum_{k=1}^{13} t_k & \sum_{k=1}^{13} t_k^2 & \sum_{k=1}^{13} t_k^3 \\ \sum_{k=1}^{13} t_k^2 & \sum_{k=1}^{13} t_k^3 & \sum_{k=1}^{13} t_k^4 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} \sum_{k=1}^{13} P_k \\ \sum_{k=1}^{13} P_k t_k \\ \sum_{k=1}^{13} P_k t_k^2 \end{pmatrix}$$

With R, this is easy to solve..?

```
> t = as.double(USA_census_to_1910$Year)
> pop = as.double(USA_census_to_1910$Population)
> A = matrix(c(13, sum(t), sum(t^2),
+               sum(t), sum(t^2), sum(t^3),
+               sum(t^2), sum(t^3), sum(t^4)),
+               nrow=3, byrow=TRUE)
> b = c(sum(pop),
+       sum(pop * t),
+       sum(pop * t^2))
> sol = try(solve(A,b))
> writeLines(sol)

Error in solve.default(A, b) :
  system is computationally singular: reciprocal condition number = 1.11839e-20
```

So we need to do some “time shifting”: the problem is that some of the entries are too large

```
> t = t - 1790
> A = matrix(c(13, sum(t), sum(t^2),
+           sum(t), sum(t^2), sum(t^3),
+           sum(t^2), sum(t^3), sum(t^4)),
+           nrow=3, byrow=TRUE)
> b = c(sum(pop),
+       sum(pop * t),
+       sum(pop * t^2))
> sol = try(solve(A,b))
> print(sol)
[1] 5544964.000 -109242.513     6849.346
```

Thus

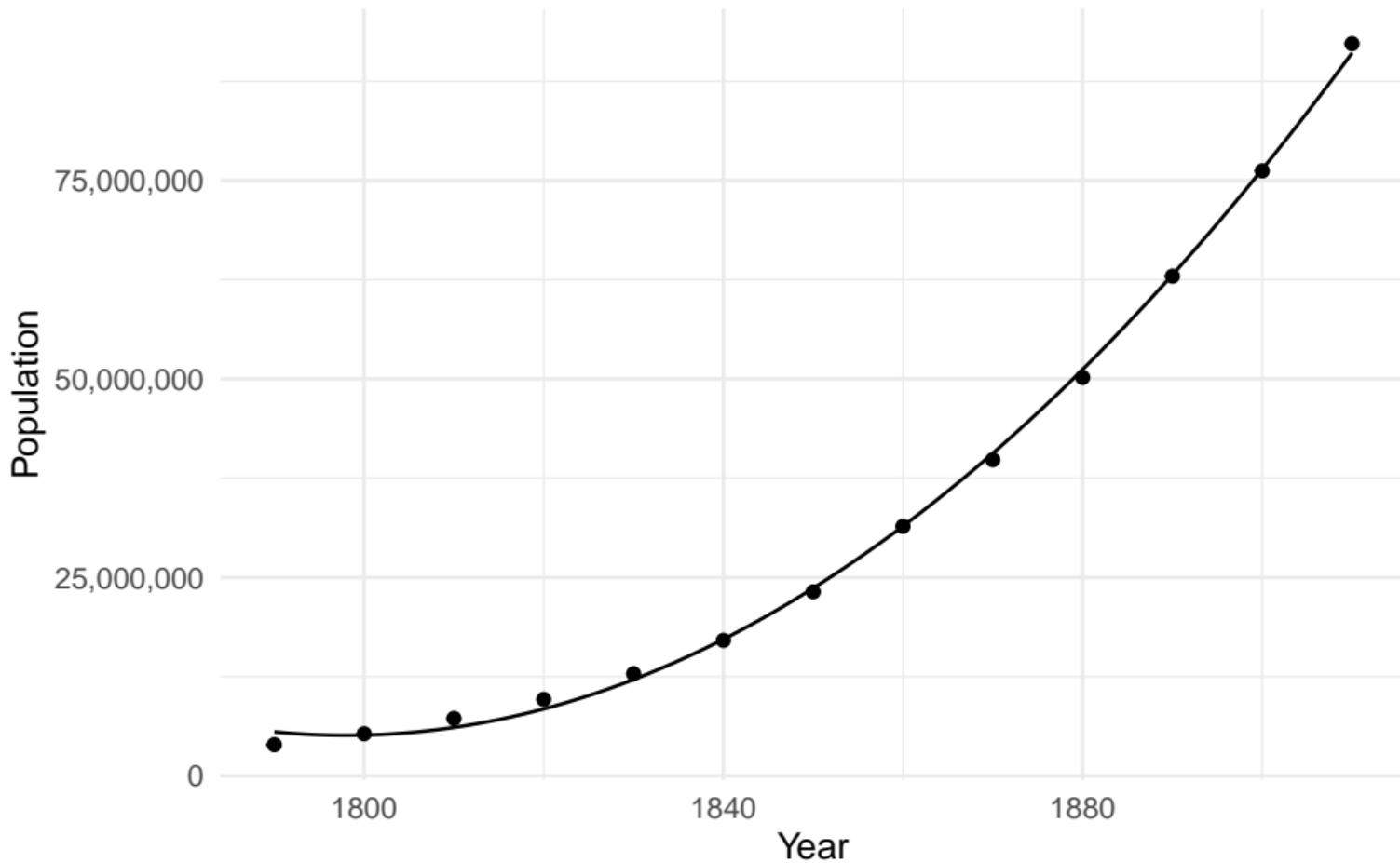
$$P(t) = 5544964 - 109243t + 6849t^2$$

(keeping in mind that time is here shifted and starts at 0)

So we define the function

```
> sol_plot = function(t, sol) {  
+   t = t - 1790  
+   return(sol[1] + sol[2]*t + sol[3]*t^2)  
+ }
```

US population from 1790 to 1910



Form the vector of errors, and compute sum of errors squared:

```
> t = USA_census_to_1910$Year  
> P = USA_census_to_1910$Population  
> E = sum((P - sol_plot(t, sol))^2)
```

Quite a large error (9,256,979,482,173), which is normal since we have used actual numbers, not thousands or millions of individuals, and we are taking the square of the error

Now for the big question...

How does our formula do for present times?

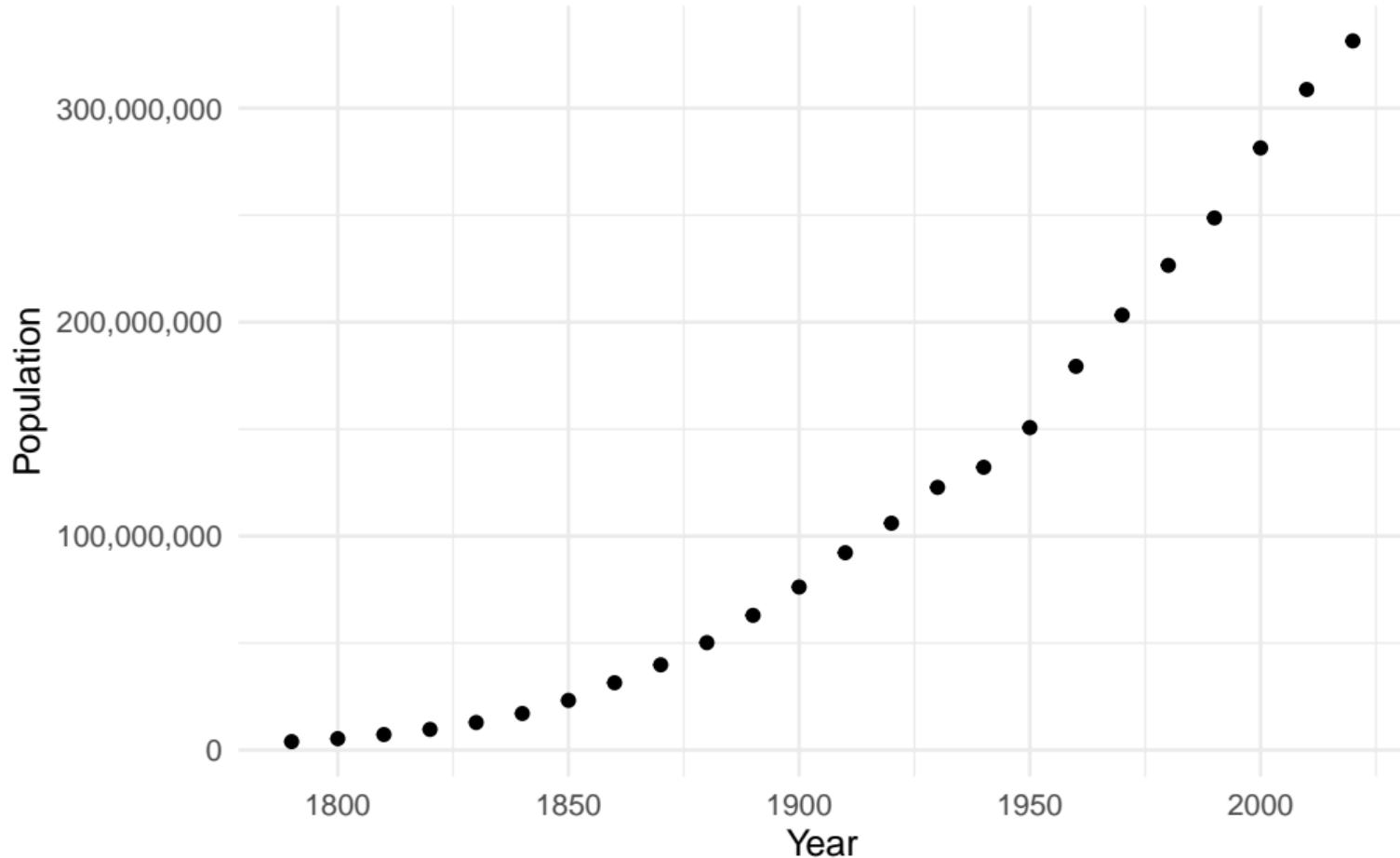
```
> format(sol_plot(2024, sol), big.mark = ",")  
[1] "355,024,999"
```

Actually, quite well: 355,024,999, compared to the 345,786,196 September 2024 estimate, overestimates the population by 9,238,803, a relative error of 2.67%

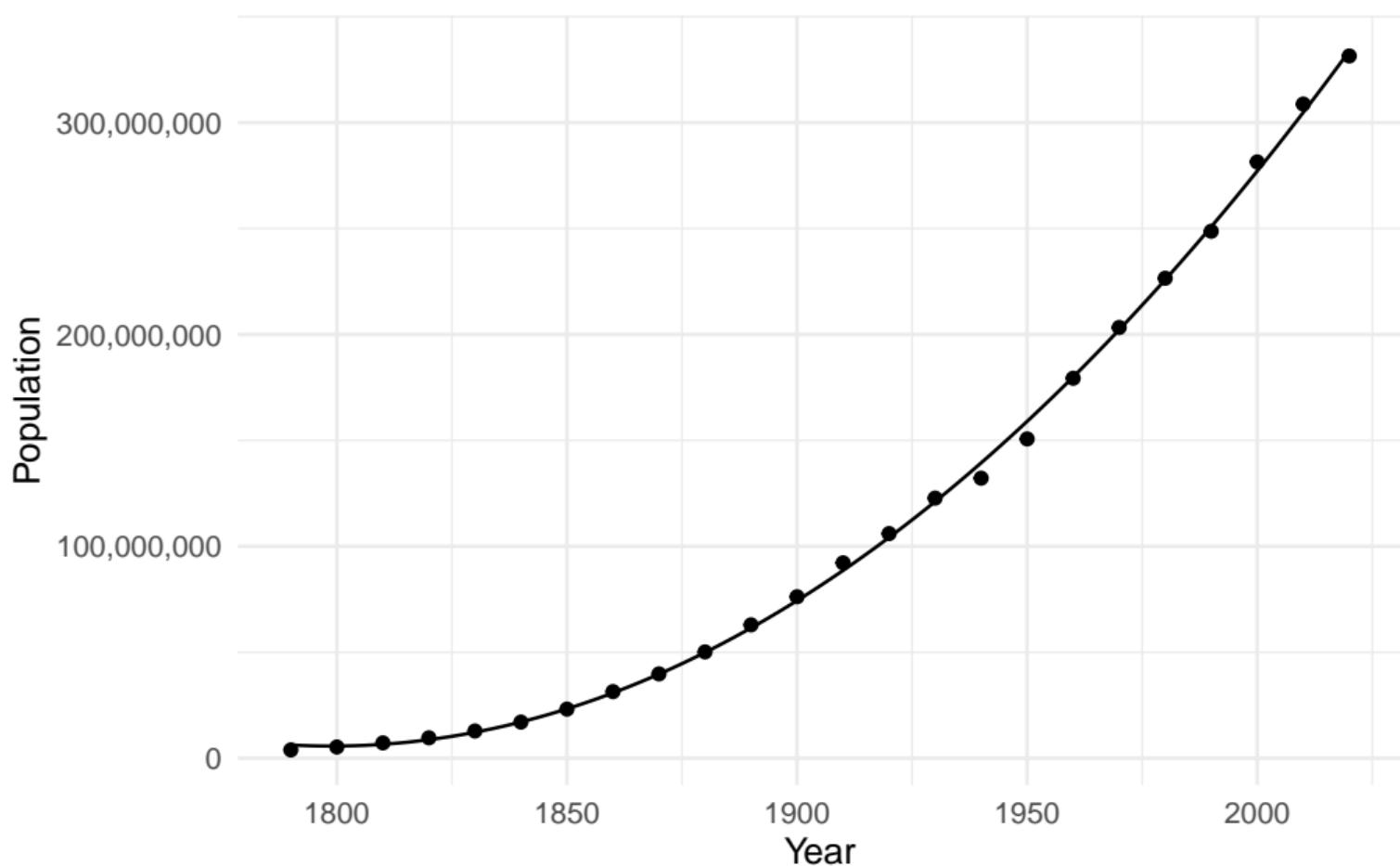
The US population from 1790 to 2020 (revised numbers)

Year	Population	Year	Population	Year	Population
1790	3,929,326	1890	62,947,714	1990	248,709,873
1800	5,308,483	1900	76,212,168	2000	281,421,906
1810	7,239,881	1910	92,228,496	2010	308,745,538
1820	9,638,453	1920	106,021,537	2020	331,449,281
1830	12,866,020	1930	122,775,046		
1840	17,069,458	1940	132,164,569		
1850	23,191,876	1950	150,697,361		
1860	31,443,321	1960	179,323,175		
1870	39,818,449	1970	203,302,031		
1880	50,189,209	1980	226,545,805		

US population from 1790 to 2020



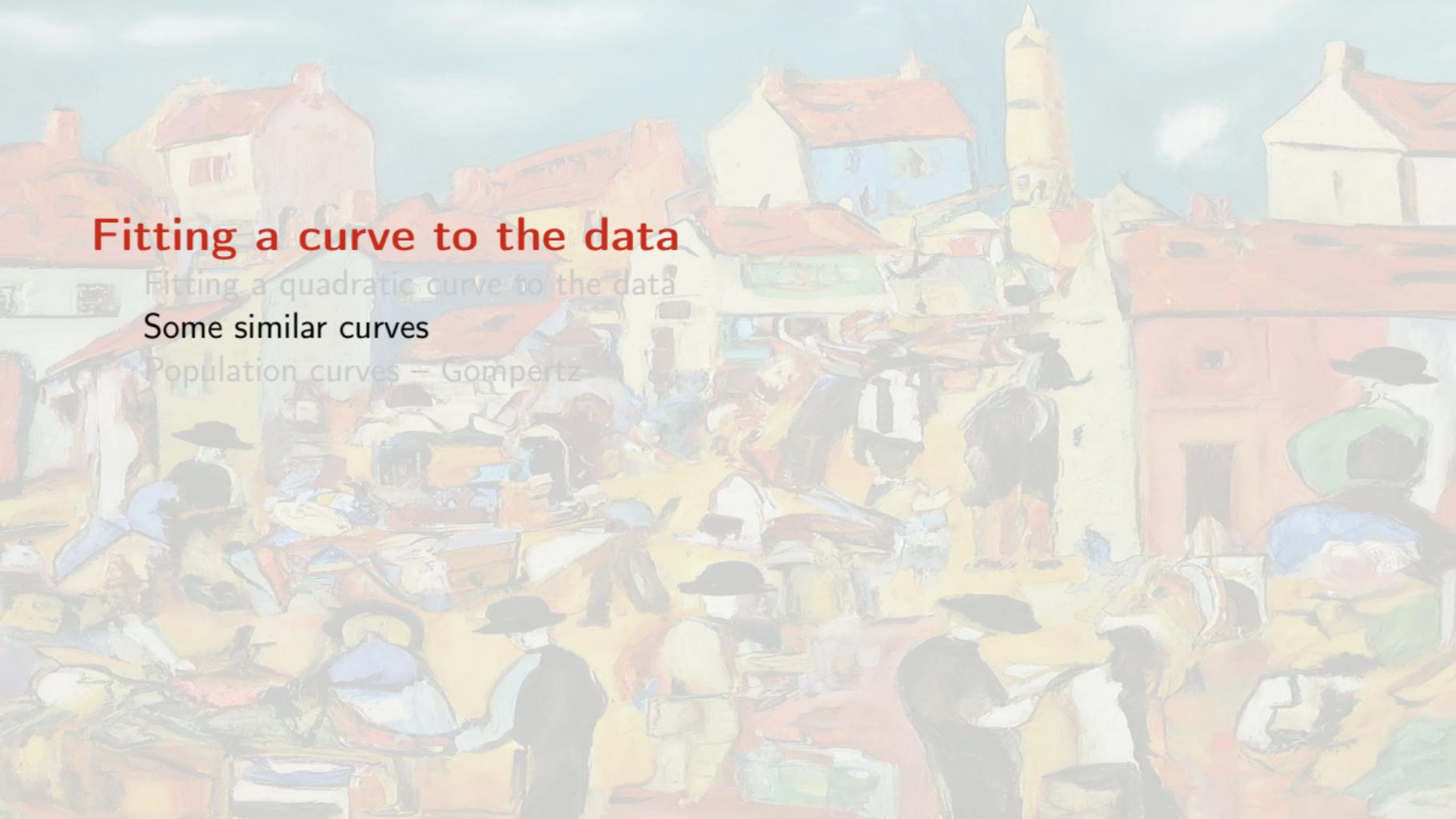
US population from 1790 to 2020 (with fit)



How does our formula do for present times?

```
> format(sol_plot(2024, sol_full), big.mark = ",")  
[1] "345,749,152"
```

Actually, quite well: 345,749,152, compared to the 345,786,196 September 2024 estimate, underestimates the population by -37,043.51, a relative error of -0.01%

A painting of a crowded outdoor market scene. In the foreground, many people wearing hats are gathered around tables with goods. In the background, there are several buildings with red-tiled roofs under a cloudy sky.

Fitting a curve to the data

Fitting a quadratic curve to the data

Some similar curves

Population curves – Gompertz

Other similar approaches

Pritchett, 1891:

$$P = a + bt + ct^2 + dt^3$$

(we have done this one, and found it to be quite good too)

Pearl, 1907:

$$P(t) = a + bt + ct^2 + d \ln t$$

Finds

$$P(t) = 9,064,900 - 6,281,430t + 842,377t^2 + 19,829,500 \ln t.$$

SHOWING (a) THE ACTUAL POPULATION¹ ON CENSUS DATES, (b) ESTIMATED POPULATION
 FROM PRITCHETT'S THIRD-ORDER PARABOLA, (c) ESTIMATED POPULATION FROM
 LOGARITHMIC PARABOLA, AND (d) (e) ROOT-MEAN SQUARE ERRORS
 OF BOTH METHODS

CENSUS YEAR	(a) OBSERVED POPULATION	(b). PRITCHETT ESTIMATE	(c) LOGARITHMIC PARABOLA ES- TIMATE	(d) ERROR OF (b)	(e) ERROR OF (c)
1790	3,929,000	4,012,000	3,693,000	+ 83,000	- 236,000
1800	5,308,000	5,267,000	5,865,000	- 41,000	+ 557,000
1810	7,240,000	7,059,000	7,293,000	- 181,000	+ 53,000
1820	9,638,000	9,571,000	9,404,000	- 67,000	- 234,000
1830	12,866,000	12,985,000	12,577,000	+ 119,000	- 289,000
1840	17,069,000	17,484,000	17,132,000	+ 415,000	+ 63,000
1850	23,192,000	23,250,000	23,129,000	+ 58,000	- 63,000
1860	31,443,000	30,465,000	30,633,000	- 978,000	- 810,000
1870	38,558,000	39,313,000	39,687,000	+ 755,000	+ 1,129,000
1880	50,156,000	49,975,000	50,318,000	- 181,000	+ 162,000
1890	62,948,000	62,634,000	62,547,000	- 314,000	- 401,000
1900	75,995,000	77,472,000	76,389,000	+ 1,477,000	+ 394,000
1910	91,972,000	94,673,000	91,647,000	+ 2,701,000	- 325,000
				935,000 ²	472,000 ²
1920		114,416,000	108,214,000		

¹ To the nearest thousand.

² Root-mean square error.

The logistic curve

Pearl and Reed try

$$P(t) = \frac{be^{at}}{1 + ce^{at}}$$

or

$$P(t) = \frac{b}{e^{-at} + c}$$

What is wrong with the logistic equation here?

- ▶ The carrying capacity is constant
- ▶ The model does not take immigration into account (for the US, this is an important component)

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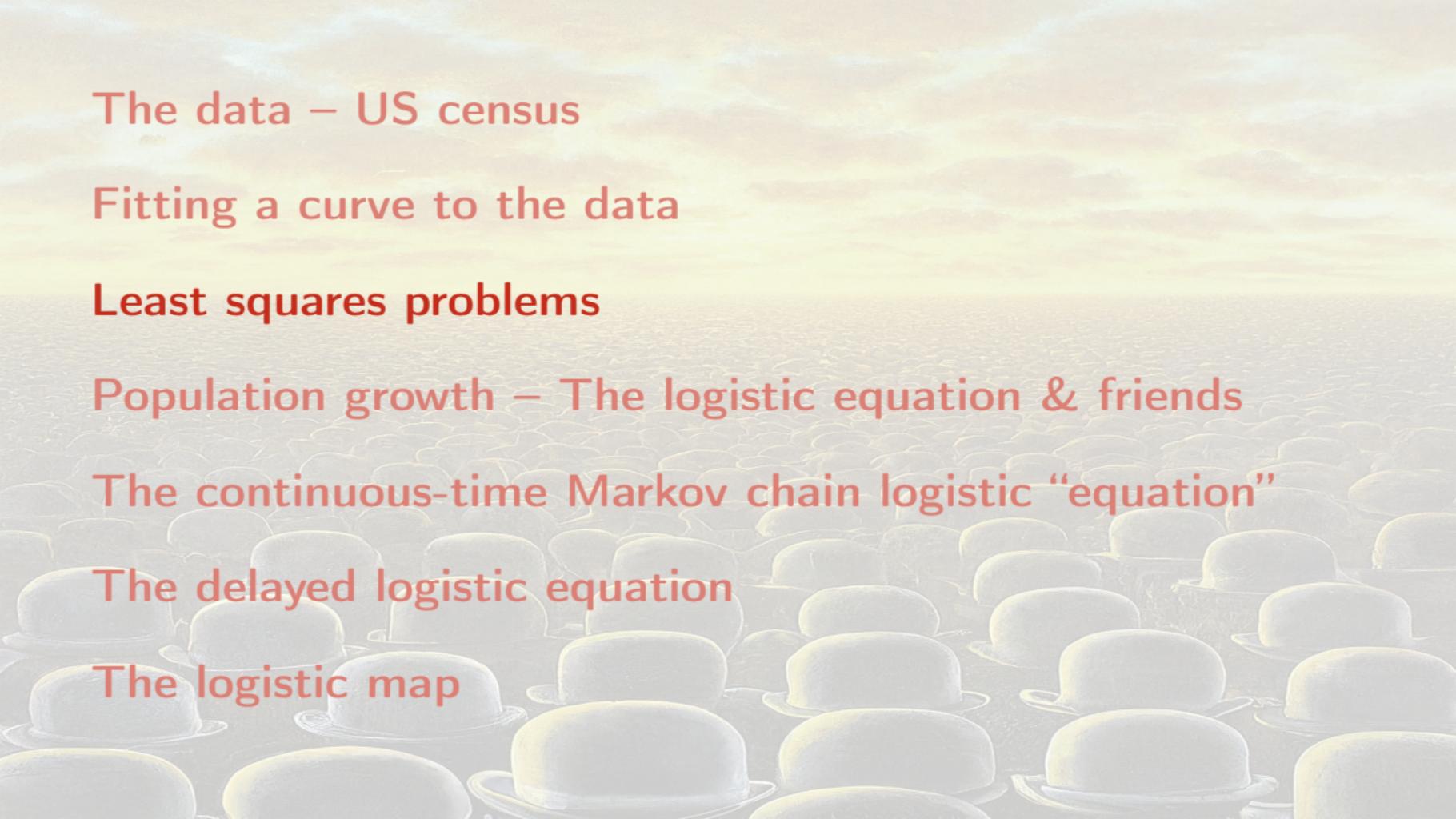
THE GOMPERTZ CURVE AS A GROWTH CURVE

BY CHARLES P. WINSOR

DEPARTMENT OF BIOLOGY, SCHOOL OF HYGIENE AND PUBLIC HEALTH, JOHNS HOPKINS
UNIVERSITY

Communicated December 2, 1931

PROPERTY	GOMPERTZ	LOGISTIC
Equation	$y = ke^{-e^{a-bx}}$	$y = \frac{k}{1 + e^{a-bx}}$
Number of constants	3	3
Asymptotes	$\begin{cases} y = 0 \\ y = k \end{cases}$	$\begin{cases} y = 0 \\ y = k \end{cases}$
Inflection	$\begin{cases} x = \frac{a}{b} \\ y = \frac{k}{e} \end{cases}$	$\begin{cases} x = \frac{a}{b} \\ y = \frac{k}{2} \end{cases}$
Straight line form of equation	$\log \log \frac{k}{y} = a - bx$	$\log \frac{k-y}{y} = a - bx$
Symmetry	Assymetrical	Symmetrical about inflection
Growth rate	$\frac{dy}{dx} = bye^{a-bx} = by \log \frac{k}{y}$	$\frac{dy}{dx} = \frac{b}{k} y(k-y)$
Maximum growth rate	$\frac{bk}{e}$	$\frac{bk}{4}$
Relative growth rate as function of time	$\frac{1}{y} \frac{dy}{dx} = be^{a-bx}$	$\frac{1}{y} \frac{dy}{dx} = \frac{b}{1+e^{-a+bx}}$
Relative growth rate as function of size	$\frac{1}{y} \frac{dy}{dx} = b(\log k - \log y)$	$\frac{1}{y} \frac{dy}{dx} = \frac{b}{k}(k-y)$



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A.k.a. if the Math Dept was less #\\$%&, you'd know this

The following are a brief extract from MATH 2740 slides...

The least squares problem (simplest version)

Definition 1

Given a collection of points $(x_1, y_1), \dots, (x_n, y_n)$, find the coefficients a, b of the line $y = a + bx$ such that

$$\|\mathbf{e}\| = \sqrt{\varepsilon_1^2 + \dots + \varepsilon_n^2} = \sqrt{(y_1 - \tilde{y}_1)^2 + \dots + (y_n - \tilde{y}_n)^2}$$

is minimal, where $\tilde{y}_i = a + bx_i$ for $i = 1, \dots, n$

We just saw how to solve this by brute force using a genetic algorithm to minimise $\|\mathbf{e}\|$, let us now see how to solve this problem “properly”

For a data point $i = 1, \dots, n$

$$\varepsilon_i = y_i - \tilde{y}_i = y_i - (a + bx_i)$$

So if we write this for all data points,

$$\varepsilon_1 = y_1 - (a + bx_1)$$

⋮

$$\varepsilon_n = y_n - (a + bx_n)$$

In matrix form

$$\mathbf{e} = \mathbf{b} - A\mathbf{x}$$

with

$$\mathbf{e} = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}, A = \begin{pmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}, \mathbf{x} = \begin{pmatrix} a \\ b \end{pmatrix} \text{ and } \mathbf{b} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

The least squares problem (reformulated)

Definition 2 (Least squares solutions)

Consider a collection of points $(x_1, y_1), \dots, (x_n, y_n)$, a matrix $A \in \mathcal{M}_{mn}$, $\mathbf{b} \in \mathbb{R}^m$. A **least squares solution** of $A\mathbf{x} = \mathbf{b}$ is a vector $\tilde{\mathbf{x}} \in \mathbb{R}^n$ s.t.

$$\forall \mathbf{x} \in \mathbb{R}^n, \quad \|\mathbf{b} - A\tilde{\mathbf{x}}\| \leq \|\mathbf{b} - A\mathbf{x}\|$$

Needed to solve the problem

Definition 3 (Best approximation)

Let V be a vector space, $W \subset V$ and $v \in V$. The **best approximation** to v in W is $\tilde{v} \in W$ s.t.

$$\forall w \in W, w \neq \tilde{v}, \quad \|v - \tilde{v}\| < \|v - w\|$$

Theorem 4 (Best approximation theorem)

Let V be a vector space with an inner product, $W \subset V$ and $v \in V$. Then $\text{proj}_W(v)$ is the best approximation to v in W

Let us find the least squares solution

$\forall \mathbf{x} \in \mathbb{R}^n$, $A\mathbf{x}$ is a vector in the **column space** of A (the space spanned by the vectors making up the columns of A)

Since $\mathbf{x} \in \mathbb{R}^n$, $A\mathbf{x} \in \text{col}(A)$

\implies least squares solution of $A\mathbf{x} = \mathbf{b}$ is a vector $\tilde{\mathbf{y}} \in \text{col}(A)$ s.t.

$$\forall \mathbf{y} \in \text{col}(A), \quad \|\mathbf{b} - \tilde{\mathbf{y}}\| \leq \|\mathbf{b} - \mathbf{y}\|$$

This looks very much like Best approximation and Best approximation theorem

Putting things together

We just stated: The least squares solution of $Ax = \mathbf{b}$ is a vector $\tilde{\mathbf{y}} \in \text{col}(A)$ s.t.

$$\forall \mathbf{y} \in \text{col}(A), \quad \|\mathbf{b} - \tilde{\mathbf{y}}\| \leq \|\mathbf{b} - \mathbf{y}\|$$

We know (reformulating a tad):

Theorem 5 (Best approximation theorem)

Let V be a vector space with an inner product, $W \subset V$ and $\mathbf{v} \in V$. Then $\text{proj}_W(\mathbf{v}) \in W$ is the best approximation to \mathbf{v} in W , i.e.,

$$\forall \mathbf{w} \in W, \mathbf{w} \neq \text{proj}_W(\mathbf{v}), \quad \|\mathbf{v} - \text{proj}_W(\mathbf{v})\| < \|\mathbf{v} - \mathbf{w}\|$$

$$\implies W = \text{col}(A), \mathbf{v} = \mathbf{b} \text{ and } \tilde{\mathbf{y}} = \text{proj}_{\text{col}(A)}(\mathbf{b})$$

So if $\tilde{\mathbf{x}}$ is a least squares solution of $A\mathbf{x} = \mathbf{b}$, then

$$\tilde{\mathbf{y}} = A\tilde{\mathbf{x}} = \text{proj}_{\text{col}(A)}(\mathbf{b})$$

We have

$$\mathbf{b} - A\tilde{\mathbf{x}} = \mathbf{b} - \text{proj}_{\text{col}(A)}(\mathbf{b}) = \text{perp}_{\text{col}(A)}(\mathbf{b})$$

and it is easy to show that

$$\text{perp}_{\text{col}(A)}(\mathbf{b}) \perp \text{col}(A)$$

So for all columns \mathbf{a}_i of A

$$\mathbf{a}_i \cdot (\mathbf{b} - A\tilde{\mathbf{x}}) = 0$$

which we can also write as $\mathbf{a}_i^T(\mathbf{b} - A\tilde{\mathbf{x}}) = 0$

For all columns \mathbf{a}_i of A ,

$$\mathbf{a}_i^T(\mathbf{b} - A\tilde{\mathbf{x}}) = 0$$

This is equivalent to saying that

$$A^T(\mathbf{b} - A\tilde{\mathbf{x}}) = 0$$

We have

$$\begin{aligned} A^T(\mathbf{b} - A\tilde{\mathbf{x}}) = 0 &\iff A^T\mathbf{b} - A^TA\tilde{\mathbf{x}} = 0 \\ &\iff A^T\mathbf{b} = A^TA\tilde{\mathbf{x}} \\ &\iff A^TA\tilde{\mathbf{x}} = A^T\mathbf{b} \end{aligned}$$

The latter system constitutes the **normal equations** for $\tilde{\mathbf{x}}$

Least squares theorem

Theorem 6 (Least squares theorem)

$A \in \mathcal{M}_{mn}$, $\mathbf{b} \in \mathbb{R}^m$. Then

1. $A\mathbf{x} = \mathbf{b}$ always has at least one least squares solution $\tilde{\mathbf{x}}$
2. $\tilde{\mathbf{x}}$ least squares solution to $A\mathbf{x} = \mathbf{b} \iff \tilde{\mathbf{x}}$ is a solution to the normal equations
 $A^T A \tilde{\mathbf{x}} = A^T \mathbf{b}$
3. A has linearly independent columns $\iff A^T A$ invertible.
In this case, the least squares solution is unique and

$$\tilde{\mathbf{x}} = (A^T A)^{-1} A^T \mathbf{b}$$

We have seen 1 and 2, we will not show 3 (it is not hard)

Suppose we want to fit something a bit more complicated..

For instance, instead of the affine function

$$y = a + bx$$

suppose we want to do the quadratic

$$y = a_0 + a_1x + a_2x^2$$

or even

$$y = k_0 e^{k_1 x}$$

How do we proceed?

Fitting the quadratic

We have the data points $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ and want to fit

$$y = a_0 + a_1x + a_2x^2$$

At (x_1, y_1) ,

$$\tilde{y}_1 = a_0 + a_1x_1 + a_2x_1^2$$

⋮

At (x_n, y_n) ,

$$\tilde{y}_n = a_0 + a_1x_n + a_2x_n^2$$

In terms of the error

$$\varepsilon_1 = y_1 - \tilde{y}_1 = y_1 - (a_0 + a_1 x_1 + a_2 x_1^2)$$

⋮

$$\varepsilon_n = y_n - \tilde{y}_n = y_n - (a_0 + a_1 x_n + a_2 x_n^2)$$

i.e.,

$$\mathbf{e} = \mathbf{b} - A\mathbf{x}$$

where

$$\mathbf{e} = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}, A = \begin{pmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{pmatrix}, \mathbf{x} = \begin{pmatrix} a_0 \\ a_1 \\ a_2 \end{pmatrix} \text{ and } \mathbf{b} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

Theorem 6 applies, with here $A \in \mathcal{M}_{n3}$ and $\mathbf{b} \in \mathbb{R}^n$

Fitting the exponential

Things are a bit more complicated here

If we proceed as before, we get the system

$$y_1 = k_0 e^{k_1 x_1}$$

⋮

$$y_n = k_0 e^{k_1 x_n}$$

$e^{k_1 x_i}$ is a nonlinear term, it cannot be put in a matrix

However: take the \ln of both sides of the equation

$$\ln(y_i) = \ln(k_0 e^{k_1 x_i}) = \ln(k_0) + \ln(e^{k_1 x_i}) = \ln(k_0) + k_1 x_i$$

If $y_i, k_0 > 0$, then their \ln are defined and we're in business..

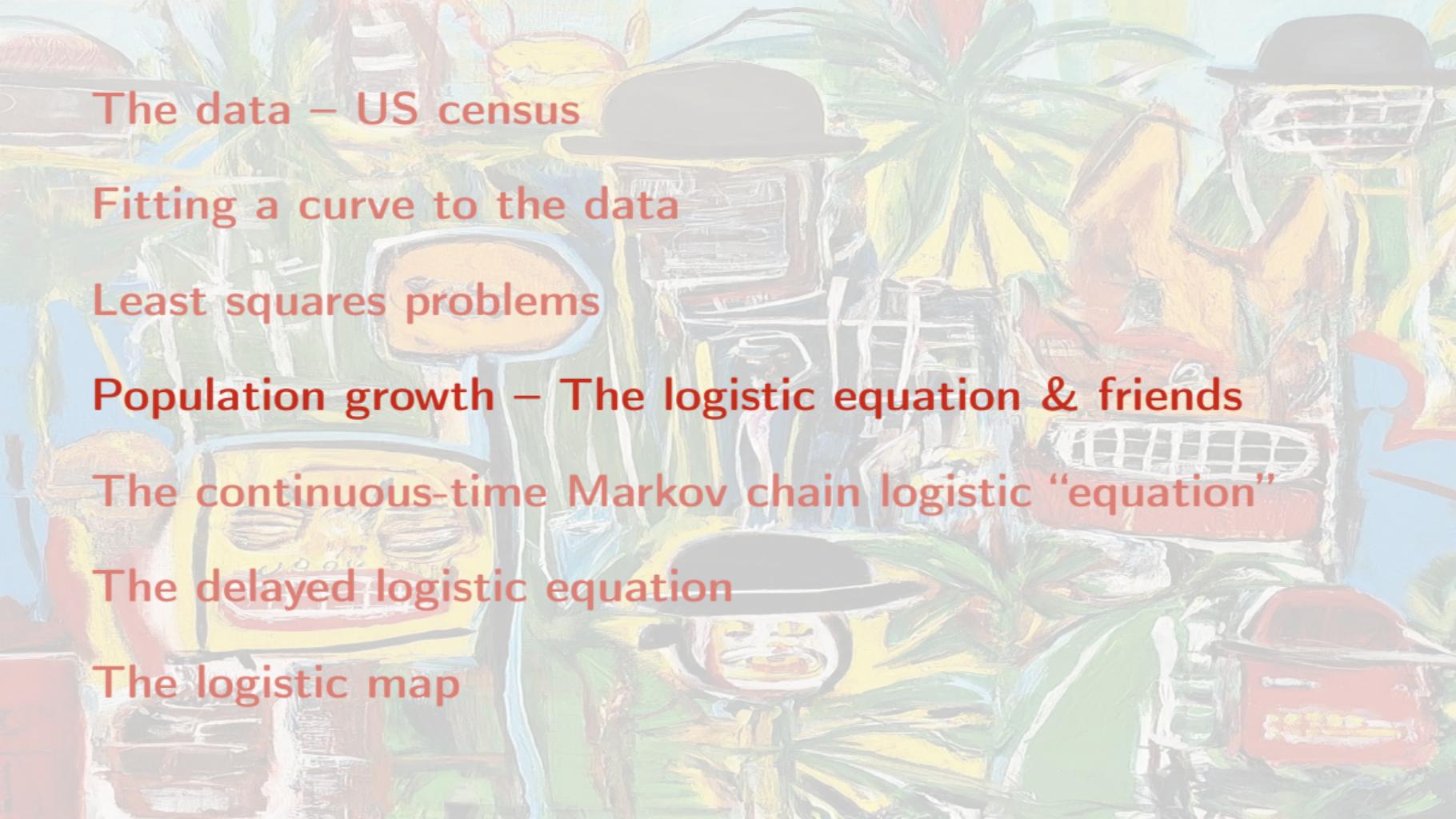
$$\ln(y_i) = \ln(k_0) + k_1 x_i$$

So the system is

$$\mathbf{y} = A\mathbf{x} + \mathbf{b}$$

with

$$A = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}, \mathbf{x} = (k_1), \mathbf{b} = (\ln(k_0)) \text{ and } \mathbf{y} = \begin{pmatrix} \ln(y_1) \\ \vdots \\ \ln(y_n) \end{pmatrix}$$

The background of the slide is a vibrant, abstract painting depicting a tropical or jungle setting. It features large green and yellow foliage, a red car, and a person wearing a wide-brimmed hat and a patterned shirt. The overall style is expressive and colorful.

The data – US census

Fitting a curve to the data

Least squares problems

Population growth – The logistic equation & friends

The continuous-time Markov chain logistic “equation”

The delayed logistic equation

The logistic map

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Ordinary differential equations

Let t be an independent variable (often time) and $x(t) \in \mathbb{R}^n$ a dependent variable

An ordinary differential equation (ODE) is an equation of the form

$$\frac{d}{dt}x(t) = f(t, x(t))$$

where $f : \mathbb{R} \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a given function that describes how $x(t)$ changes with t

Some equations involve higher order derivatives, but we will not consider any here so we do not present them

Initial value problems

An **initial value problem** (IVP) is an ODE with an **initial condition** (IC)

$$\frac{d}{dt}x(t) = f(t, x(t)) \quad (1a)$$

$$x(t_0) = x_0 \quad (1b)$$

where $t_0 \in \mathbb{R}$ is the initial time and $x_0 \in \mathbb{R}^n$ is the initial value

In practice, solutions to (1a) form families of curves and the initial condition (1b) allows to pick one of these curves

Classification of ODEs

If $f(t, x(t)) = f(x(t))$, i.e., the function f does not depend on t , the ODE is **autonomous**

Most of what we consider here will be autonomous, so assume that for now

If $f(x(t))$ is linear in $x(t)$, the ODE is **linear**

Simplifying notation

We often drop the time dependence of x on t and write ' for d/dt . Further taking into account that f is autonomous, we write (1) as

$$x' = f(x) \tag{2a}$$

$$x(t_0) = x_0 \tag{2b}$$

Existence and uniqueness of solutions

There is a theory that studies the existence and uniqueness of solutions to (2); see, e.g., MATH 3440 (Ordinary Differential Equations)

Here, we take a shortcut and use one of the easiest forms

Theorem 7 (Existence and uniqueness of solutions to IVPs)

If f is C^1 (has continuous first-order partials) in x , then there exists a unique solution to (2) in some interval $[t_0 - \varepsilon, t_0 + \varepsilon]$ for some $\varepsilon > 0$

(Also works for nonautonomous equations)

Studying ODE/IVP

In short, there are three non-mutually exclusive ways to tackle an IVP such as (1) or (2)

1. Analytically: find a formula for $x(t)$
2. Numerically: approximate $x(t)$
3. Qualitatively: study the behaviour of $x(t)$ without finding $x(t)$

Don't expect to be able to do 1 more than a few times in this course (or anywhere for that matter!); so we mention it but focus on 2 and 3

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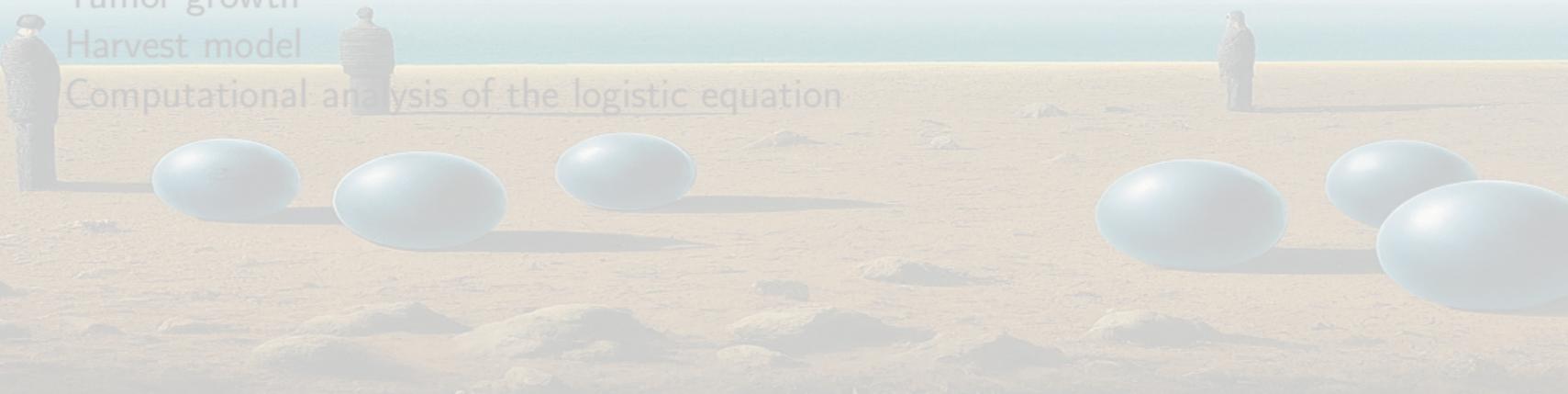
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Tumor growth

Harvest model

Computational analysis of the logistic equation



Our goal: the logistic ODE

The logistic *curve* mentioned by Pearl and Reed is the solution to the **logistic** ODE

$$\frac{d}{dt}N(t) = rN(t) \left(1 - \frac{N(t)}{K}\right)$$

often denoted without the time dependence and using ' for d/dt

$$N' = rN \left(1 - \frac{N}{K}\right) \tag{3}$$

r is the **intrinsic growth rate**, K is the **carrying capacity**

This equation was introduced by Pierre-François Verhulst (1804-1849) in 1844

Deriving the logistic equation

Our aim here is to derive (3) from first principles

This illustrates the mathematical modelling process when using a differential equations approach

The birth-death process

The simplest model for population growth is the **birth-death** process

Let $N(t)$ (N for short if unambiguous) be the total number of individuals in an isolated population at time t

Neglecting all other sources of change, N is

- ▶ positively influenced (increases) because of births into the population
- ▶ negatively influenced (decreases) because of deaths in the population

Where ODEs come in

We said N increases/decreases because of births/deaths...

This sounds a lot like what derivatives do. Remember first-year calculus: if $f(x)$ is a function $\mathbb{R} \rightarrow \mathbb{R}$, then f is increasing at x if $f'(x) > 0$ and decreasing at x if $f'(x) < 0$

Returning to $N(t)$, we thus should have $N'(t) > 0$ because of births and $N'(t) < 0$ because of deaths

Intuitively, if births happen more often than deaths, the population should increase, while if deaths are more frequent than births, it should decrease

The birth-death equation

Assume that

- ▶ birth happens at the **per capita** rate b
- ▶ death happens at the *per capita* rate d

Rates constant *per capita* versus “just” constant

Birth increases the population, so

$$N' = b(N)$$

with $b(N) : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ the birth rate function

Two easiest choices, for $b \in \mathbb{R}_+ \setminus \{0\}$:

1. $b(N) = b$, a constant
2. $b(N) = bN$, a linear function of N (a *per capita* rate, for which N'/N is constant)

An example (2022-06-01 to 2023-06-01)

Suppose time units are years. Consider data from regional health authorities and assume that the number of kids under 1 year old is a good proxy for the number of births

	Portage la Prairie	Winnipeg
Population	16,389	832,214
Births (raw number)	176	7,574
Births (<i>per capita</i>)	0.0107	0.0091

If $b(N) = b$, we should use $b = 176$ for PIP and $b = 7,574$ for Winnipeg. On the other hand, if $b(N) = bN$, we should use $b = 0.0107$ for PIP and $b = 0.0091$ for Winnipeg.. so could get by with $b = 0.01$ for both

Per capita is typically more realistic

It is more realistic to assume that the birth rate is proportional to the population size, because that means that the parameter b is a property of the species more so than of where they are located

Note that there are important differences, though: birth rates are generally consistent across a country (and even that varies), but differ from country to country

We will see later in the course that using a constant birth rate can be feasible as well, once we understand its role on the model behaviour

Modelling assumptions

Modelling is all about making assumptions and understanding the consequences of these assumptions

Use the *per capita* rate bN for births and the *per capita* rate dN for deaths

This gives the birth-death model

$$N' = bN - dN$$

This model must be “equipped” with an initial condition, e.g. $N(t_0) = N_0 \geq 0$

The birth-death model

All things considered, the model for the population with only birth and death is therefore

$$N' = bN - dN \quad (4a)$$

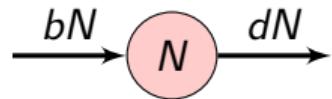
$$N(t_0) = N_0 \quad (4b)$$

Compartmental models and flow diagrams

The birth-death equation is a **compartmental model** using a single compartment $N(t)$

A **compartment** is defined as a kinetically homogeneous group of individuals

A **flow diagram** is a graphical representation of a compartmental model



What can we say about model (4)?

(4a) is a scalar first-order linear autonomous ODE \Rightarrow we easily find the explicit solution

$$N(t) = N(t_0)e^{(b-d)(t-t_0)}, \quad t \geq t_0 \quad (5)$$

To check that (5) is a solution to (4), we differentiate it and check it satisfies (4a); we also check it satisfies (4b):

$$\begin{aligned} N'(t) &= \frac{d}{dt} \left(N(t_0)e^{(b-d)(t-t_0)} \right) \\ &= N(t_0) \frac{d}{dt} \left(e^{(b-d)(t-t_0)} \right) \\ &= N(t_0)(b-d)e^{(b-d)(t-t_0)} \\ &= (b-d)N(t_0)e^{(b-d)(t-t_0)} \\ &= (b-d) \left(N(t_0)e^{(b-d)(t-t_0)} \right) \\ &= (b-d)N(t) \end{aligned}$$

$$N(t_0) = N(t_0)e^{(b-d)(t_0-t_0)} = N(t_0)e^0 = N_0$$

So the behaviour is easy to understand

$$N(t) = N(t_0)e^{(b-d)(t-t_0)}, \quad t \geq t_0 \quad (5)$$

For $t > t_0$, $t - t_0 > 0$, so the behaviour of (5) is determined by the sign of $b - d$

- ▶ If $b > d$, then $N(t)$ grows exponentially
- ▶ If $b = d$, then $N(t)$ remains constant (and equal to $N(t_0)$)
- ▶ If $b < d$, then $N(t)$ decays exponentially to 0

This analysis is possible because we have the explicit solution (5). That is almost never the case, so what can we do?

Qualitative analysis

As remarked earlier, (4a) is a scalar first-order linear autonomous ODE, so the qualitative analysis is also super easy, but the ideas that follow are general and are used later in more complex models

- ▶ Check that the model “makes sense” (we sometimes say that the model is *well-posed*)
- ▶ Seek an **equilibrium solution** (an **equilibrium** for short), i.e., a constant solution $N(t) = N^*$ such that $N' = 0$ when $N(t) = N^*$
- ▶ Consider the sign of N' for $N < N^*$ and $N > N^*$ to determine the *stability* of the equilibrium solution

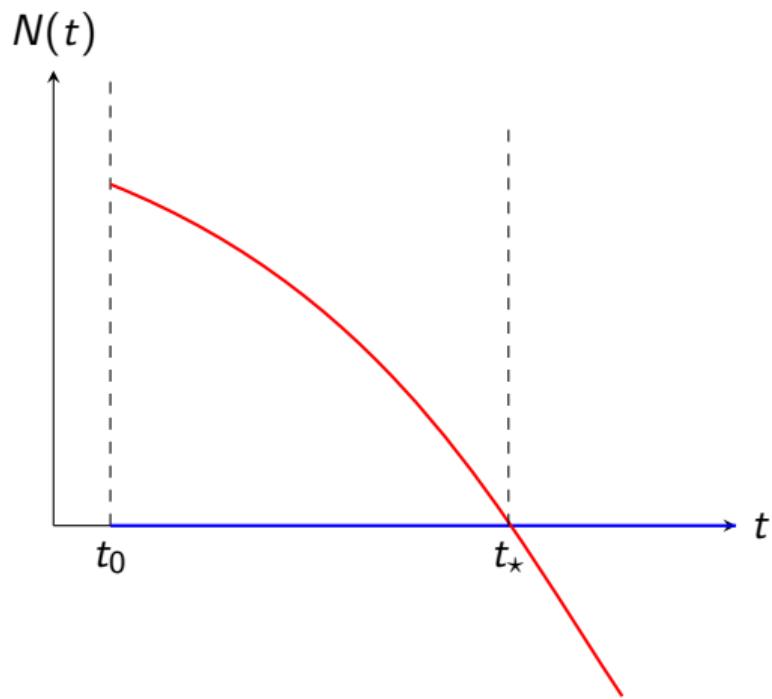
First, a remark – The model makes sense

The model (4) makes sense only if its solutions exist uniquely and $N(t) \geq 0$ for all $t \geq t_0$

The existence and uniqueness of solutions is guaranteed by Theorem 7, since the function $f(N) = bN - dN$ is C^1 (it is actually C^∞)

Now remark that if $N(t_0) = 0$, then $N(t) = 0$ for all $t \geq t_0$ because $N' = bN - dN = 0$ for $N = 0$

Now suppose that $N(t_0) > 0$. Then there does not exist $t_* > t_0$ such that $N(t_*) = 0$. If there were, then at t_* we would have two solutions such that $N(t_*) = 0$: the one that is identically 0 and the one that starts with $N(t_0) > 0$, contradicting uniqueness of solutions



Equilibrium

An equilibrium solution N^* satisfies $N^*' = 0$, i.e.,

$$bN^* - dN^* = 0$$

This gives $N^* = 0$ or $b = d$

If $b = d$, then (4a) reduces to $N' = 0$, which has the general solution $N(t) = C$ (C the integration constant), so, with the initial condition (4b), we have $N(t) = N_0$ for all $t \geq t_0$

So let us now consider the case $b \neq d$ and $N^* = 0$

Stability of the equilibrium $N^* = 0$

Write the ODE (4a) as

$$N' = f(N)$$

to emphasise that $f(N) = bN - dN$ is the right-hand side of the ODE

We have seen that if we start with $N(t_0) = 0$, then $N(t) = 0$ for all $t \geq t_0$ so assume $N(t_0) > 0$. This means that $N(t) > 0$ for all $t \geq t_0$

As a consequence, the sign of $f(N)$ is the same as the sign of $b - d$

- ▶ If $b > d$, then $f(N) > 0$
- ▶ If $b = d$, then $f(N) = 0$
- ▶ If $b < d$, then $f(N) < 0$

The situation

- ▶ If $b > d$, then $f(N) > 0 \Rightarrow N(t)$ is increasing for all $t \geq t_0 \Rightarrow N(t) \rightarrow \infty$ as $t \rightarrow \infty$
- ▶ If $b = d$, then $f(N) = 0 \Rightarrow N(t) = N_0$ for all $t \geq t_0$
- ▶ If $b < d$, then $f(N) < 0 \Rightarrow N(t)$ is decreasing for all $t \geq t_0 \Rightarrow N(t) \rightarrow 0$ as $t \rightarrow \infty$, since we have also seen that $N(t) > 0$ for all $t \geq t_0$ when $N(t_0) > 0$

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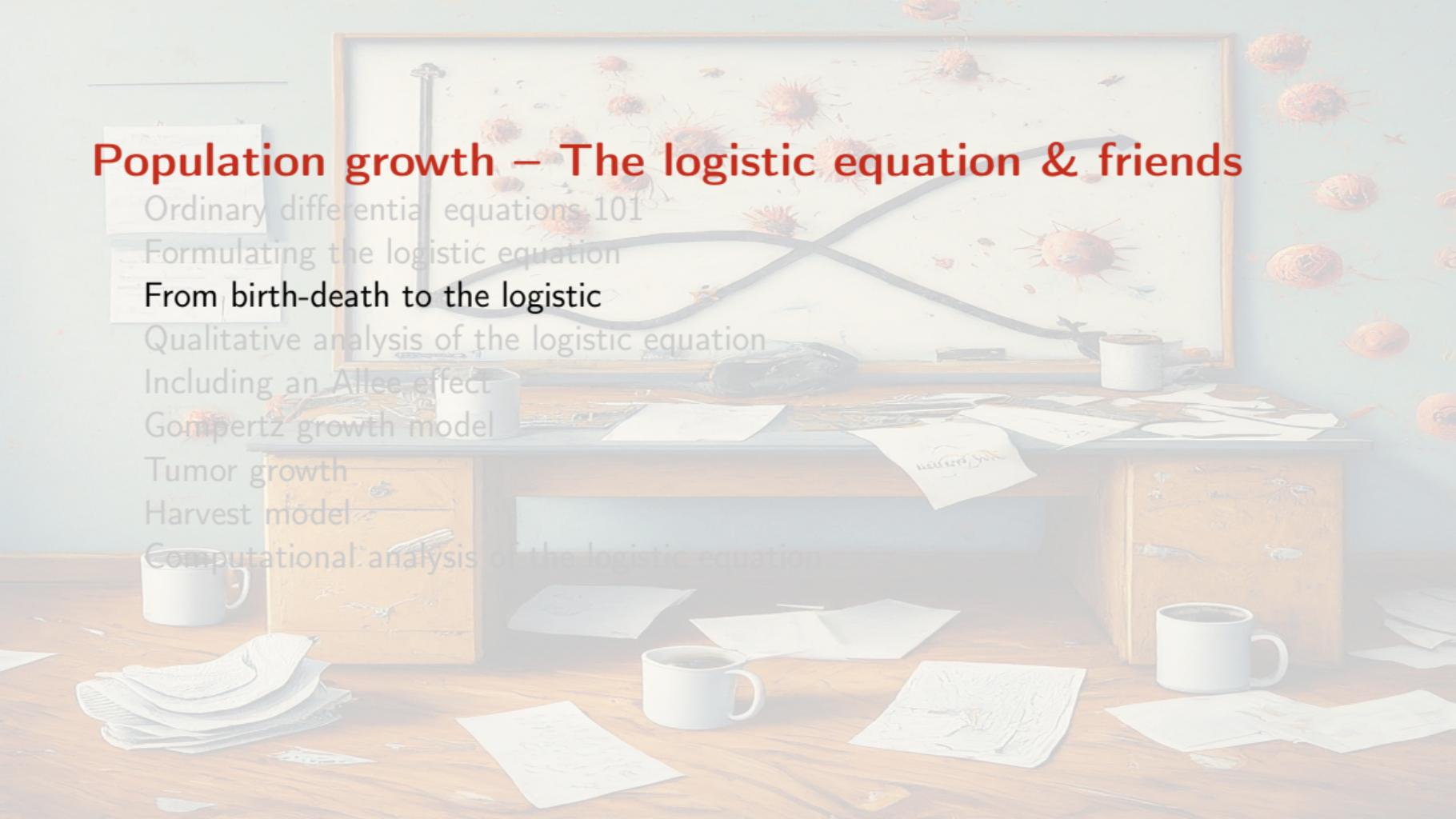
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Deriving the logistic equation

The birth-death model does not account for the fact that (competitive) interactions between individuals reduces their ability to survive, potentially resulting in death

For instance, resources are limited

This gives

$$N' = bN - dN - \text{competition}$$

Accounting for competition

Competition describes the mortality that occurs when two individuals meet

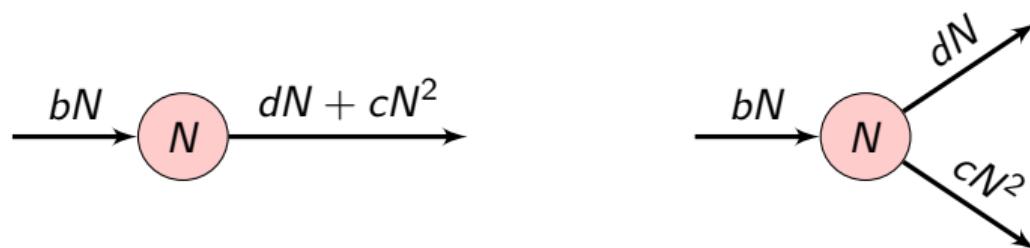
- ▶ In chemistry, if there is a concentration X of one product and Y of another product, then XY , called **mass action**, describes the number of interactions of molecules of the two products
- ▶ Here, we assume that X and Y are of the same type (individuals). So there are N^2 contacts
- ▶ These N^2 contacts lead to death of one of the individuals at the rate c

Therefore, the **logistic** equation is

$$N' = bN - dN - cN^2 \tag{6}$$

Flow diagram(s) of the logistic equation

$$N' = bN - dN - cN^2 \quad (6)$$



(Left is more compact. Right emphasises that there are two different ways to leave the compartment)

Reinterpreting the logistic equation

The equation

$$N' = bN - dN - cN^2 \quad (6)$$

is rewritten as

$$N' = (b - d)N - cN^2$$

- ▶ $b - d$ represents the rate at which the population increases (or decreases) in the absence of competition. It is called the **intrinsic growth rate** of the population

- ▶ c is the rate of **intraspecific** competition. The prefix **intra** refers to the fact that the competition is occurring between members of the same species, that is, within the species

Yet another interpretation of the logistic equation

We have

$$N' = (b - d)N - cN^2$$

Factor out an N :

$$N' = ((b - d) - cN)N$$

This gives us another interpretation of the logistic equation. Writing

$$\frac{N'}{N} = (b - d) - cN$$

we have the *per capita* growth rate N'/N given by a constant $b - d$ minus a *density dependent inhibition* factor cN

Obtaining the well-known form (3)

$$\begin{aligned}N' &= (b - d)N - cN^2 \\&= ((b - d) - cN)N \\&= \left(r - \frac{r}{r}cN\right)N \quad \text{with } r = b - d \text{ the growth rate} \\&= rN \left(1 - \frac{c}{r}N\right) \\&= rN \left(1 - \frac{N}{K}\right)\end{aligned}$$

with $c/r = 1/K$

$K = r/c$ is the carrying capacity

Another interpretation of the logistic equation (3)

Think in terms of the *per capita* growth rate and rewrite slightly the equation

$$N' = rN \left(1 - \frac{N}{K}\right)$$

as

$$\frac{N'}{N} = r \frac{K - N}{K}$$

This gives a more intuitive understanding of the role of K in regulating the population: when N is smaller than K , the population grows, when N is larger than K , the population decreases

The parameter r sets how fast this regulation occurs

Units

It is important, especially later when we look at numerics, to understand the units of the parameters

On the left, $dN(t)/dt$ has units of N/t (or $\#/t$), i.e., population per unit time

Consider three potential right hand sides, e.g., for death

$$N' = -d, \quad N' = -dN \quad \& \quad N' = -dN^2$$

First case: d has units of $\#/t$. Second case, d has units of $1/t$ (since dN has units $\#/t$ with N having units $\#$). Third case, d has units of $1/(t\#)$ (since N^2 has units of $\#\#$)

Several ways to tackle this equation

1. The equation is separable [explicit method]
2. The equation is a Bernoulli equation [explicit method]
3. Use qualitative analysis
4. Use numerical methods

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Studying the logistic equation qualitatively

We study

$$N' = rN \left(1 - \frac{N}{K}\right) \quad (3)$$

For this, write

$$f(N) = rN \left(1 - \frac{N}{K}\right)$$

Consider the initial value problem consisting of (3) and an initial condition

$$N' = f(N), \quad N(0) = N_0 > 0 \quad (7)$$

- ▶ f is C^1 so solutions to (7) exist and are unique

Equilibria of the logistic equation

Equilibria of (3) are points such that $f(N) = 0$. So we solve $f(N) = 0$ for N :

$$rN \left(1 - \frac{N}{K}\right) = 0 \iff rN = 0 \text{ or } 1 - \frac{N}{K} = 0$$

So we find two points:

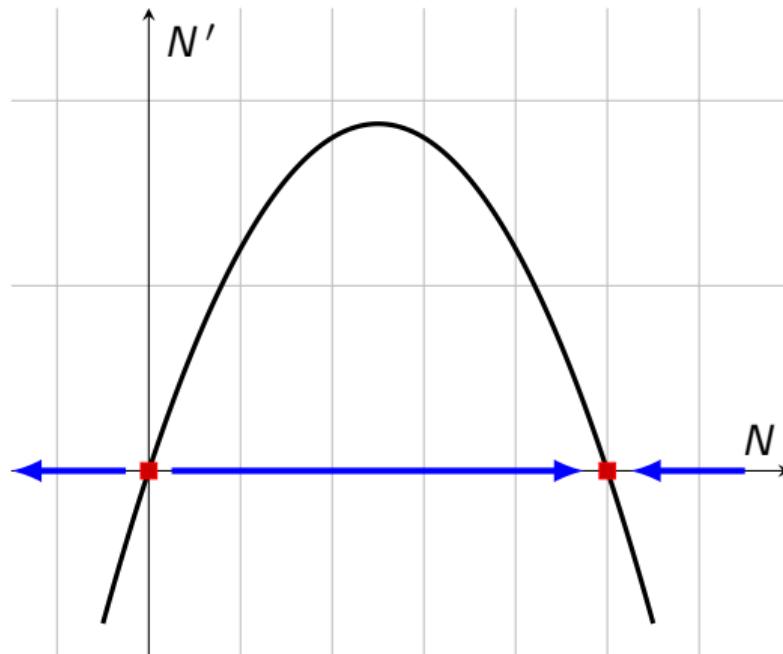
- ▶ $N = 0$
- ▶ $N = K$

By uniqueness of solutions to (7), solutions cannot cross the lines (solutions) $N(t) = 0$ and $N(t) = K$

Several cases

- ▶ $N = 0$ for some t , then $N(t) = 0$ for all $t \geq 0$, by uniqueness of solutions
- ▶ $N \in (0, K)$, then $rN > 0$ and $N/K < 1$ so $1 - N/K > 0$, which implies that $f(N) > 0$. As a consequence, $N(t)$ increases if $N \in (0, K)$
- ▶ $N = K$, then $rN > 0$ but $N/K = 1$ so $1 - N/K = 0$, which implies that $f(N) = 0$. As a consequence, $N(t) = K$ for all $t \geq 0$, by uniqueness of solutions
- ▶ $N > K$, the $rN > 0$ and $N/K > 1$, implying that $1 - N/K < 0$ and in turn, $f(N) < 0$. As a consequence, $N(t)$ decreases if $N \in (K, +\infty)$

Stability of the equilibria



Theorem 8

Consider the initial value problem (7). Then

- ▶ If $N_0 = 0$, then $N(t) = 0$ for all $t \geq t_0$
- ▶ If $N_0 > 0$, then $N(t)$ is such that

$$\lim_{t \rightarrow \infty} N(t) = K$$

so that K is the number of individuals that the environment can support, the **carrying capacity** of the environment

We could be more precise and break up the second case depending on whether $N_0 < K$, $N_0 = K$ or $N_0 > K$, but the end result is the same

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Including an Allee effect

Logistic equation assumes that when the population is less than the carrying capacity, the population grows. But what if the population is too small?

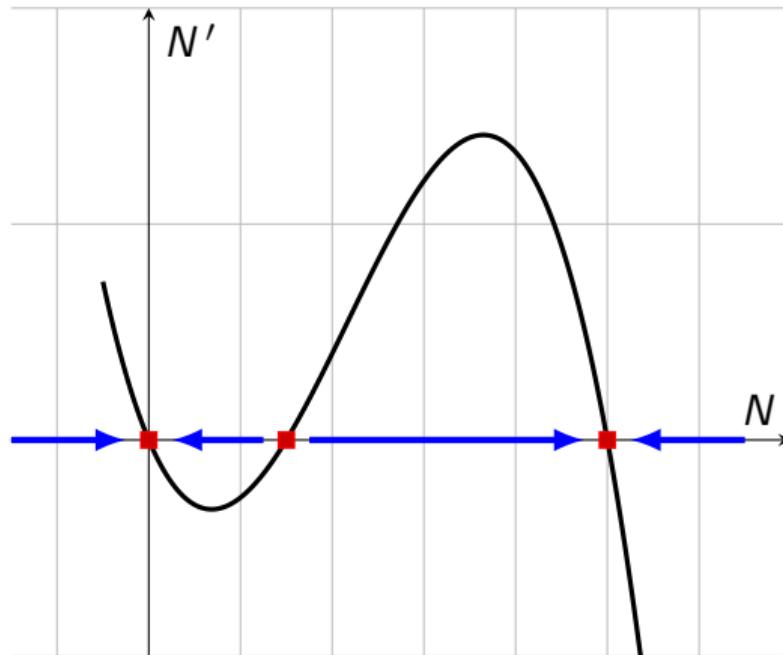
There may not be enough individuals to find mates, or to find food, or to protect themselves from predators. This is an **Allee effect**

Logistic equation with an Allee effect

$$N' = rN \left(\frac{N}{A} - 1 \right) \left(1 - \frac{N}{K} \right) \quad (8)$$

- ▶ $r > 0$ growth rate
- ▶ $K > 0$ carrying capacity
- ▶ $A > 0$ Allee threshold

Stability of the equilibria



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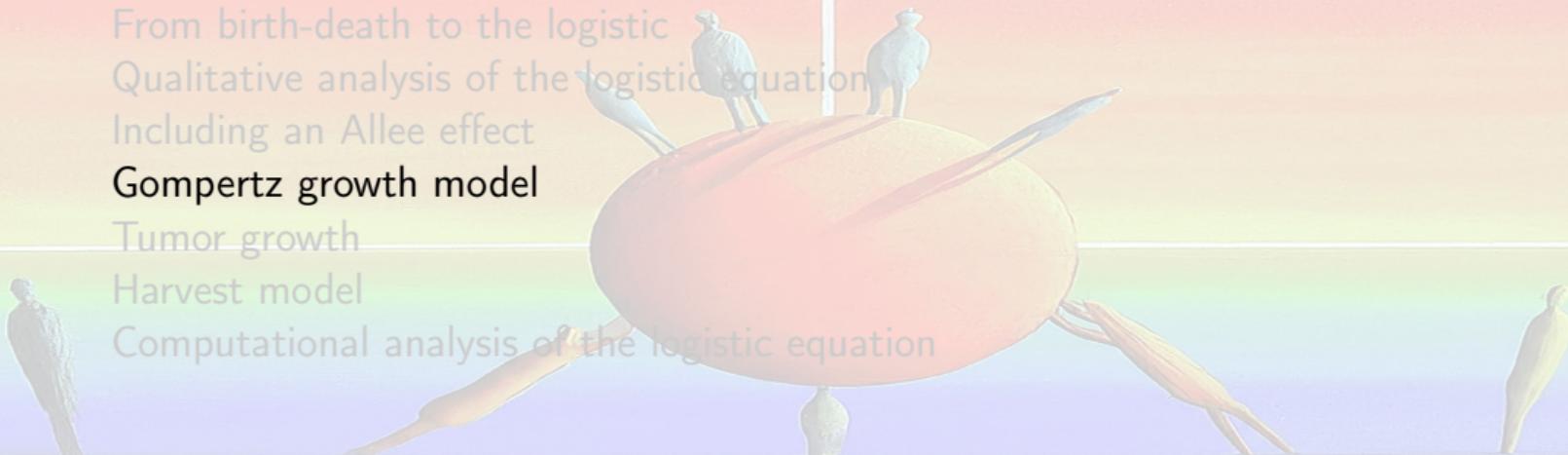
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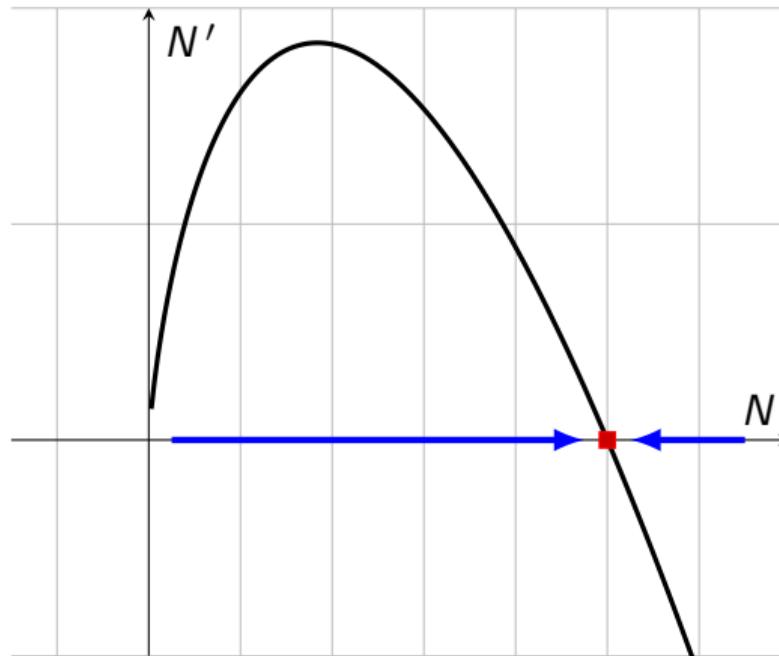
Computational analysis of the logistic equation



Gompertz growth model

$$N' = rN \ln \left(\frac{K}{N} \right) \quad (9)$$

Stability of the equilibria



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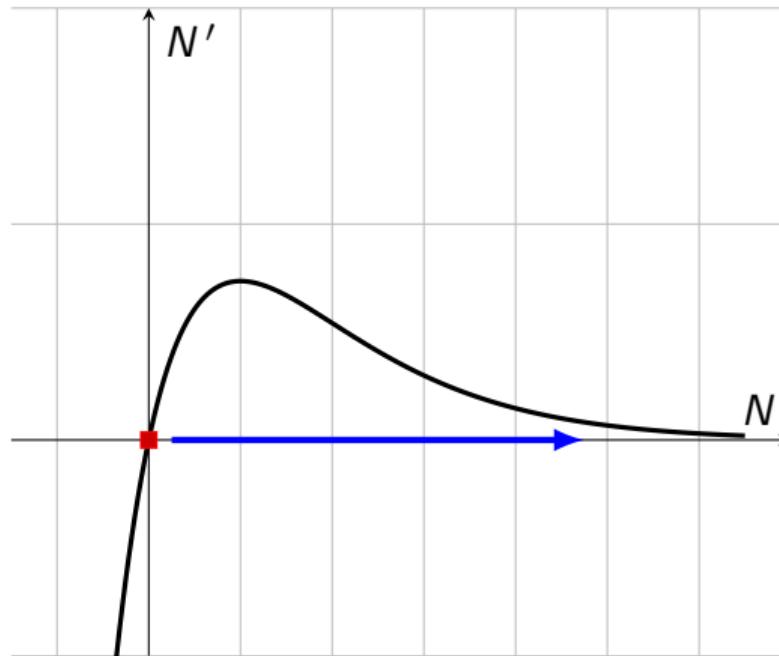


Tumor growth

$$N' = rN e^{-bN} \quad (10)$$

- ▶ $r > 0$ growth rate
- ▶ $b > 0$

Stability of the equilibria



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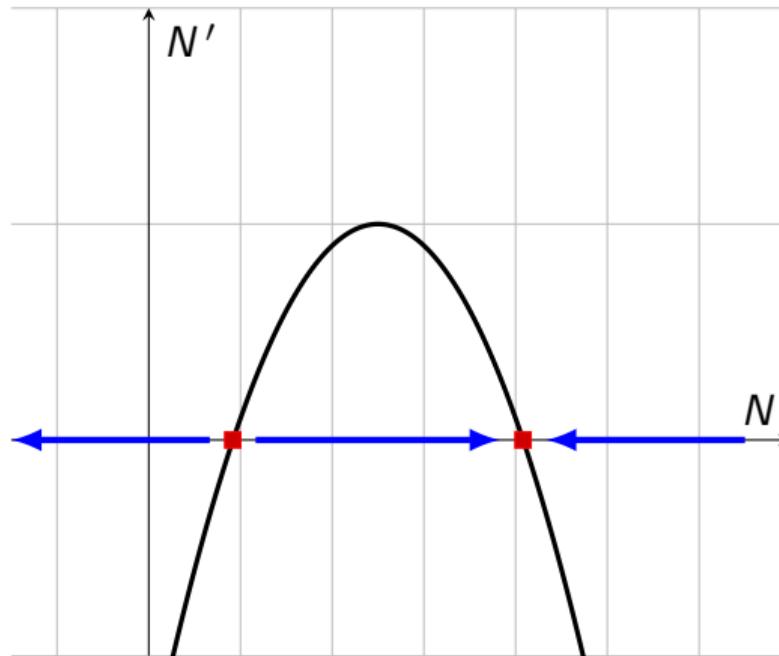
Computational analysis of the logistic equation

Logistic model with harvesting

$$N' = rN \left(1 - \frac{N}{K}\right) - H \quad (11)$$

- ▶ $r > 0$ growth rate
- ▶ $K > 0$ carrying capacity
- ▶ $H > 0$ harvest rate

Stability of the equilibria



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The data – US census

Fitting a curve to the data

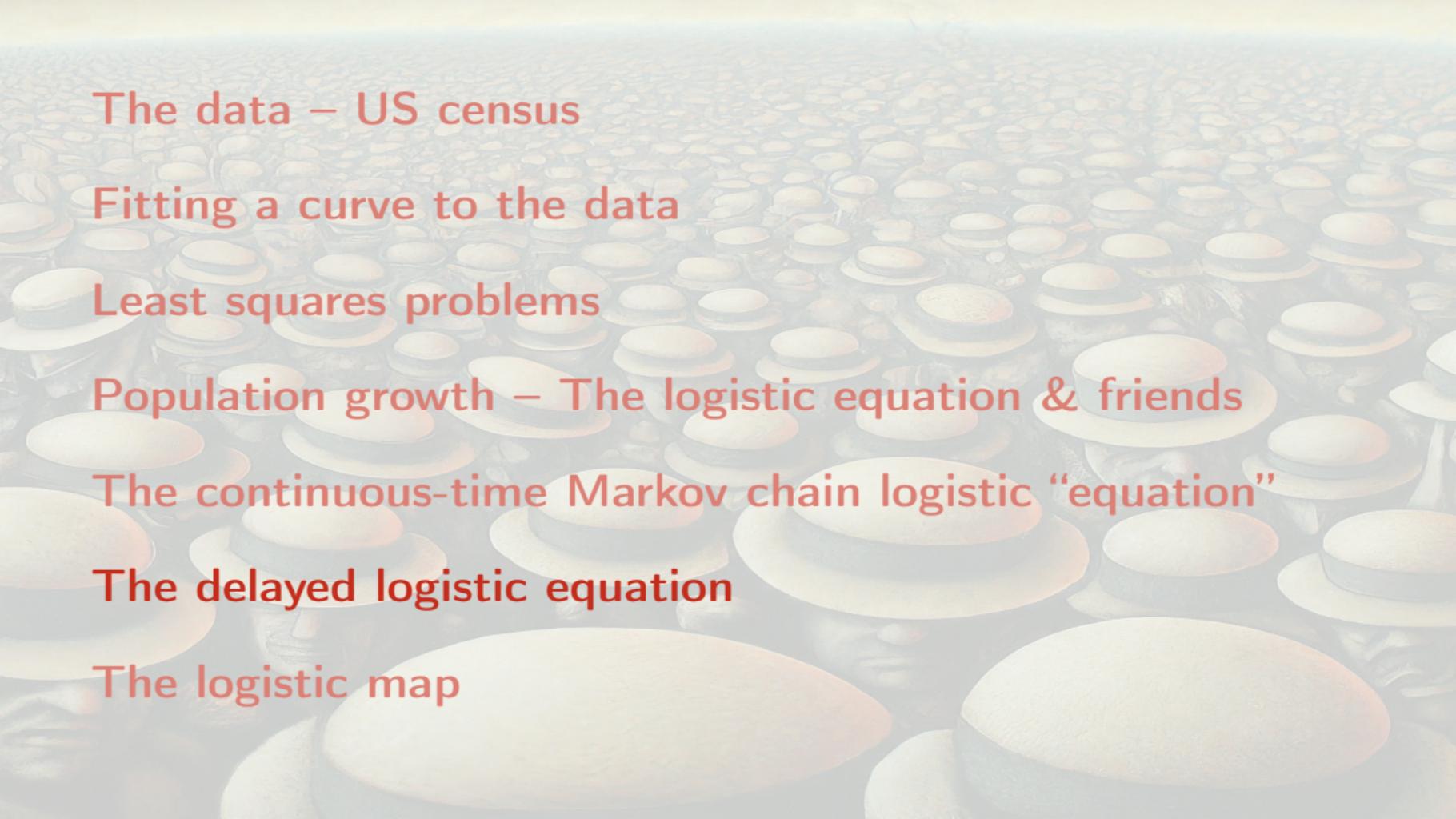
Least squares problems

Population growth – The logistic equation & friends

The continuous-time Markov chain logistic “equation”

The delayed logistic equation

The logistic map

The background of the slide features a dense, overlapping crowd of numerous people, all wearing what appears to be a traditional white fez or turban-like hat. The hats are light-colored and have a slightly textured appearance. The people's faces are visible but are heavily blurred, giving the image a sense of depth and population. The overall color palette is warm, with earthy tones from the hats and skin.

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The delayed logistic equation

Consider the equation as

$$\frac{N'}{N} = (b - d) - cN$$

that is, the per capita rate of growth of the population depends on the net growth rate $b - d$, and some density dependent inhibition cN (resulting of competition)

Suppose that instead of instantaneous inhibition, there is some delay τ between the time the inhibiting event takes place and the moment when it affects the growth rate

For example, two individuals fight for food, and one later dies of the injuries sustained during this fight

The delayed logistic equation

In the case of a time τ between inhibiting event and inhibition, the equation would be written as

$$\frac{N'}{N} = (b - d) - cN(t - \tau)$$

Using the change of variables introduced earlier, this is written

$$N'(t) = rN(t) \left(1 - \frac{N(t - \tau)}{K}\right) \quad (\text{DDE1})$$

Such an equation is called a **delay differential equation** (DDE). It is much more complicated to study than (3). In fact, some things remain unknown about (DDE1)

Delayed initial value problem

The IVP takes the form

$$\begin{aligned}N'(t) &= rN(t) \left(1 - \frac{N(t-\tau)}{K}\right) \\ N(t) &= \phi(t) \text{ for } t \in [-\tau, 0]\end{aligned}\tag{IVP2}$$

where $\phi(t)$ is some continuous function

Hence, initial conditions (called initial data in this case) must be specified on an interval, instead of being specified at a point, to guarantee existence and uniqueness of solutions

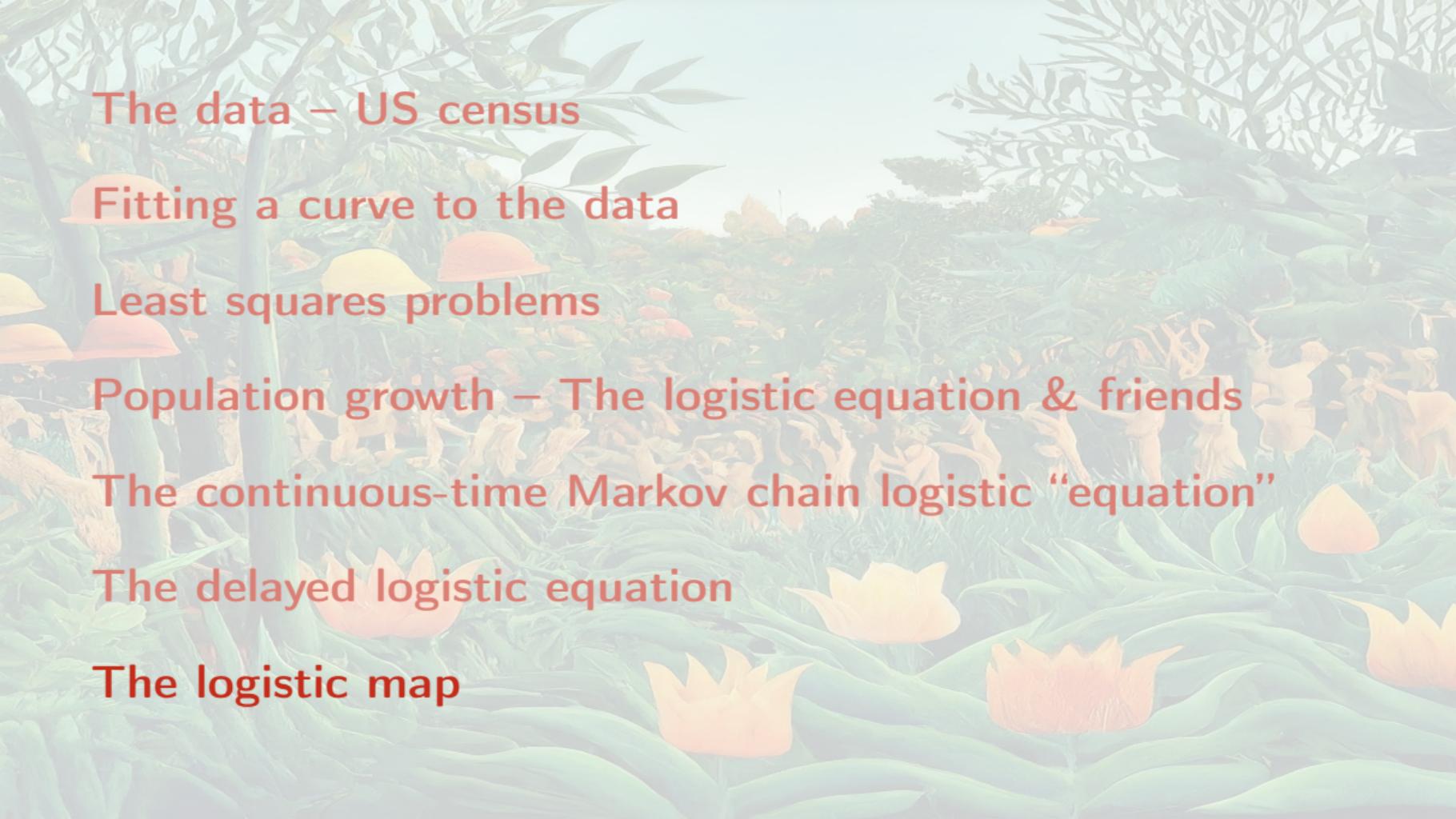
We will not learn how to study this type of equation (this is graduate level mathematics). I will give a few results

To find equilibria, remark that delay should not play a role, since N should be constant. Thus, equilibria are found by considering the equation with no delay, which is (3)

Theorem 9

Suppose that $r\tau < \pi/2$. Then solutions of (IVP2) with positive initial data $\phi(t)$ starting close enough to K tend to K . If $r\tau < 37/24$, then all solutions of (IVP2) with positive initial data $\phi(t)$ tend to K . If $r\tau > \pi/2$, then K is an unstable equilibrium and all solutions of (IVP2) with positive initial data $\phi(t)$ on $[-\tau, 0]$ are oscillatory

There is a gray zone between $37/24$ ($\simeq 1.5417$) and $\pi/2$ ($\simeq 1.5708$). The global aspect was proved for $r\tau < 37/24$ in 1945 by Wright. Although there is very strong numerical evidence that this is in fact true up to $\pi/2$, nobody has yet managed to prove it [Edit: now done!]

A background image of a field of tulips, with many green leaves and orange flowers visible.

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Discrete-time systems

So far, we have seen continuous-time models, where $t \in \mathbb{R}_+$. Another way to model natural phenomena is by using a discrete-time formalism, that is, to consider equations of the form

$$x_{t+1} = f(x_t)$$

where $t \in \mathbb{N}$ or \mathbb{Z} , that is, t takes values in a discrete valued (countable) set

Time could for example be days, years, etc.

The logistic map

The logistic **map** is, for $t \geq 0$,

$$N_{t+1} = rN_t \left(1 - \frac{N_t}{K}\right) \quad (\text{DT1})$$

To transform this into an initial value problem, we need to provide an initial condition $N_0 \geq 0$ for $t = 0$

Some mathematical analysis

Suppose we have a system in the form

$$x_{t+1} = f(x_t)$$

with initial condition given for $t = 0$ by x_0 . Then,

$$x_1 = f(x_0)$$

$$x_2 = f(x_1) = f(f(x_0)) \stackrel{\Delta}{=} f^2(x_0)$$

⋮

$$x_k = f^k(x_0)$$

The $f^k = \underbrace{f \circ f \circ \cdots \circ f}_{k \text{ times}}$ are the **iterates** of f

Fixed points

Definition 10 (Fixed point)

Let f be a function. A point p such that $f(p) = p$ is called a **fixed point** of f

Theorem 11

Consider the closed interval $I = [a, b]$. If $f : I \rightarrow I$ is continuous, then f has a fixed point in I

Theorem 12

Let I be a closed interval and $f : I \rightarrow \mathbb{R}$ be a continuous function. If $f(I) \supset I$, then f has a fixed point in I .

Periodic points

Definition 13 (Periodic point)

Let f be a function. If there exists a point p and an integer n such that

$$f^n(p) = p, \quad \text{but} \quad f^k(p) \neq p \text{ for } k < n,$$

then p is a periodic point of f with (least) period n (or a n -periodic point of f).

Thus, p is a n -periodic point of f iff p is a 1-periodic point of f^n .

Stability of fixed points, of periodic points

Theorem 14

Let f be a continuously differentiable function (that is, differentiable with continuous derivative, or C^1), and p be a fixed point of f .

1. If $|f'(p)| < 1$, then there is an open interval $\mathcal{I} \ni p$ such that $\lim_{k \rightarrow \infty} f^k(x) = p$ for all $x \in \mathcal{I}$.
2. If $|f'(p)| > 1$, then there is an open interval $\mathcal{I} \ni p$ such that if $x \in \mathcal{I}$, $x \neq p$, then there exists k such that $f^k(x) \notin \mathcal{I}$.

Definition 15

Suppose that p is a n -periodic point of f , with $f \in C^1$.

- If $|(f^n)'(p)| < 1$, then p is an **attracting** periodic point of f .
- If $|(f^n)'(p)| > 1$, then p is an **repelling** periodic point of f .

Parametrized families of functions

Consider the equation (DT1), which for convenience we rewrite as

$$N_{t+1} = rN_t(1 - N_t), \quad (\text{DT2})$$

where r is a parameter in \mathbb{R}_+ , and N will typically be taken in $[0, 1]$. Let

$$f_r(x) = rx(1 - x).$$

The function f_r is called a **parametrized family** of functions.

Bifurcations

Definition 16 (Bifurcation)

Let f_μ be a parametrized family of functions. Then there is a **bifurcation** at $\mu = \mu_0$ (or μ_0 is a bifurcation point) if there exists $\varepsilon > 0$ such that, if $\mu_0 - \varepsilon < a < \mu_0$ and $\mu_0 < b < \mu_0 + \varepsilon$, then the dynamics of $f_a(x)$ are “different” from the dynamics of $f_b(x)$.

An example of “different” would be that f_a has a fixed point (that is, a 1-periodic point) and f_b has a 2-periodic point.

Back to the logistic map

Consider the simplified version (DT2),

$$N_{t+1} = rN_t(1 - N_t) \stackrel{\Delta}{=} f_r(N_t).$$

Are solutions well defined?

Suppose $N_0 \in [0, 1]$, do we stay in $[0, 1]$? f_r is continuous on $[0, 1]$, so it has extrema on $[0, 1]$. We have

$$f'_r(x) = r - 2rx = r(1 - 2x),$$

which implies that f_r increases for $x < 1/2$ and decreases for $x > 1/2$, reaching a maximum at $x = 1/2$.

$f_r(0) = f_r(1) = 0$ are the minimum values, and $f_r(1/2) = r/4$ is the maximum. Thus, if we want $N_{t+1} \in [0, 1]$ for $N_t \in [0, 1]$, we need to consider $r \leq 4$.

- ▶ Note that if $N_0 = 0$, then $N_t = 0$ for all $t \geq 1$.
- ▶ Similarly, if $N_0 = 1$, then $N_1 = 0$, and thus $N_t = 0$ for all $t \geq 1$.
- ▶ This is true for all t : if there exists t_k such that $N_{t_k} = 1$, then $N_t = 0$ for all $t \geq t_k$.
- ▶ This last case might occur if $r = 4$, as we have seen.
- ▶ Also, if $r = 0$ then $N_t = 0$ for all t .

For these reasons, we generally consider

$$N \in (0, 1)$$

and

$$r \in (0, 4).$$

Fixed points: existence

Fixed points of (DT2) satisfy $N = rN(1 - N)$, giving:

- ▶ $N = 0$;
- ▶ $1 = r(1 - N)$, that is, $p \triangleq \frac{r - 1}{r}$.

Note that $\lim_{r \rightarrow 0^+} p = 1 - \lim_{r \rightarrow 0^+} 1/r = -\infty$, $\frac{\partial}{\partial r} p = 1/r^2 > 0$ (so p is an increasing function of r), $p = 0 \Leftrightarrow r = 1$ and $\lim_{r \rightarrow \infty} p = 1$. So we come to this first conclusion:

- ▶ 0 always is a fixed point of f_r .
- ▶ If $0 < r < 1$, then p takes negative values so is not relevant.
- ▶ If $1 < r < 4$, then p exists.

Stability of the fixed points

Stability of the fixed points is determined by the (absolute) value f'_r at these fixed points. We have

$$|f'_r(0)| = r,$$

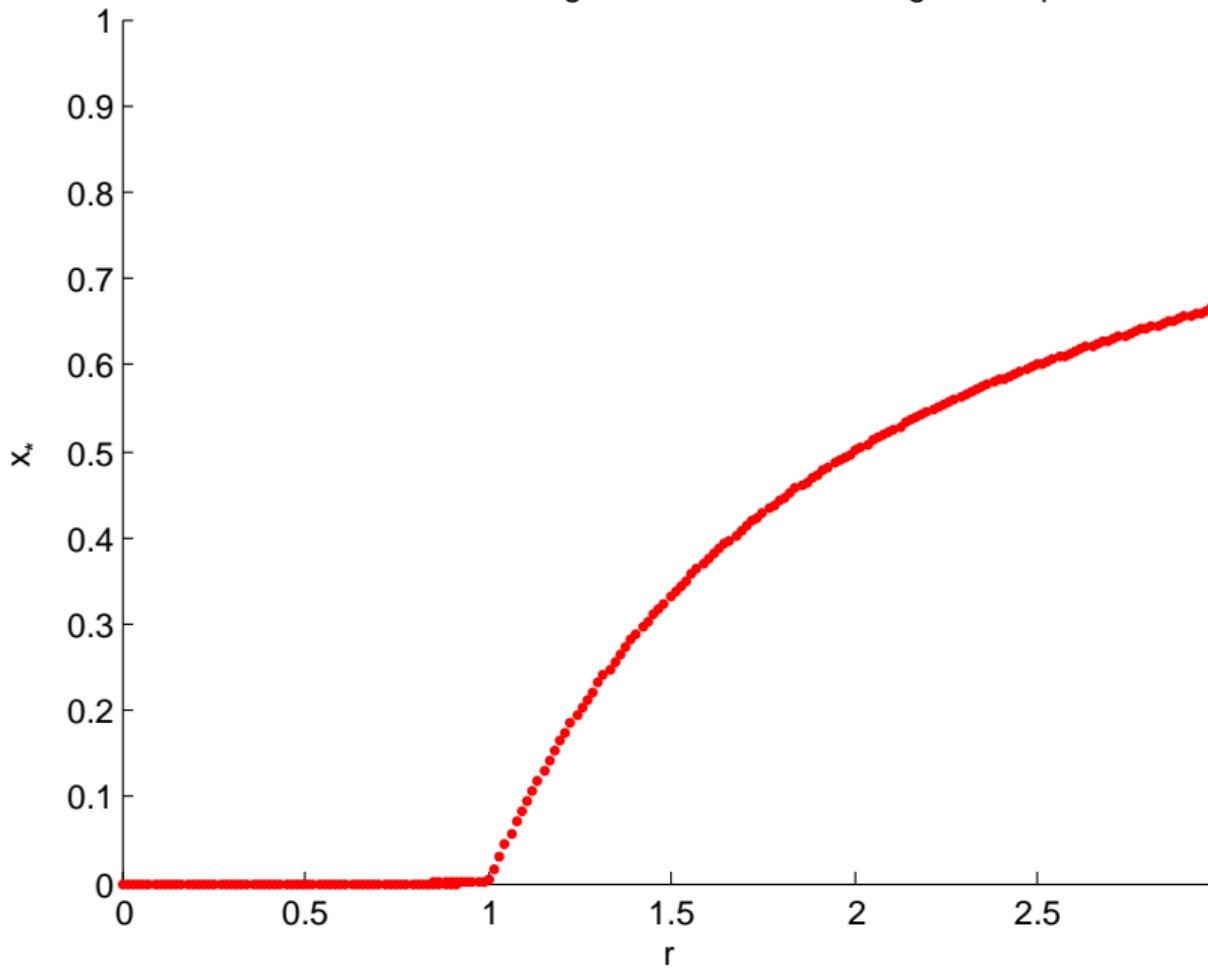
and

$$\begin{aligned}|f'_r(p)| &= \left| r - 2r \frac{r-1}{r} \right| \\&= |r - 2(r-1)| \\&= |2 - r|\end{aligned}$$

Therefore, we have

- ▶ if $0 < r < 1$, then the fixed point $N = p$ does not exist and $N = 0$ is attracting,
- ▶ if $1 < r < 3$, then $N = 0$ is repelling, and $N = p$ is attracting,
- ▶ if $r > 3$, then $N = 0$ and $N = p$ are repelling.

Bifurcation diagram for the discrete logistic map



Another bifurcation

Thus the points $r = 1$ and $r = 3$ are bifurcation points. To see what happens when $r > 3$, we need to look for period 2 points.

$$\begin{aligned}f_r^2(x) &= f_r(f_r(x)) \\&= rf_r(x)(1 - f_r(x)) \\&= r^2x(1 - x)(1 - rx(1 - x)).\end{aligned}\tag{12}$$

0 and p are points of period 2, since a fixed point x^* of f satisfies $f(x^*) = x^*$, and so, $f^2(x^*) = f(f(x^*)) = f(x^*) = x^*$.

This helps localizing the other periodic points. Writing the fixed point equation as

$$Q(x) \stackrel{\Delta}{=} f_r^2(x) - x = 0,$$

we see that, since 0 and p are fixed points of f_μ^2 , they are roots of $Q(x)$. Therefore, Q can be factorized as

$$Q(x) = x(x - p)(-r^3x^2 + Bx + C),$$

Substitute the value $(r - 1)/r$ for p in Q , develop Q and (12) and equate coefficients of like powers gives

$$Q(x) = x \left(x - \frac{r-1}{r} \right) (-r^3x^2 + r^2(r+1)x - r(r+1)). \quad (13)$$

We already know that $x = 0$ and $x = p$ are roots of (13). So we search for roots of

$$R(x) := -r^3x^2 + r^2(r+1)x - r(r+1).$$

Discriminant is

$$\begin{aligned}\Delta &= r^4(r+1)^2 - 4r^4(r+1) \\ &= r^4(r+1)(r+1-4) \\ &= r^4(r+1)(r-3).\end{aligned}$$

Therefore, R has distinct real roots if $r > 3$. Remark that for $r = 3$, the (double) root is $p = 2/3$. For $r > 3$ but very close to 3, it follows from the continuity of R that the roots are close to $2/3$.

Descartes' rule of signs

Theorem 17 (Descartes' rule of signs)

Let $p(x) = \sum_{i=0}^m a_i x^i$ be a polynomial with real coefficients such that $a_m \neq 0$. Define v to be the number of variations in sign of the sequence of coefficients a_m, \dots, a_0 . By 'variations in sign' we mean the number of values of n such that the sign of a_n differs from the sign of a_{n-1} , as n ranges from m down to 1. Then

- ▶ the number of positive real roots of $p(x)$ is $v - 2N$ for some integer N satisfying $0 \leq N \leq \frac{v}{2}$,
- ▶ the number of negative roots of $p(x)$ may be obtained by the same method by applying the rule of signs to $p(-x)$.

Example of use of Descartes' rule

Example 18

Let

$$p(x) = x^3 + 3x^2 - x - 3.$$

Coefficients have signs $++--$, i.e., 1 sign change. Thus $v = 1$. Since $0 \leq N \leq 1/2$, we must have $N = 0$. Thus $v - 2N = 1$ and there is exactly one positive real root of $p(x)$.

To find the negative roots, we examine $p(-x) = -x^3 + 3x^2 + x - 3$. Coefficients have signs $-++-$, i.e., 2 sign changes. Thus $v = 2$ and $0 \leq N \leq 2/2 = 1$. Thus, there are two possible solutions, $N = 0$ and $N = 1$, and two possible values of $v - 2N$.

Therefore, there are either two or no negative real roots. Furthermore, note that $p(-1) = (-1)^3 + 3 \cdot (-1)^2 - (-1) - 3 = 0$, hence there is at least one negative root. Therefore there must be exactly two.

Back to the logistic map and the polynomial R ..

We use Descartes' rule of signs.

- ▶ R has signed coefficients $- + -$, so 2 sign changes implying 0 or 2 positive real roots.
- ▶ $R(-x)$ has signed coefficients $---$, so no negative real roots.
- ▶ Since $\Delta > 0$, the roots are real, and thus it follows that both roots are positive.

To show that the roots are also smaller than 1, consider the change of variables $z = x - 1$. The polynomial R is transformed into

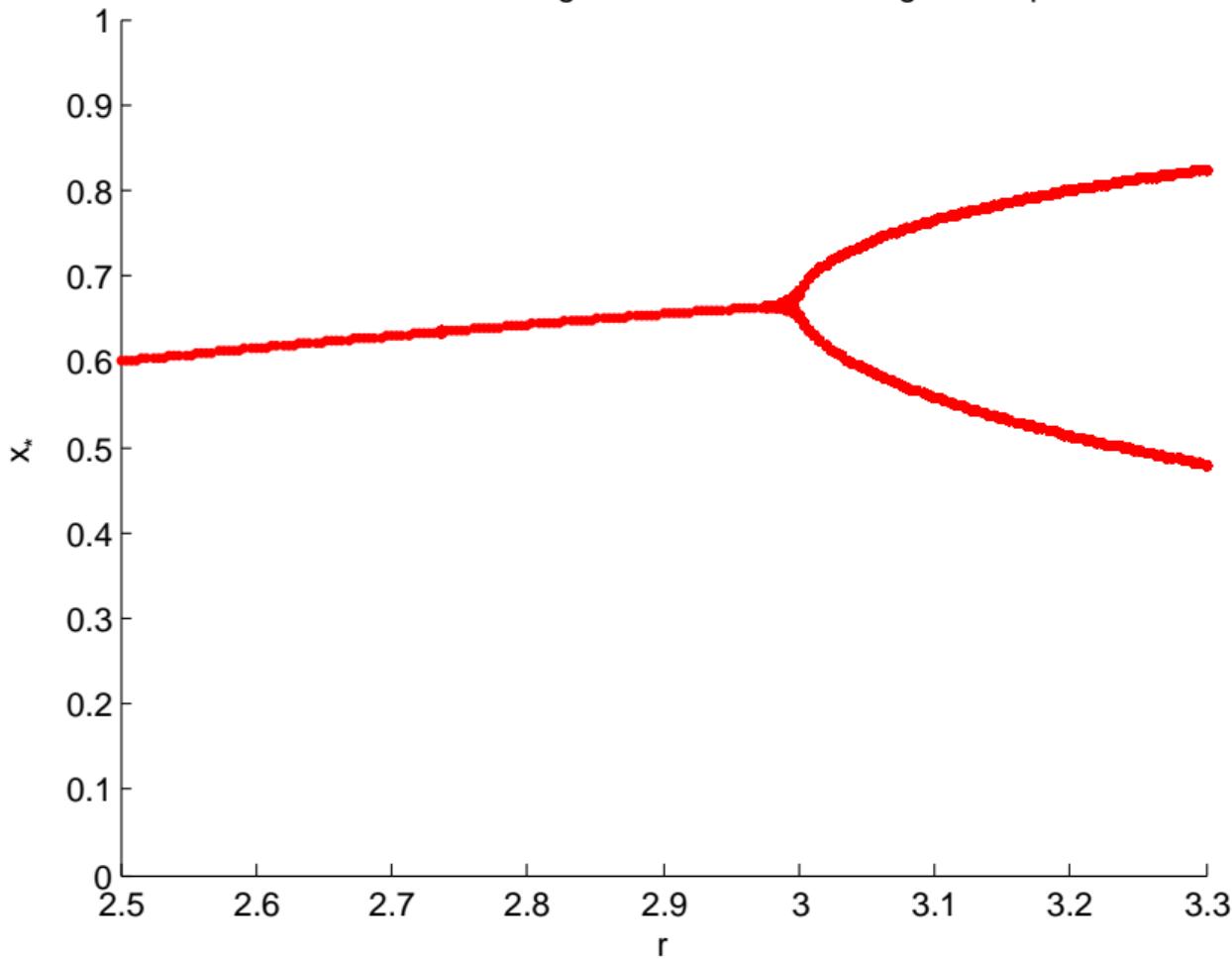
$$\begin{aligned}R_2(z) &= -r^3(z+1)^2 + r^2(r+1)(z+1) - r(r+1) \\&= -r^3z^2 + r^2(1-r)z - r.\end{aligned}$$

For $r > 1$, the signed coefficients are $---$, so R_2 has no root $z > 0$, implying in turn that R has no root $x > 1$.

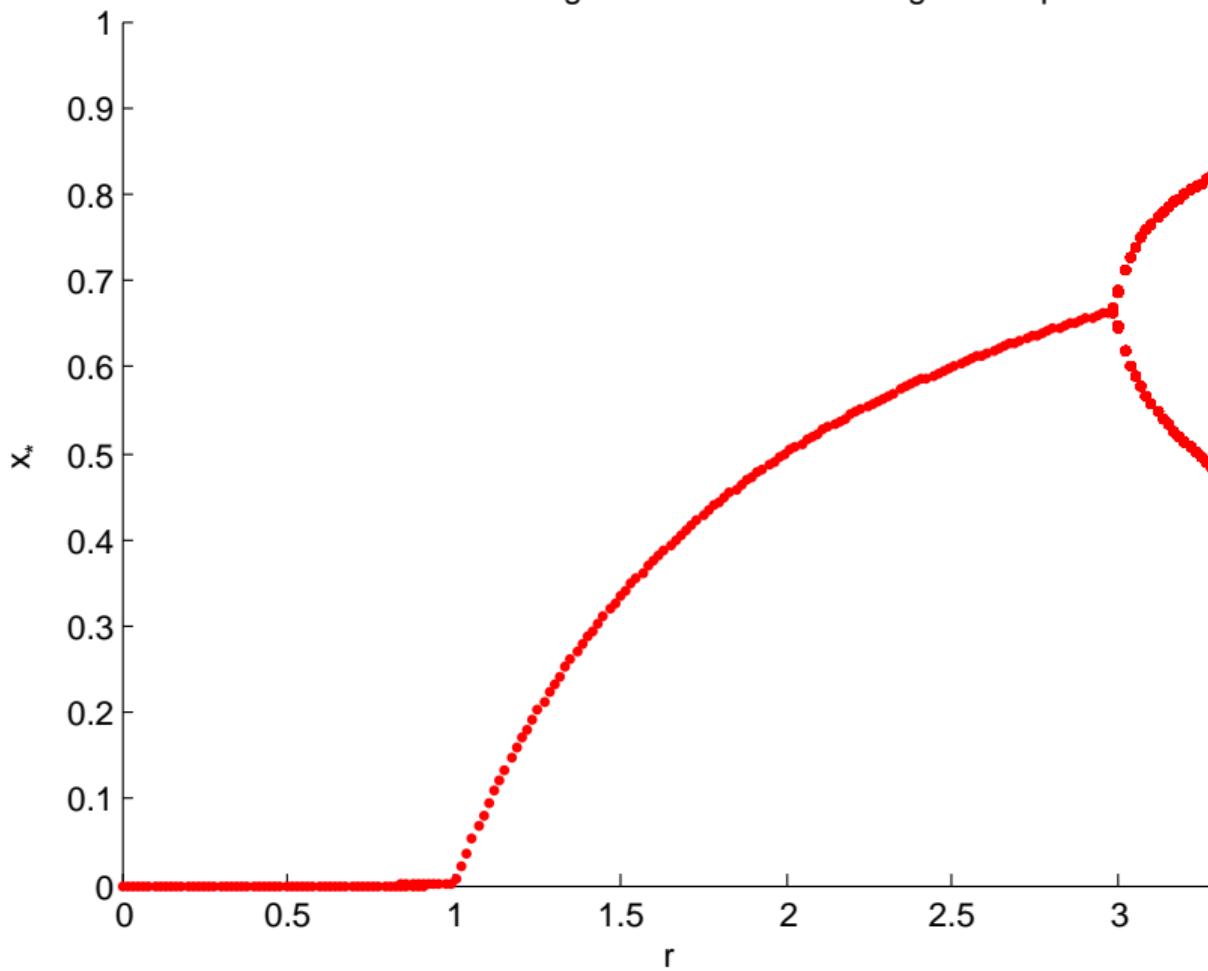
Summing up

- ▶ If $0 < r < 1$, then $N = 0$ is attracting, p does not exist and there are no period 2 points.
- ▶ At $r = 1$, there is a bifurcation (called a **transcritical** bifurcation).
- ▶ If $1 < r < 3$, then $N = 0$ is repelling, $N = p$ is attracting, and there are no period 2 points.
- ▶ At $r = 3$, there is another bifurcation (called a **period-doubling** bifurcation).
- ▶ For $r > 3$, both $N = 0$ and $N = p$ are repelling, and there is a period 2 point.

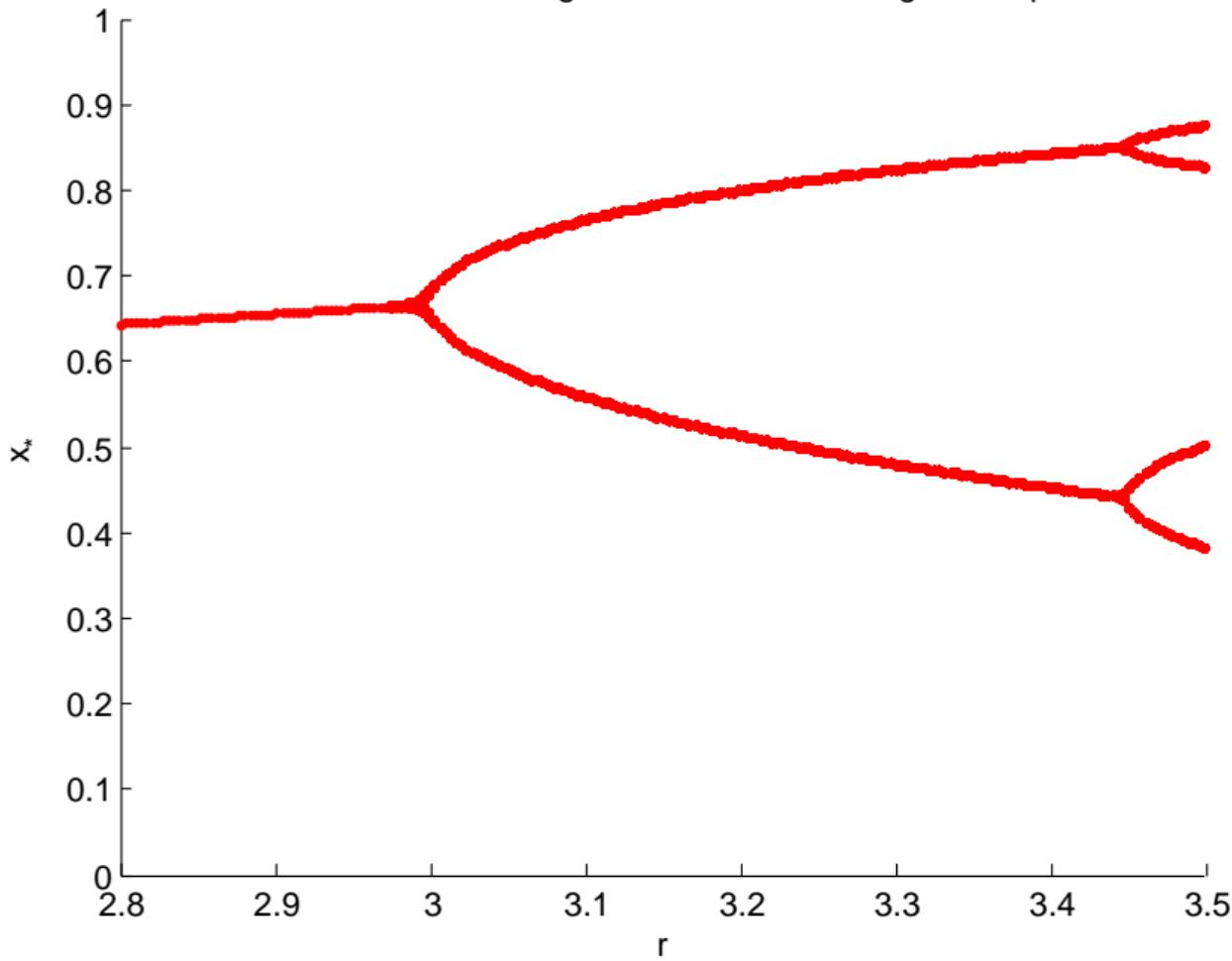
Bifurcation diagram for the discrete logistic map



Bifurcation diagram for the discrete logistic map



Bifurcation diagram for the discrete logistic map



The period-doubling cascade to chaos

The logistic map undergoes a sequence of period doubling bifurcations, called the **period-doubling cascade**, as r increases from 3 to 4.

- ▶ Every successive bifurcation leads to a doubling of the period.
- ▶ The bifurcation points form a sequence, $\{r_n\}$, that has the property that

$$\lim_{n \rightarrow \infty} \frac{r_n - r_{n-1}}{r_{n+1} - r_n}$$

exists and is a constant, called the Feigenbaum constant, equal to 4.669202...

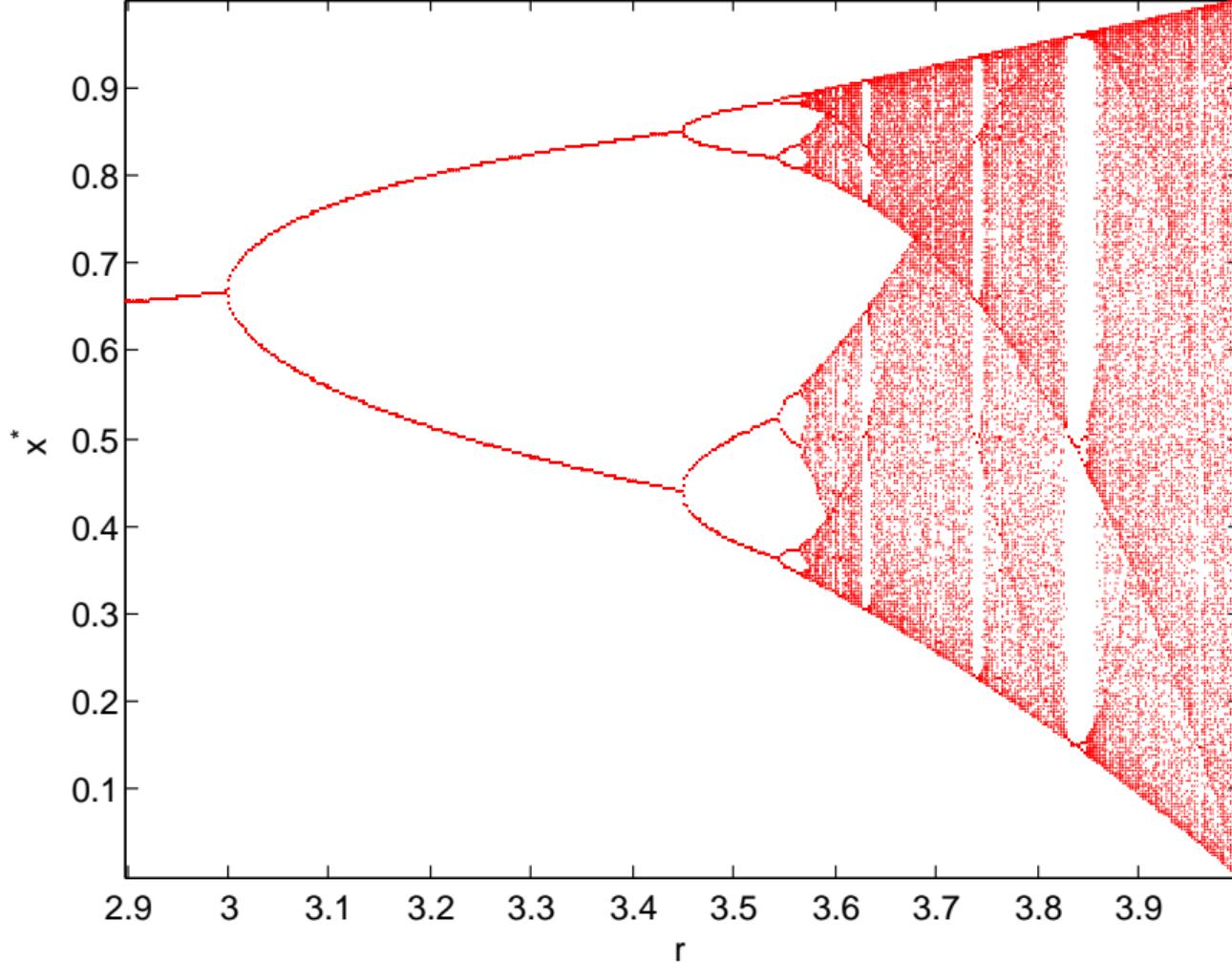
- ▶ This constant has been shown to exist in many of the maps that undergo the same type of cascade of period doubling bifurcations.

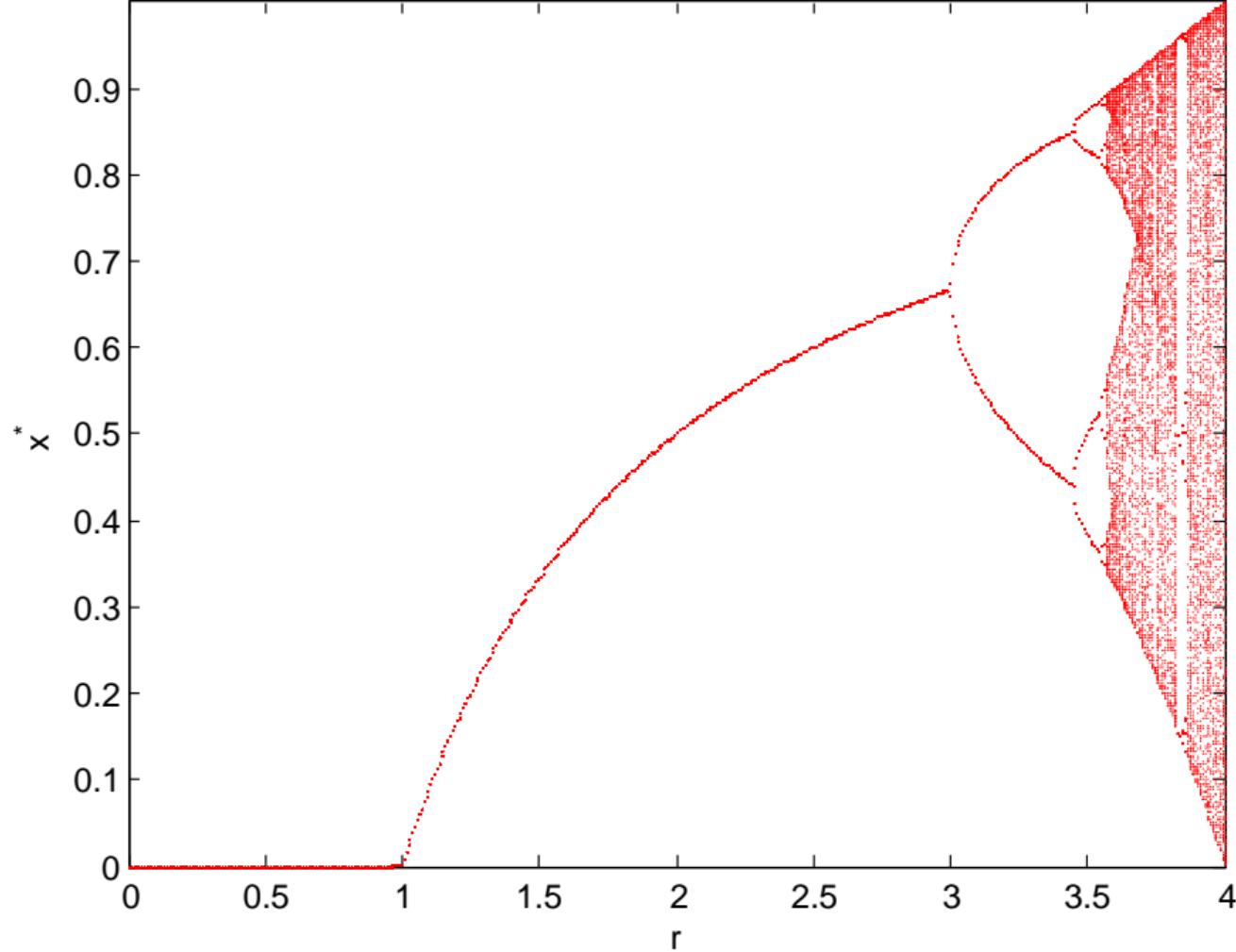
Chaos

After a certain value of r , there are periodic points with all periods. In particular, there are periodic points of period 3.

By a theorem (called **Sarkovskii's theorem**), the presence of period 3 points implies the presence of points of all periods.

At this point, the system is said to be in a **chaotic regime**, or **chaotic**.





Conclusion – A word of caution

We have used four different modelling paradigms to describe the growth of a population in a **logistic** framework:

- ▶ The ODE version has monotone solutions converging to the carrying capacity K
- ▶ The CTMC version behaves like the ODE version, but with a stochastic component
- ▶ The DDE version has oscillatory solutions, either converging to K or, if the delay is too large, periodic about K
- ▶ The discrete time version has all sorts of behaviours, including chaotic

The **choice of modelling method** is almost as **important** in the outcome of the model as the precise formulation/hypotheses of the **model**