

8 Epidemic Data

9 Epidemic Data II

10 Epidemic Data III

11 Epidemic Data Tools



Mathematics
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 8
Epidemic Data
Monday 21 January 2019

Announcements

- Thanks everyone for doing the contributions survey for Assignment 1.
- Don't stress about the ratings about each other's contributions. The issue is whether some group members did not pull their weight. If somebody didn't try and others had to pick up the slack, that person should be penalized. I will not penalize somebody because they tried but felt they didn't contribute as much to the final document as they could have. Do try to even out the work across the assignments.
- Make sure everyone in your group gets a chance to be in control of the \LaTeX for one assignment.

More Announcements!

- **Assignment 2:**

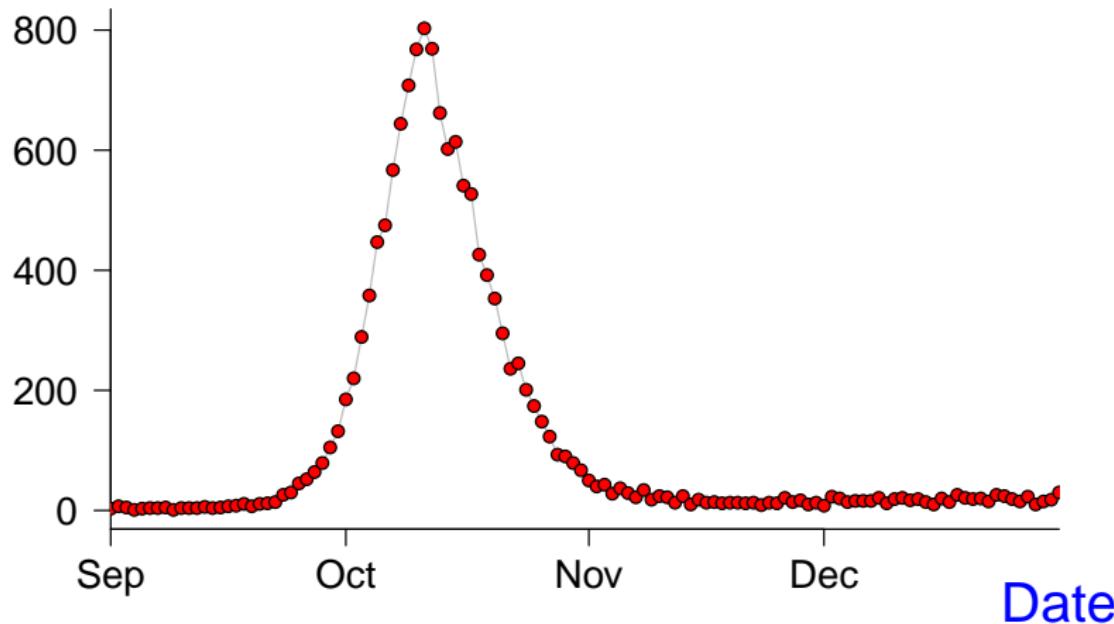
Due Monday 4 February 2019 in class (and by e-mail) at 9:30am.

- **Midterm test:**

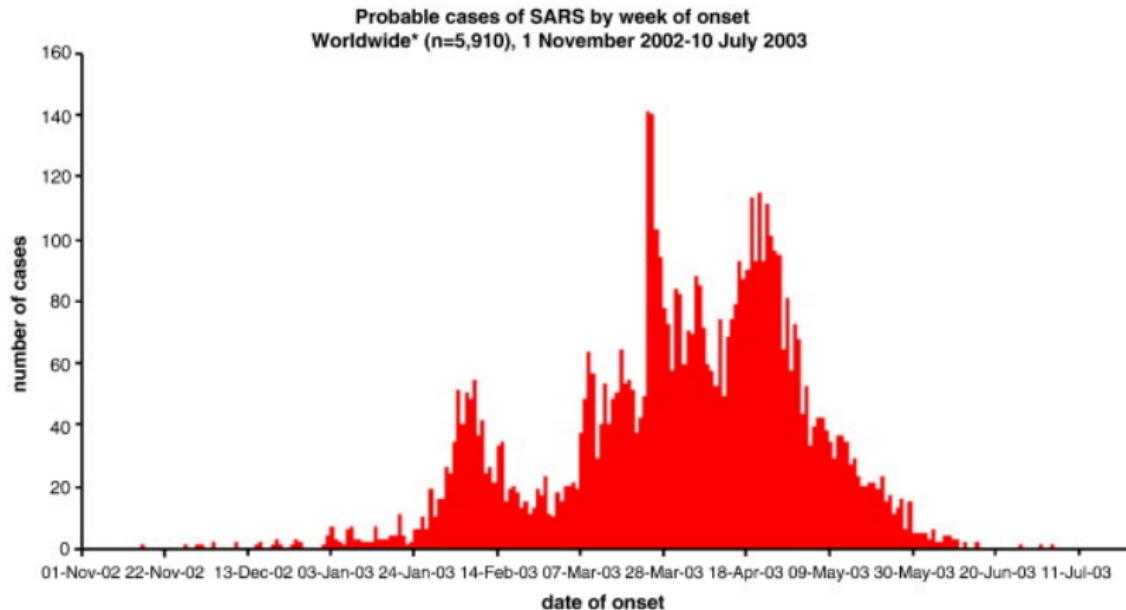
- *Date:* Monday 11 March 2019
- *Time:* 9:30am–11:20am
- *Location:* Hamilton Hall 410

P&I Mortality, Philadelphia, 1918

P&I Deaths

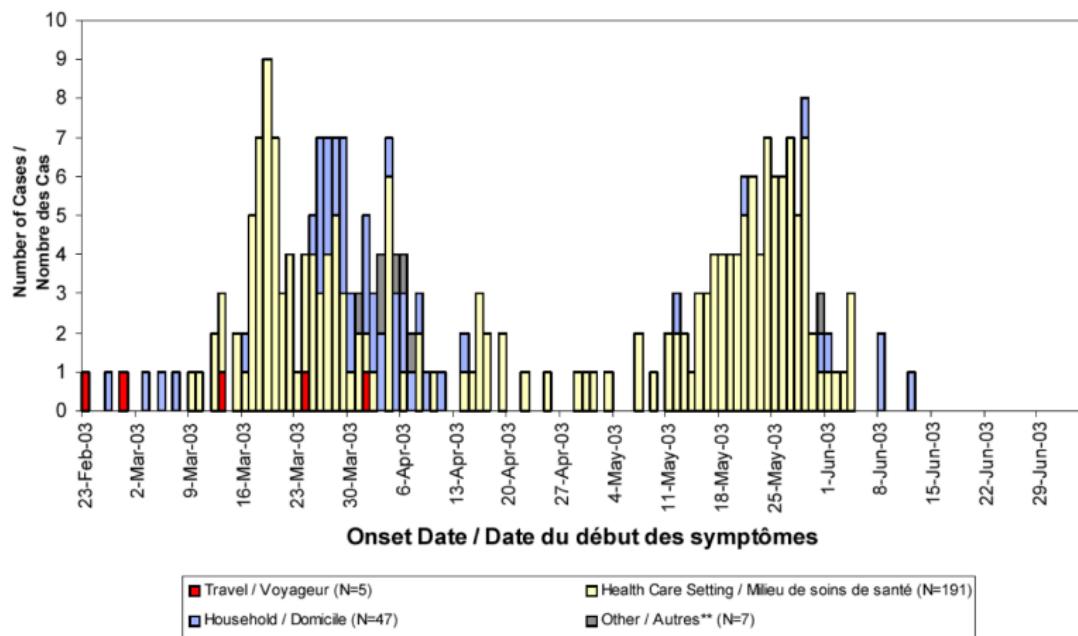


SARS in 2003 (Worldwide)



*This graph does not include 2,527 probable cases of SARS (2,521 from Beijing, China), for whom no dates of onset are currently available.

SARS in 2003 (Toronto)

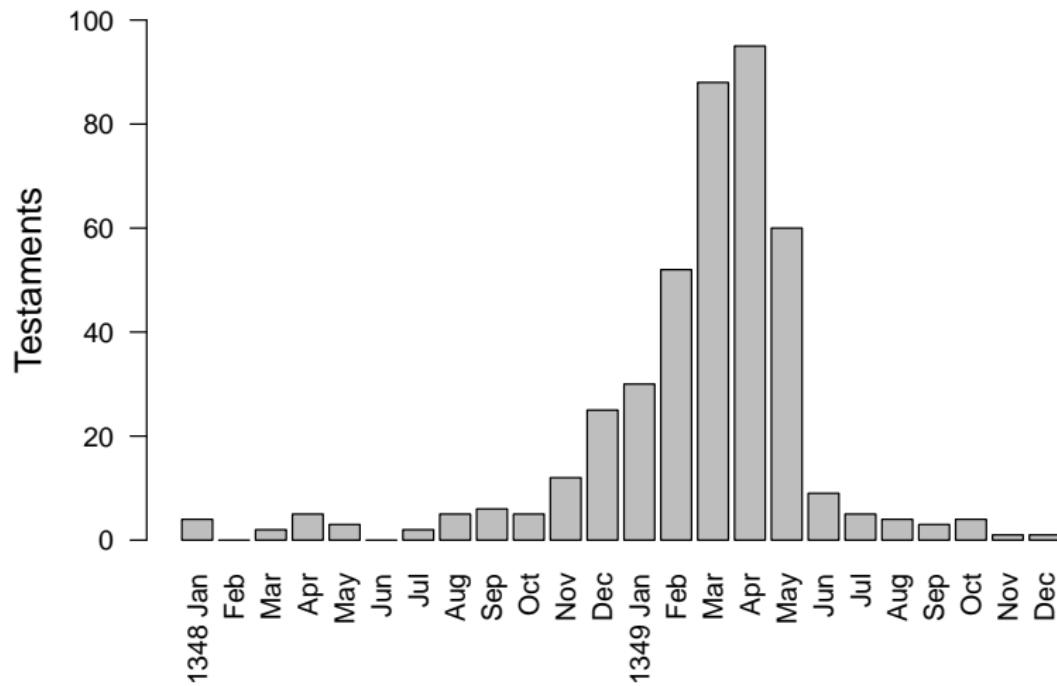


$N = 249$ (of 250 reported)

Some SARS Facts

- High case fatality
 - 1918 flu < 3%
 - SARS > 10%
- Long hospital stays
 - Mean time from admission to discharge or death:
~ 25 days in Hong Kong
- 8098 probable cases, 774 deaths
- How bad would it have been if it had not been controlled?

The Black Death in London, England, 1348–1349



London Bill of Mortality, 26 Sept to 3 Oct 1665

The Diseases and Casualties this Week.		London 41		From the 26 of September to the 3 of October.	
Frighted	1	1 Day	1 Day	1 Day	1665
Gout	1	St. George Boulphane	1	St. Martin Lodgate	12 10
Gout	1	St. Helens	2	St. Martin Outward	5 5
Gripping in the Guts	3	St. James Duke place	2	St. Martin Vintry	4 4
Jaundies	25	St. James Garlickhithe	1	St. Martin Frideswide	4 4
Impotethame	2	St. John Bow	11	St. Michael Martreth	4 4
Infants	8	St. John Evangelist	10	St. Michael Paget	7 7
King-evil	9	St. John Zacharie	9	St. Michael Cornhill	3 3
Mazgrave	2	St. Katharine Coleman	20	St. Michael Queenhithe	25 23
Plague	5533	St. Katherine Creechard	9	St. Michael Royal	3 3
Purples	2	St. Lawrence Jewry	14	St. Michael Wood street	20 7
Rickets	10	St. Lawrence Pouynme	10	St. Nicholas Breadfere	4 4
Riting of the Lights	13	St. Leonard Shoreditch	16	St. Nicholas Barefoot	4 4
Rupure	13	St. Magnus Parfitt	5	St. Nicholas Barking	4 4
Scurvy	1	St. Margaret Lothbury	7	St. Nicholas Cole	4 4
Spotted Fever	65	St. Margaret Newficheare	13	St. Nicholas Colewate	4 4
Stilborn	10	St. Mary Aldermary	14	St. Olave Hartfere	12 12
Stone	3	St. Mary Bawtry	4	St. Olave Jewry	5 4
Scopping of the stomach	6	St. Mary le Bow	1	St. Pancras Chappel	4 4
Suddenly	1	St. Mary Botham	6	St. Peter Cheape	1 1
Surfeit	36	St. Mary le Chappel	11	St. Peter Cornhill	9 9
Teeth	111	St. Mary Hill	2	St. Peter Powl	10 10
Thrush	3	St. Mary le Marchant	4	St. Peter Powl	8 8
Tifick	5	St. Mary Somersett	44	St. Swithin Lammasday	43 38
Vomiting	4	St. Mary Steyning	7	St. Thomas Aquinas	6 6
Windes	1	St. Mary Woolchurch	4	St. Thomas Aquinas	6 6
Wormes	12	St. Peter ad Vincula	7	Trinity Perfit	10 9
		St. Martin Ironmonger Lane	2		
{ Males — 68		St. Martin Leadenhall	39	1149 Plague	943
Christened Females — 78		St. Michael Aldgate	371	Septuagesima	364 352
In all — 146		St. Michael Biffonegate	153	St. Sepulchre Paul	137 95
Decreased in the Burials this Week — 1837		St. Dunstan West	65	St. Thomas Newgate	40 36
Parishes clear of the Plague — 7		St. George Southwarke	140	Trinity Minster	14 21
Parishes Infected — 123		St. George Cripplegate	195	At the Pellowe	6 6
		St. Olave Southwark	378	Civillized in the 16 Parishes without the Wall — 45 Buried, and at the Pellowe — 258 Plague — 1922	
{ Giles in the fields — 25		St. Olave Southwark	178	Septuagesima	35 31
Jackyn Perfit		St. Botolph Bishopsgate	49	St. Mary Abingdon	35 31
Fd. 14		St. Botolph Bishopsgate	97	St. Mary Abingdon	38 301
James Clerkenwell		St. Dunstan West	65	St. Mary Abingdon	21 18
Kath. next the Tower — 3 39		St. George Southwarke	140	St. Swithin	67 463
		St. Dunstan West	23	Septuagesima	163 352
Civillized in the 12 Parishes in Middlesex and Surrey — 40 Buried		St. George Cripplegate	195	Septuagesima	1469
		St. Olave Southwark	378	Septuagesima	109 141
{ Cisterne Dame — 12 110		St. Martin in the fields — 109		St. Margaret Wewminster	109 197
St. Paul Crokent Garden — 25		St. Mary Savoy — 19 16		At the Pellowe	4
				Civillized in the 5 Parishes in the City and Liberties of Wewminster — 48 Buried — 650 Plague — 590	

Mortality Bills are typically handwritten

But handwriting is usually very clear

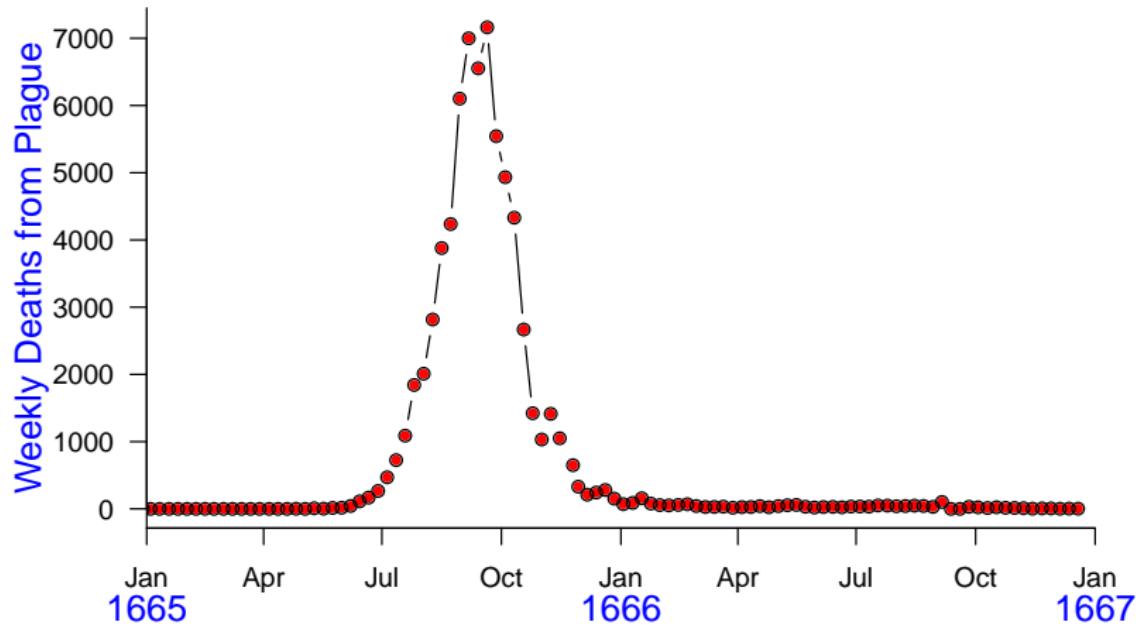
A historical ledger page from London, dated 29th [unclear]. The page is divided into columns for location, burials, and plague cases.

Location	Buried	Plag.
St Alban Woodstreet	2	1
Alhallows Bark-	2	
Alhallows Breadstreet	1	
Alhallows Great	1	

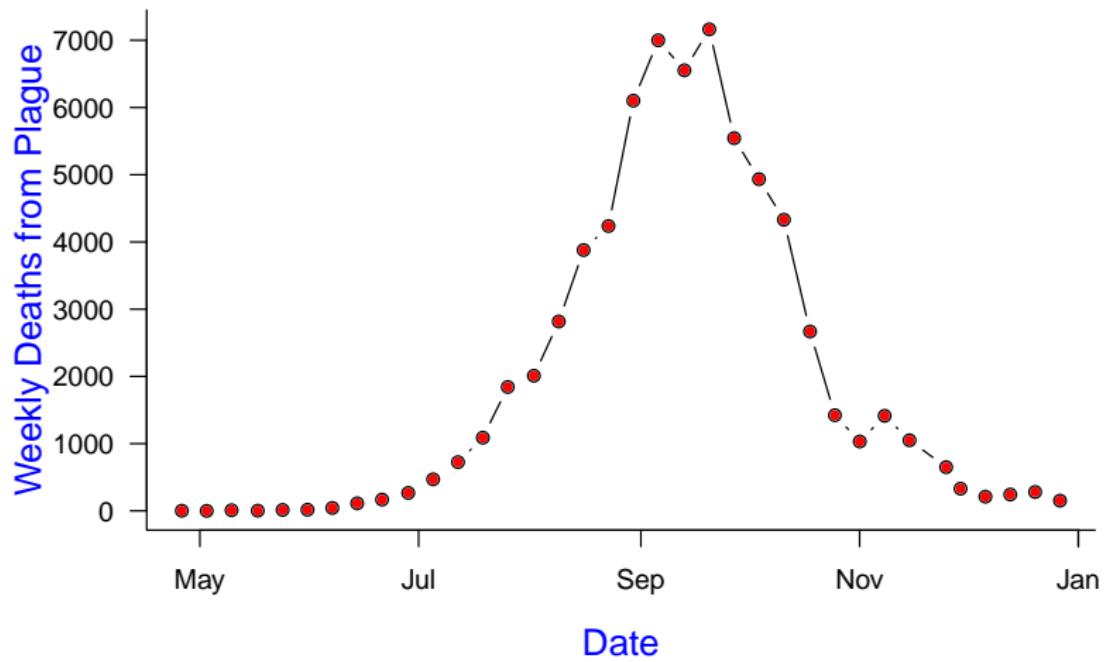
But handwriting is usually very clear

St Christopher's —————— Christened in 971 the Parishes :		
St Andrew Holborn ——————	66	40
St Bartholomew Great	+	+
St Bartholomew Less ——————		
St Bridget ——————	24	14
Bridewell Precept ——————	1	1
Christened in the 16 Parishes :		

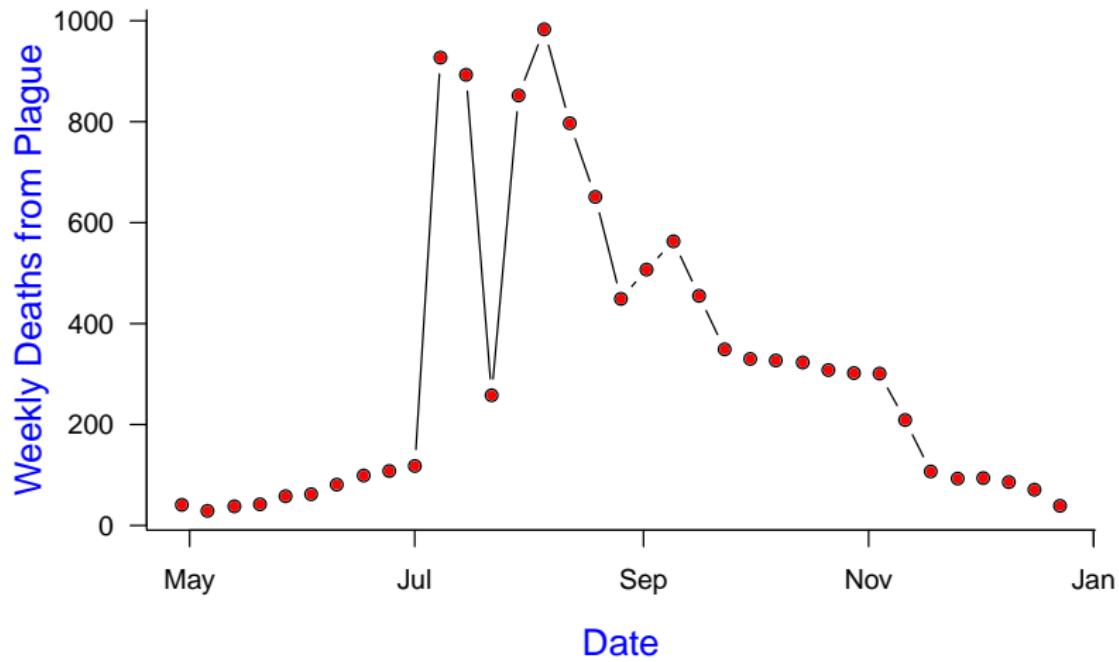
The Great Plague of London, 1665



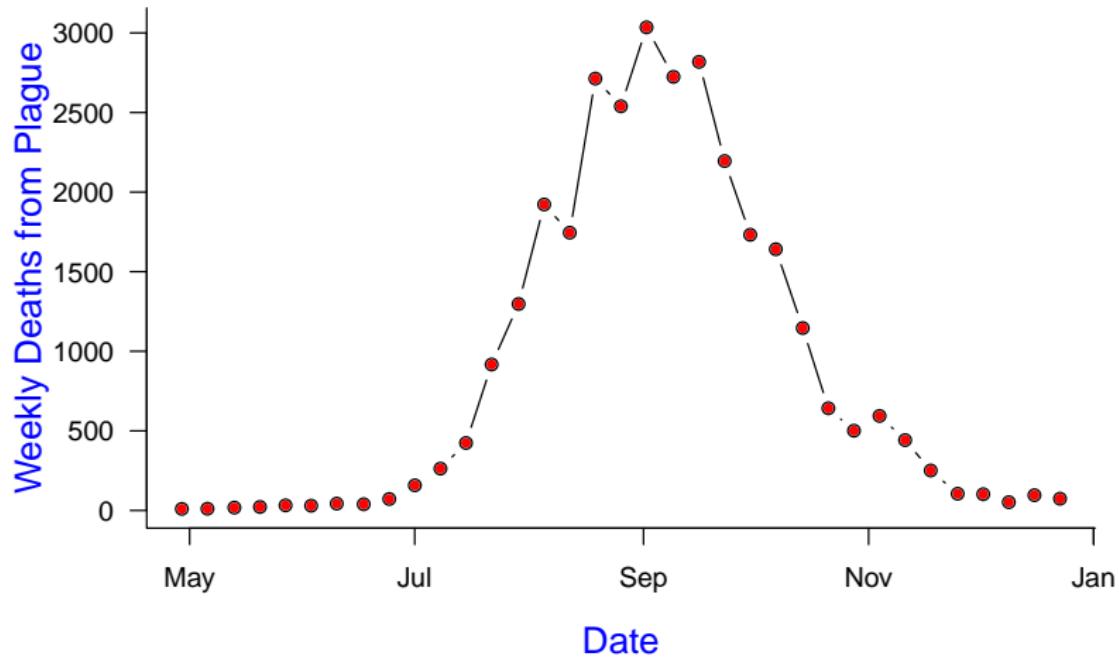
The Great Plague of London, 1665



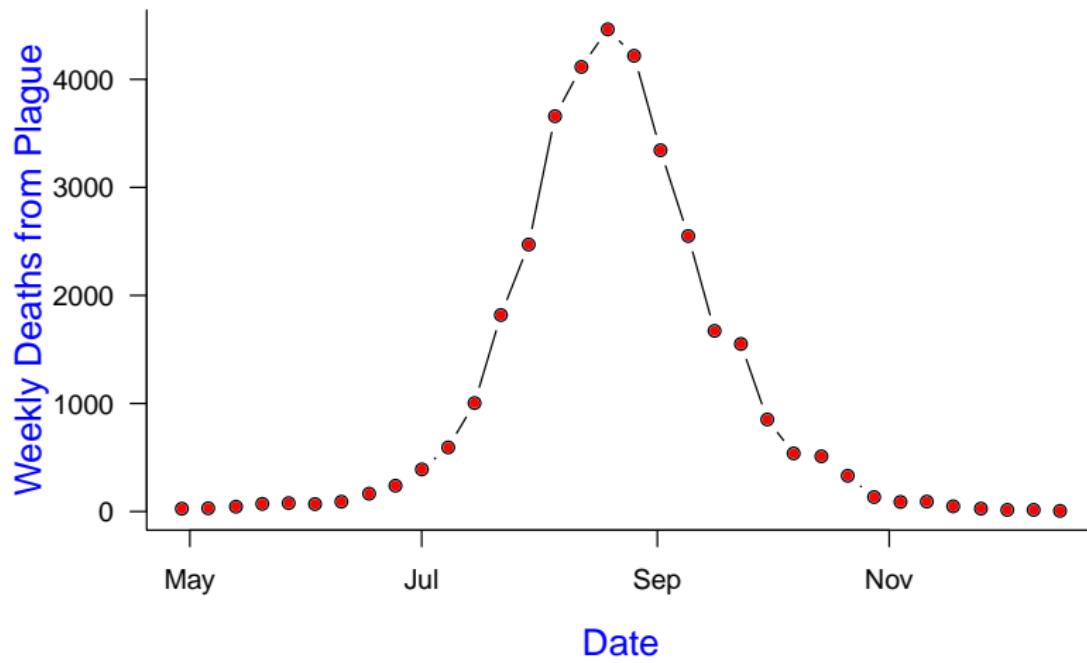
London Plague of 1593



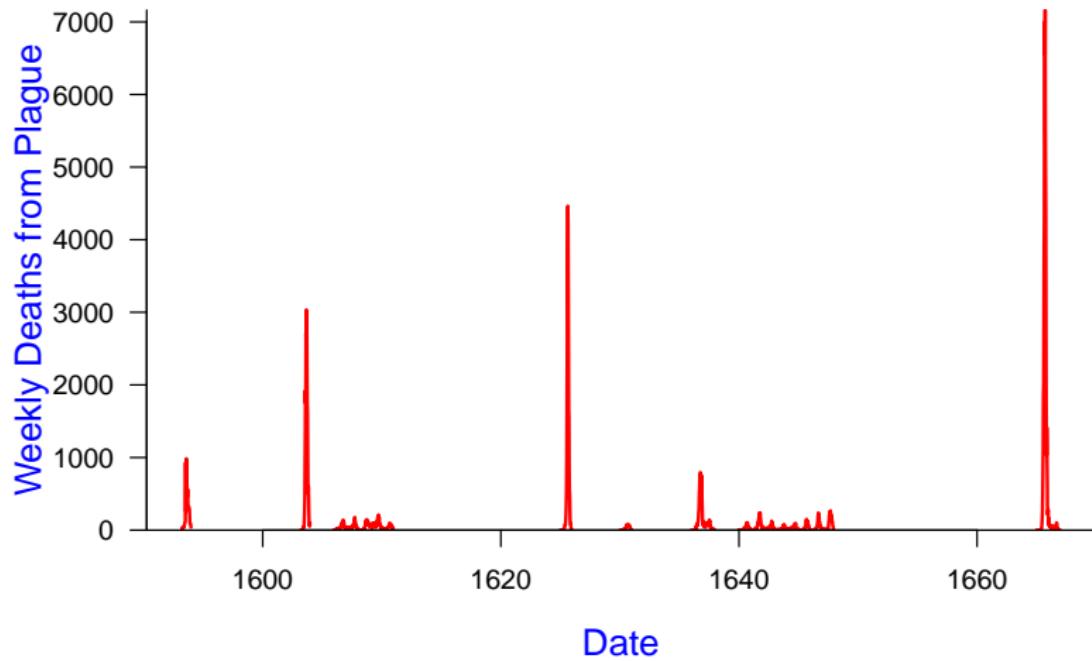
London Plague of 1603



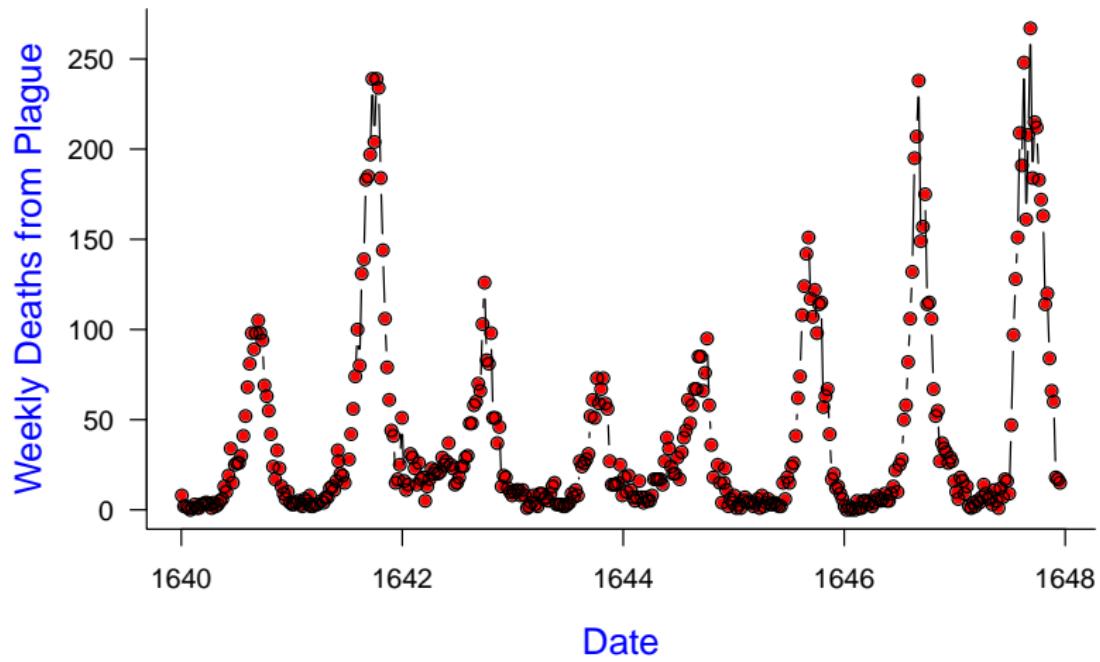
London Plague of 1625



Weekly Deaths from Plague in London, 1592–1666



Weekly Plague in London, 1640–1648



Some Plague Facts

- Plague epidemics recorded from Roman times to early 1900s.
- $\gtrsim 1/3$ Europe's population died in "Black Death" of 1348
 - ~ 300 years for the population to reach the same level.
- Recently (2011) established (at McMaster!) that the pathogen that caused The Black Death was *Yersinia pestis*

[Bos et al. 2011, *Nature* 478, 506–510]

- More recently (2014) established (again at McMaster!) that the pathogen that caused The Plague of Justinian (541–543 AD) was *Yersinia pestis*

[Wagner et al. 2014, *Lancet Infectious Diseases* 14, 319–326]

- *Y. pestis* still a concern?
Yes: Rodent reservoir, antibiotic-resistant strains, bioterrorism
- **Spatial data** for any plagues? Yes, for London in 1665...

Visualization of spatial structure of Great Plague

- GIS encoding of parish boundaries
- Overlay parish boundaries on more modern map for reference
- Colour parishes as they become infected
- Is there evidence for spatial spread or was the spatial pattern random?
- DE low-tech animation...
- CBC high-tech animation...
 - *The Nature of Things*, 21 August 2014.
[http://www.cbc.ca/natureofthings/episodes/
secrets-in-the-bones-the-hunt-for-the-black-death-killer](http://www.cbc.ca/natureofthings/episodes/secrets-in-the-bones-the-hunt-for-the-black-death-killer)



Mathematics
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 9
Epidemic Data II
Monday 28 Jan 2019

Announcements

■ Assignment 2:

Due Monday 4 February 2019 in class (and by e-mail) at 9:30am.

■ Midterm test:

- *Date:* Monday 11 March 2019
- *Time:* 9:30am–11:20am
- *Location:* Hamilton Hall 410

Please consider...

5 minute Student Respiratory Illness Survey:

<https://surveys.mcmaster.ca/limesurvey2/index.php/893454>

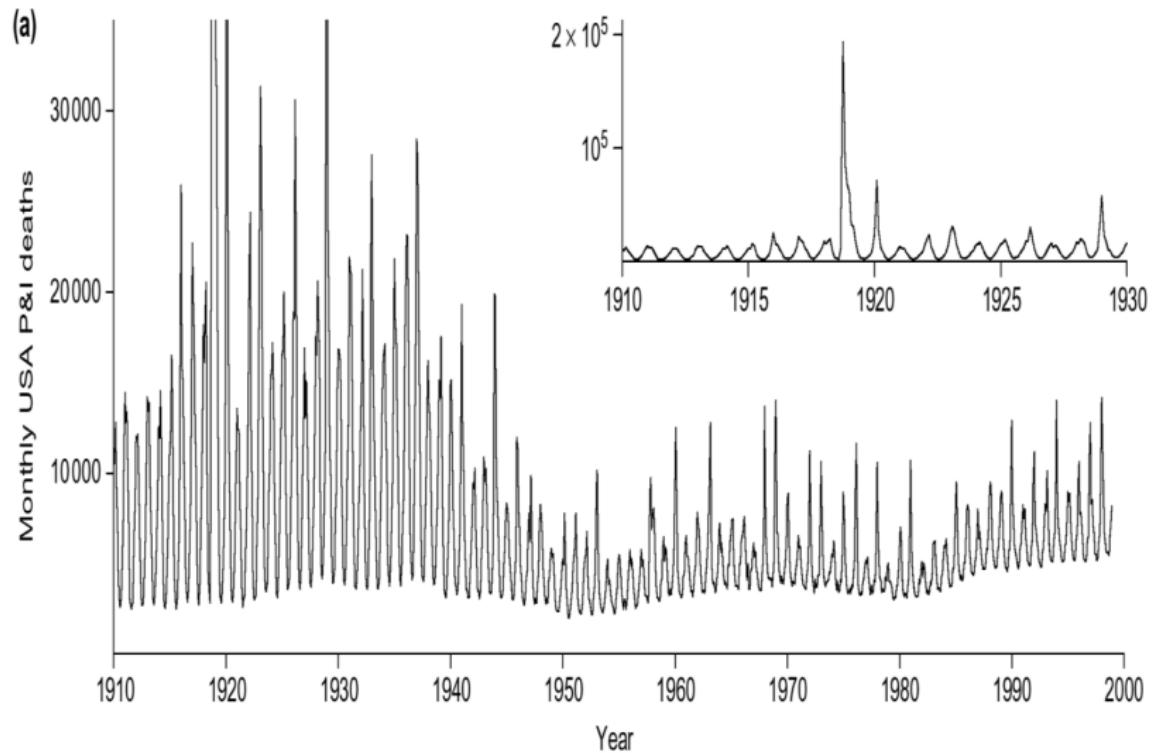
Please complete this anonymous survey to help us monitor the patterns of respiratory illness, over-the-counter drug use, and social contact within the McMaster community. There are no risks to filling out this survey, and your participation is voluntary. You do not need to answer any questions that make you uncomfortable, and all information provided will be kept strictly confidential. Thanks for participating.

–Dr. Marek Smieja (Infectious Diseases)

Visualization of entire course of the Great Plague

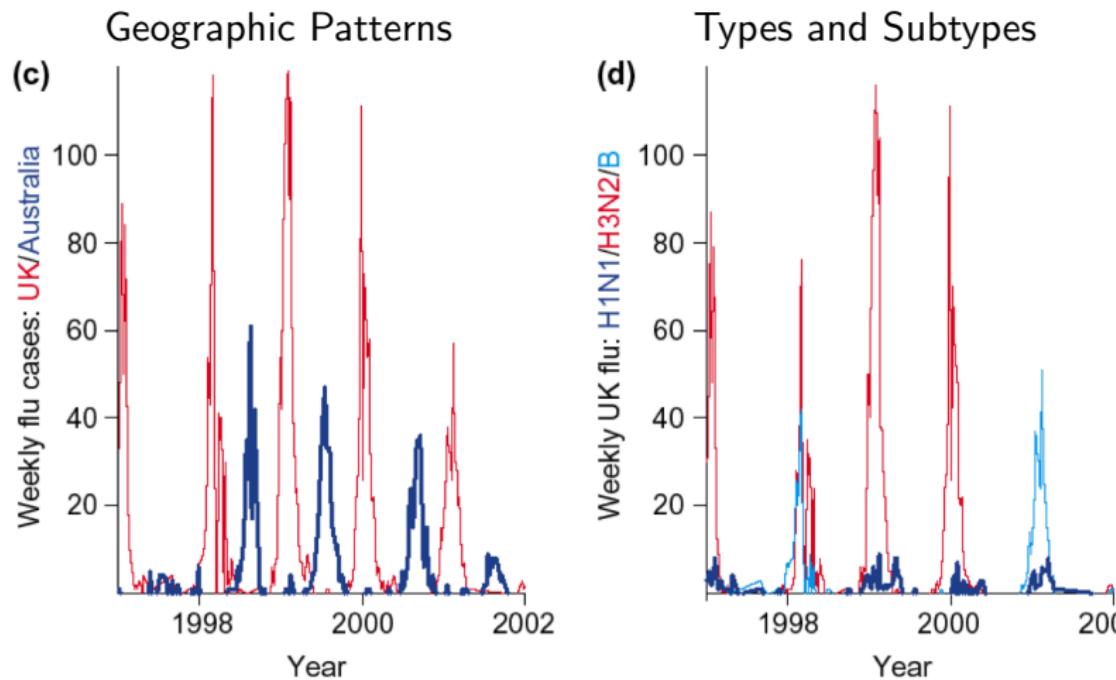
- What happened after initial spatial spread?
- Visualize full spatial epidemic structure
- Show magnitude of epidemic in each parish with cylinder.
- [Epidemic Visualization](#) (EpiVis) software by Junling Ma.

P&I mortality in U.S.A., 1910–1998



Earn, Dushoff & Levin 2002, *Trends in Ecology and Evolution* 17, 334–340

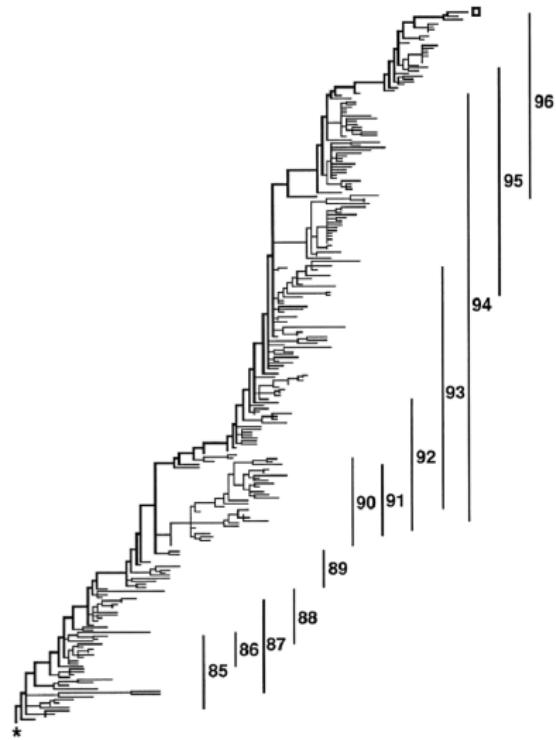
Influenza Incidence Patterns (lab confirmed)



Earn, Dushoff & Levin 2002, *Trends in Ecology and Evolution* 17, 334–340

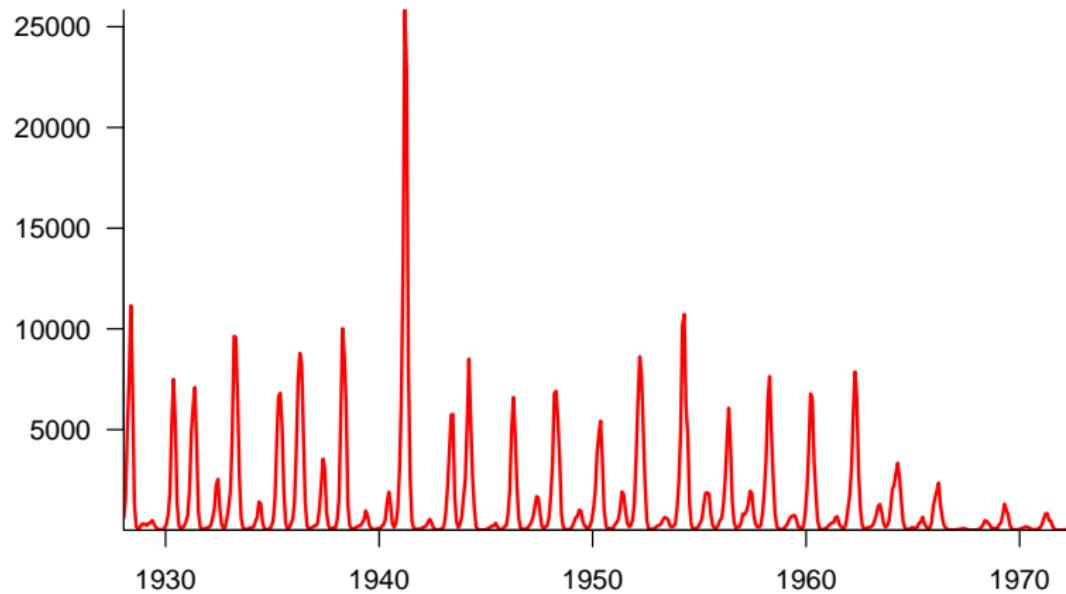
Influenza Evolution

Molecular phylogenetic reconstruction of influenza A/H3N2 evolution, 1985–1996 (Fitch *et al.* 1997)



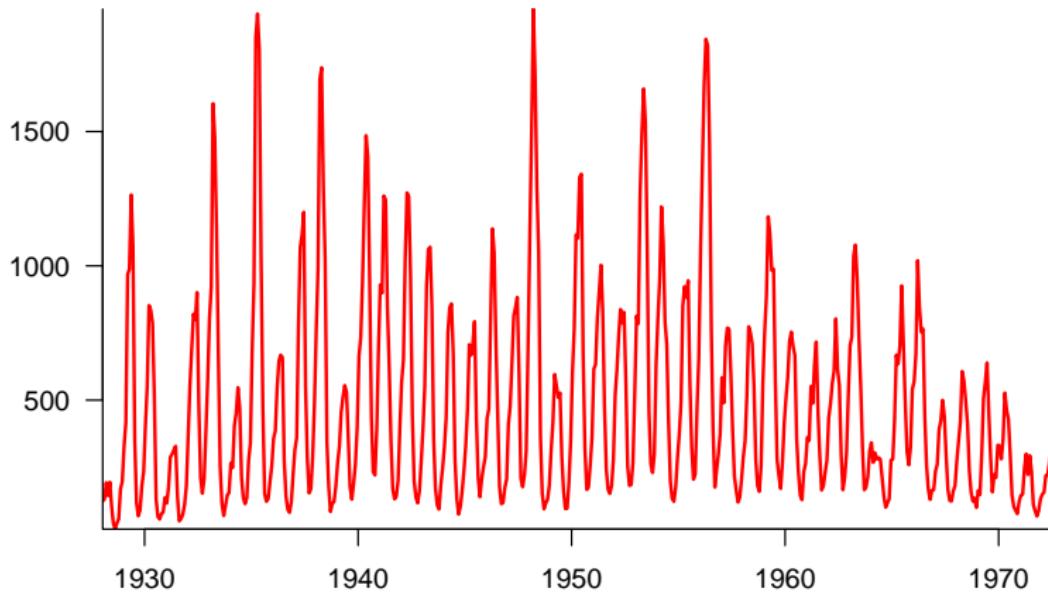
Measles in New York City, 1928–1972

Monthly Cases



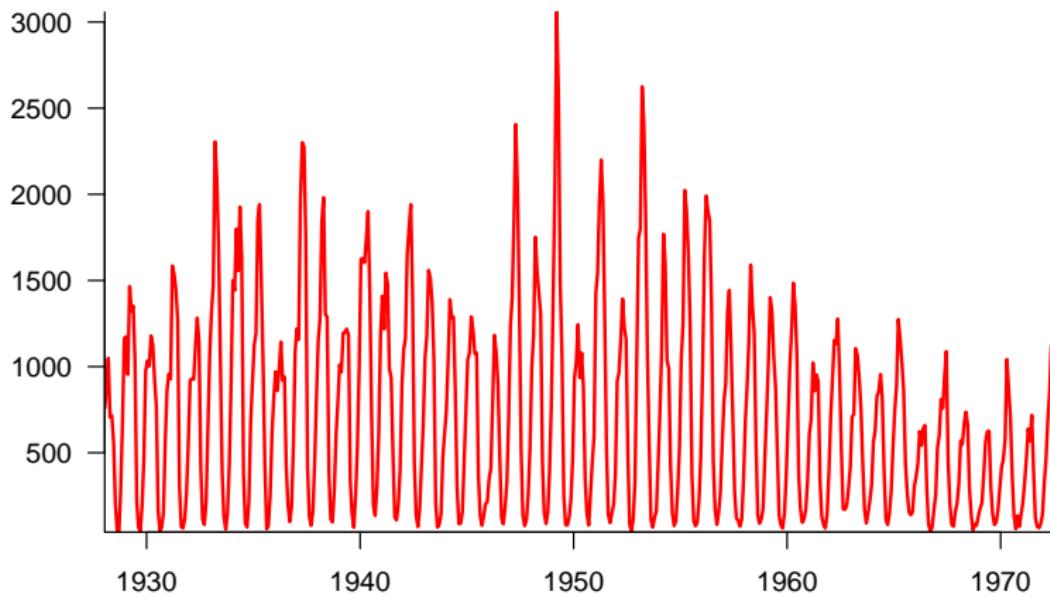
Mumps in New York City, 1928–1972

Monthly Cases

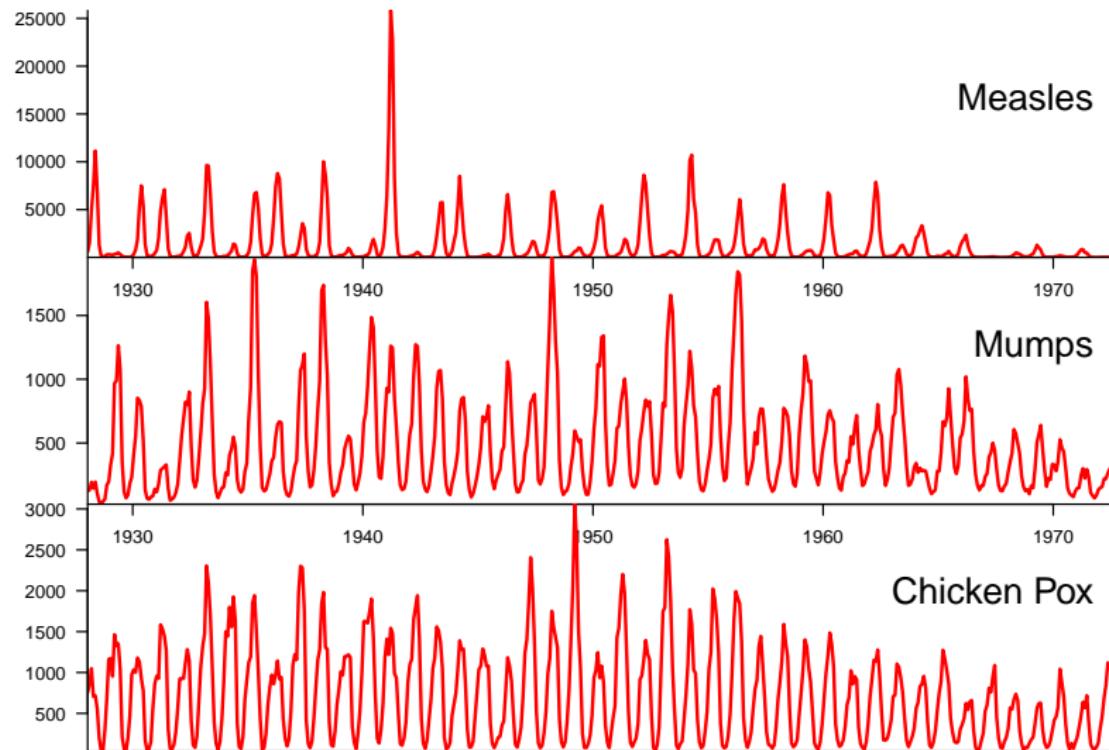


Chicken Pox in New York City, 1928–1972

Monthly Cases

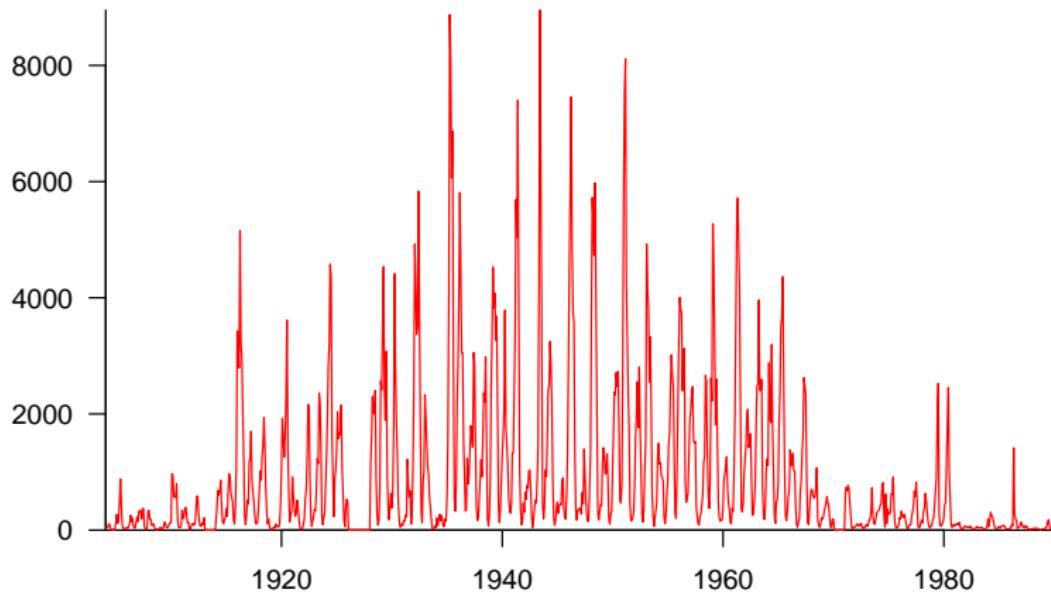


Childhood diseases in New York City, 1928–1972



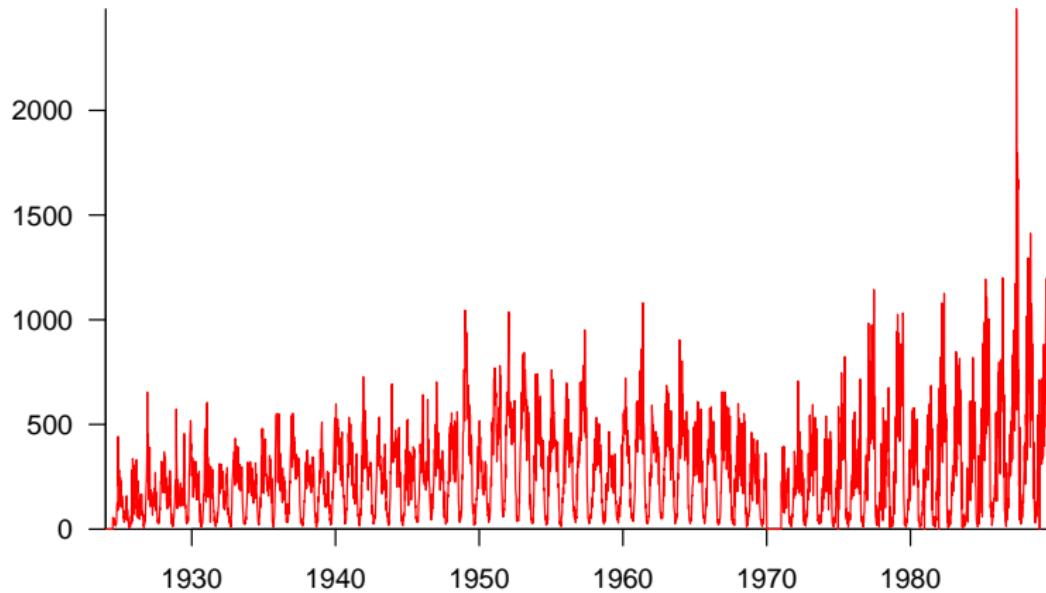
Measles in Ontario, 1904–1989

Monthly Cases



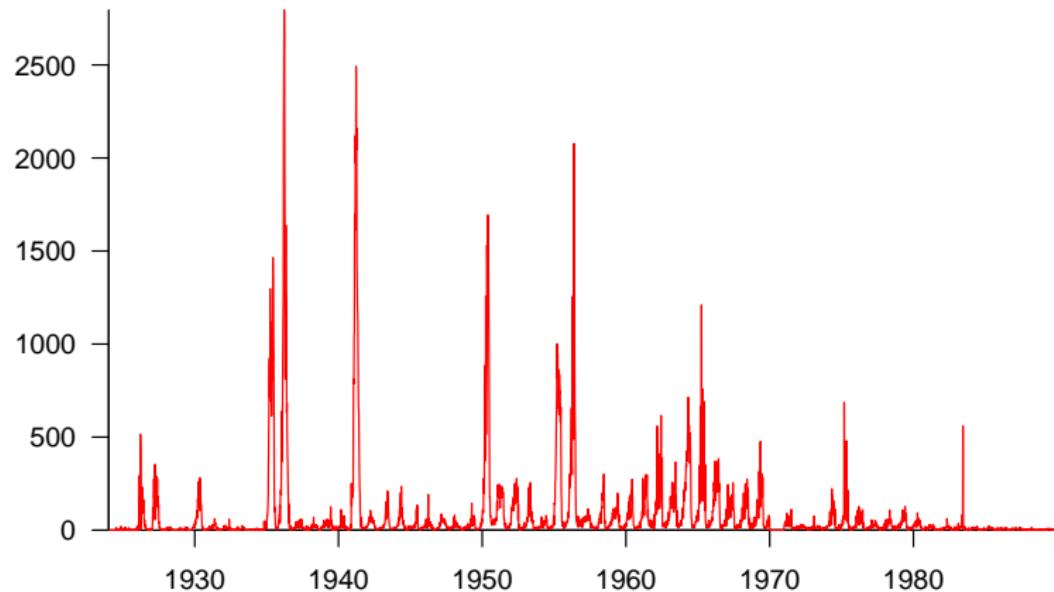
Chicken Pox in Ontario, 1924–1989

Monthly Cases



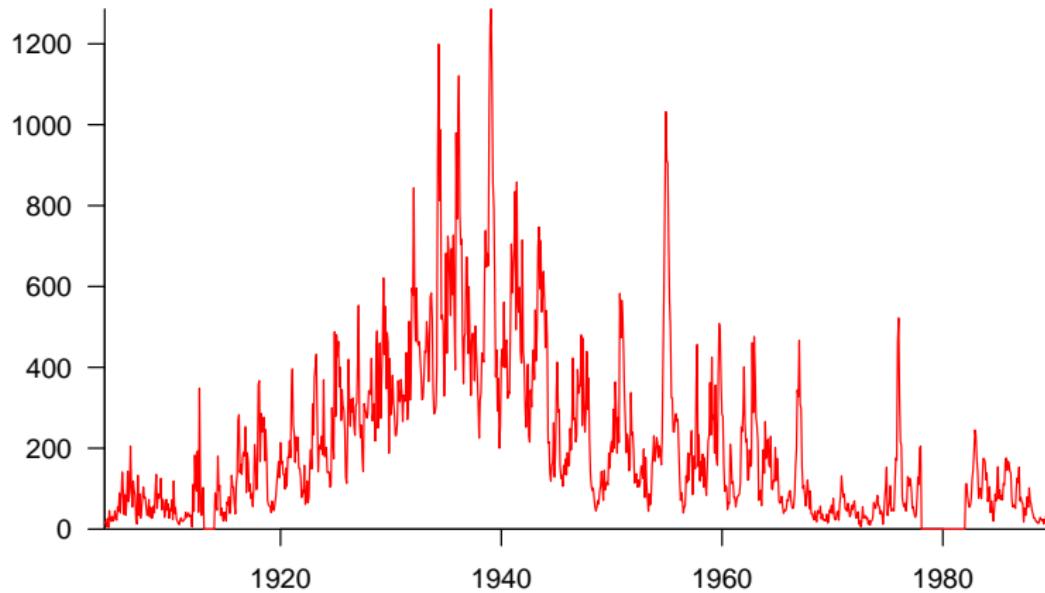
Rubella in Ontario, 1924–1989

Weekly Cases

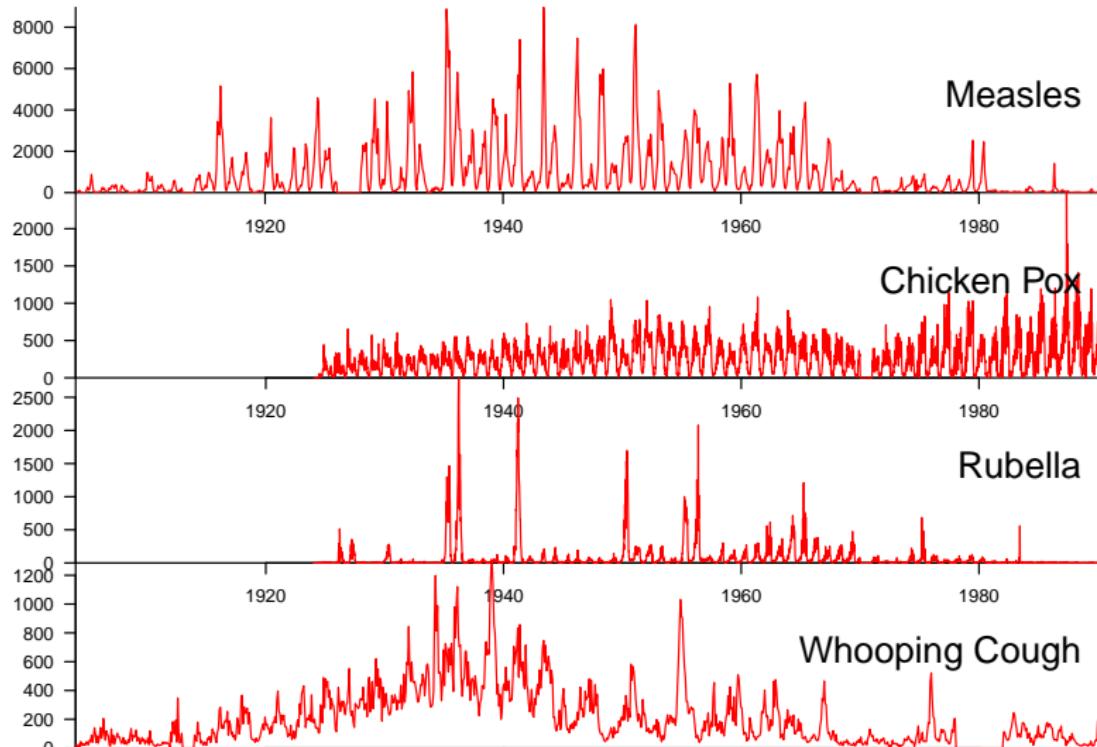


Whooping Cough in Ontario, 1904–1989

Monthly Cases



Childhood diseases in Ontario, 1904–1989



Ontario Disease Notification Data

Province of Ontario

YEAR: 1939 COUNTY..... MUNICIPALITY.....

Month	Week End.	COUNTY.....												MUNICIPALITY.....														
		CSM		C.P.		DIP.		DYS. A/B		EN. LETH.		ERYS.		G.C.		FLU.		INF. JAUN.		G.M.		MEAS.		MUMPS		PARA. TYPH.		
		C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	
Jan.	7	1		452	1	3	0	1	0			5	1	101	0	8	1	17	0	17	0	670	1	56	0	2	0	
	14	2	2	1	490	0	8	0				5	0	82	0	21	1	18	0	18	0	850	0	92	0	1	0	
	21	3	2	1	511	0	9	3			0	1	5	0	89	0	16	2	26	0	22	0	932	0	98	0		
	28	4	1	0	384	0	2	0				2	0	73	0	164	0	10	0	28	0	933	1	24	0			
	Total		5	2	189	1	27	3	1	0	0	1	7	0	218	4	71	0	65	2	338	5	240	0	3	0		
Feb.	4	5		355	0	7	1	1	0			3	0	83	0	57	1	24	0	25	0	1335	1	110	0	2	0	
	11	6	2	1	363	0	1	0	1	0		7	0	82	0	27	1	49	1	29	0	1033	0	91	0	1	0	
	18	7	2	1	354	1	2	0				4	1	68	0	103	1	35	0	44	0	1161	0	59	0			
	25	8	1	1	308	0	2	0				9	0	560	177	0	19	0	28	0	999	0	73	0				
	Total		5	3	189	1	27	3	1	0		7	0	218	4	71	0	65	2	338	5	240	0	3	0			
Mar.	4	9	1	1	271	0	7	1	3	1		7	0	93	0	114	19	21	0	40	0	131	2	109	0	1	0	
	11	10	2	1	239	0	7	0	2	0		8	1	61	0	137	18	31	0	32	0	845	0	91	0	2	0	
	18	11			166	0						6	0	66	0	1322	6	5	0	59	0	969	2	69	0	1	0	
	25	12	1	2	236	0	1	0	1	0		7	0	63	0	806	16	9	0	20	0	879	0	120	0	case	PAH	
	Total		8	3	189	1	27	3	1	0		7	1	283	0	163	4	66	0	151	0	353	1	389	0	34	0	
Apr.	1	13	2	0	139	0	3	0	1	0		8	0	95	0	667	6	1	0	24	0	950	0	89	0	3	0	
	8	14	2	0	162	0	1	0	1	0		5	0	67	0	731	22			14	0	790	0	65	0	1	0	
	15	15	2	0	108	0	1	0				0	1	11	0	41	0	529	16	2	0	16	0	745	0	56	0	
	22	16	1	1	134	0	2	0	1	0		6	0	64	0	245	8	2	0	26	0	845	0	54	0			
	29	17	5	1	167	0	4	0	2	1		3	0	55	0	124	9	2	1	13	0	746	1	120	0			
	Total		12	2	110	0	10	3	0	3		33	0	312	0	121	1	1	9	0	40	0	384	0	47	0		
		6	18	2	0	104	0	1	0	2		4	0	71	0	76	3	1	0	14	0	877	0	63	0	3	0	

Dominion Bureau of Statistics Disease Notification Data

VITAL STATISTICS BRANCH - COMMUNICABLE DISEASE SECTION

Cases of ~~Influenza~~ Reported by Provincial Health Departments, Year 1924

WEEK ENDING	P.E.I.	N.S.	N.B.	QUE.	ONT.	MAN.	SASK.	ALTA.	B.C.	CANADA
	W15-22	W15-22								
Jan 5		11						1		12
2	12	29						18		47
3	19	37						32		69
4	26	75 152		68	181	36	13 64	97	4 88 602	
5 FEB 2	12	1					53			66
6	9	5					40			45
7	16	31					14			45
8	23	- 2 50	1 2	267	202	48	4 111	116	1 7 797	
9 MAR 1		2					21			23
10	1						9			9
11	15	3					11			14
12	22	60					34			94
13	29	2 61		144	140	52	15 90	15	7 17 515	
14 APR 5		9					11			20
15	12	1					12			13
16	19	26	1				8			35
17	26	14 50	3 4	42	140	39	16 47	67	5 33 394	
18 MAY 3		26					2			28



Mathematics
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 10
Epidemic Data III
Monday 28 Jan 2019

Announcements

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■ Midterm test:

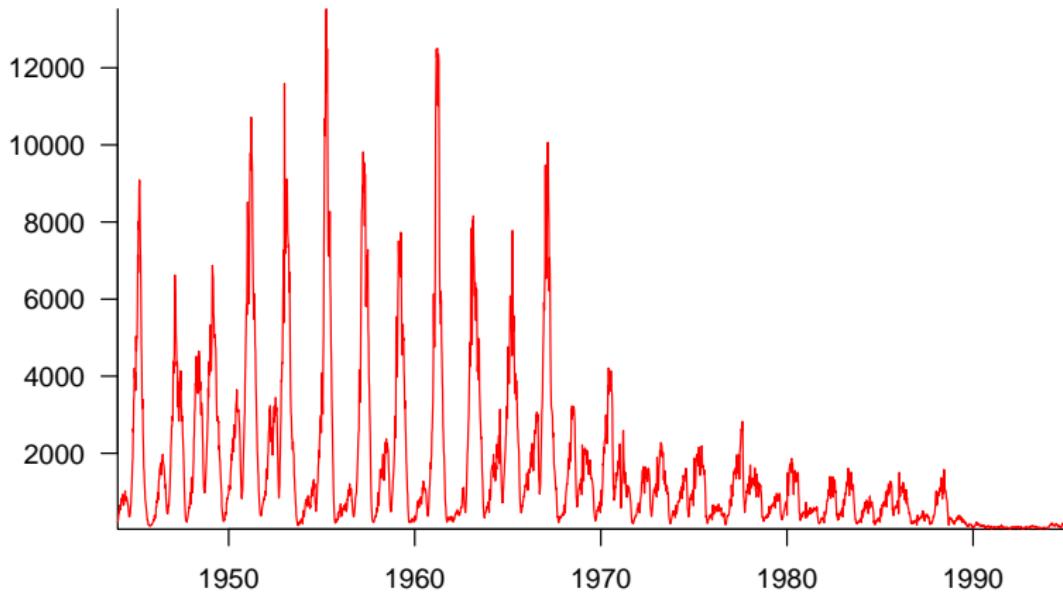
- *Date:* Monday 11 March 2019
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Recurrent epidemics of childhood infections

- Childhood diseases in New York City, 1928–1972
- Childhood diseases in Ontario, 1904–1989

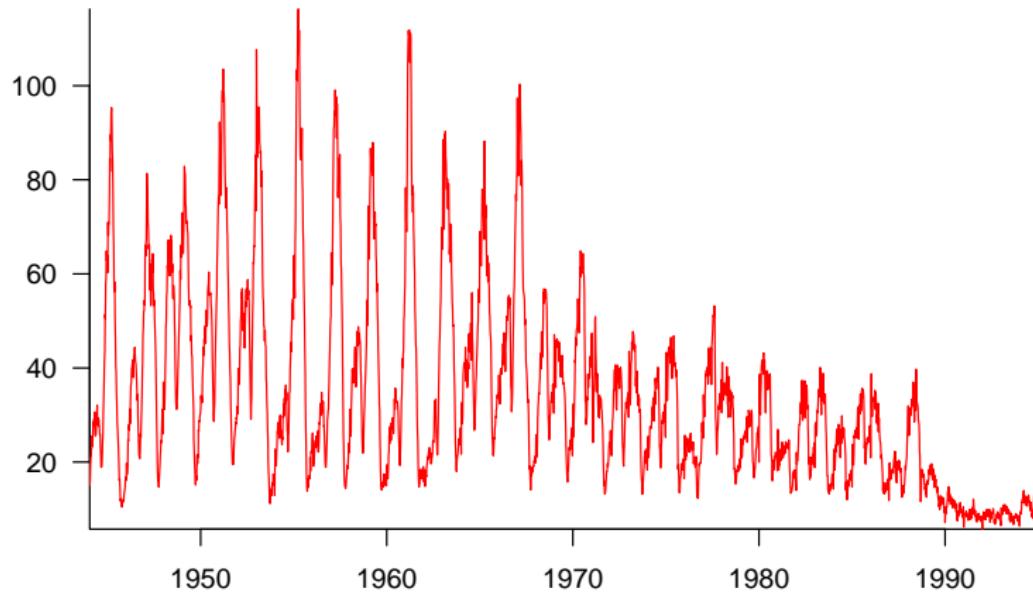
Measles incidence in England and Wales, 1944–1995

Weekly Cases



Measles incidence in England and Wales, 1944–1995

Sqrt(Weekly Cases)



Why study measles epidemics?

- In 2017, $\sim 110,000$ deaths from measles
- A major cause of *vaccine-preventable* deaths.
- Potential impact in developed countries during vaccine scares (e.g., MMR scare in UK in 1990s).

- Understand past patterns
- Predict future patterns
- Manipulate future patterns
- Develop vaccination strategy that can...



Other reasons to model infectious disease epidemics

- Mathematical models make hypotheses and inferences precise
 - Give better advice to policymakers
 - Make better predictions
- Host-pathogen dynamics are important aspects of ecosystem dynamics
 - Infectious disease models more likely to be successful than predator-prey models
- Excellent data for human infectious diseases
 - Models can be tested!

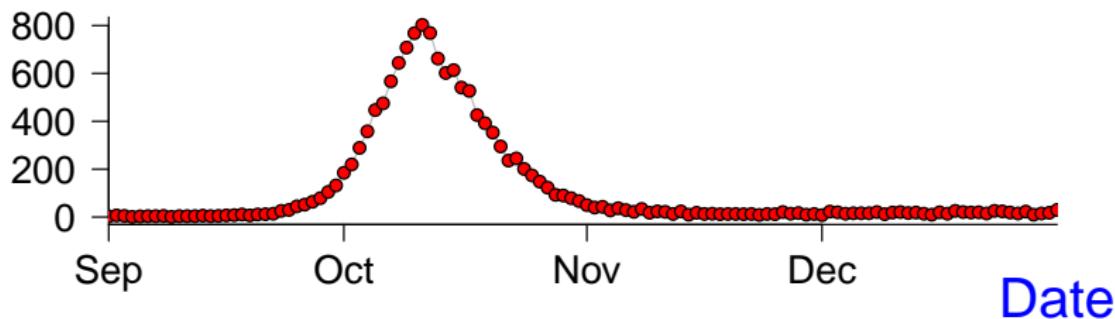
Modelling population dynamics of childhood infections

- The basic SIR model cannot explain recurrent epidemics.
- What should we do?... The usual options:
 - 1 Get depressed, drop the course.
 - 2 Keep developing models until we can explain recurrent epidemics.
- First, let's talk about tools that allow us to make our questions about time series data more precise.

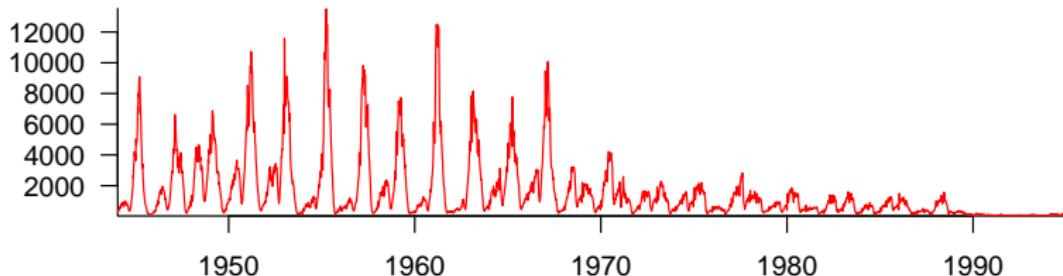
Epidemic Data Analysis

Time Plots of Temporal Epidemic Patterns

1918 P&I

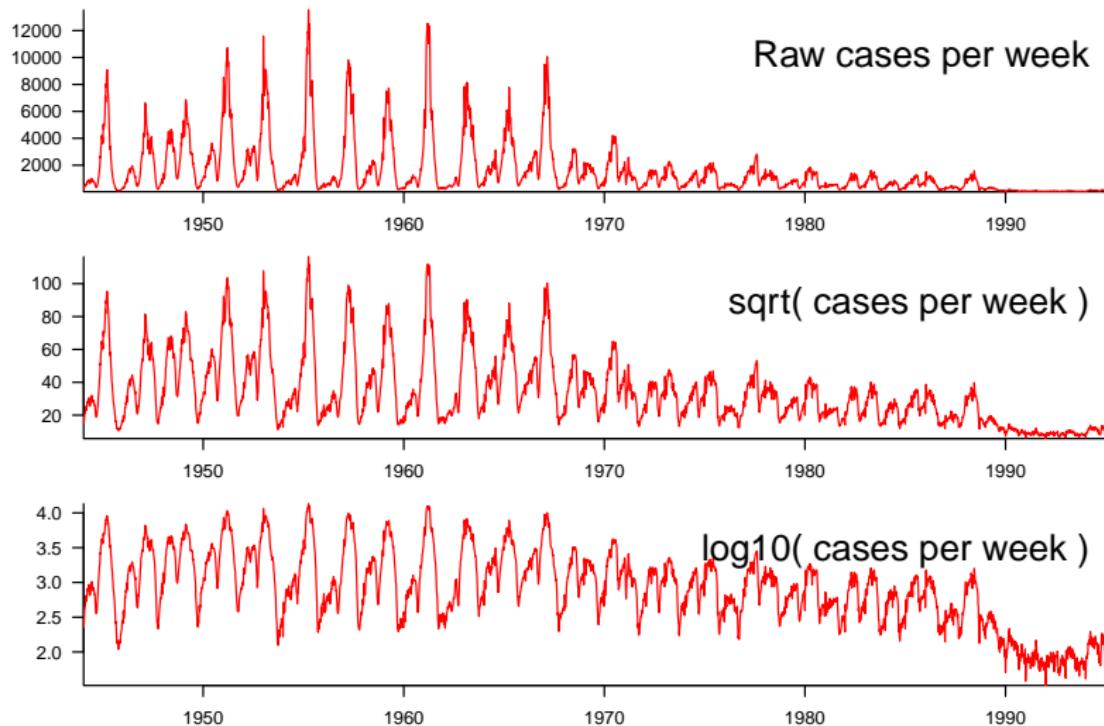


Weekly Measles in England and Wales



Time Plots of Transformed Data

- Reveal unobvious aspects of time series



Times Plots of Smoothed Data

- Reveal trends clouded by noise or seasonality
- *Moving Average:*

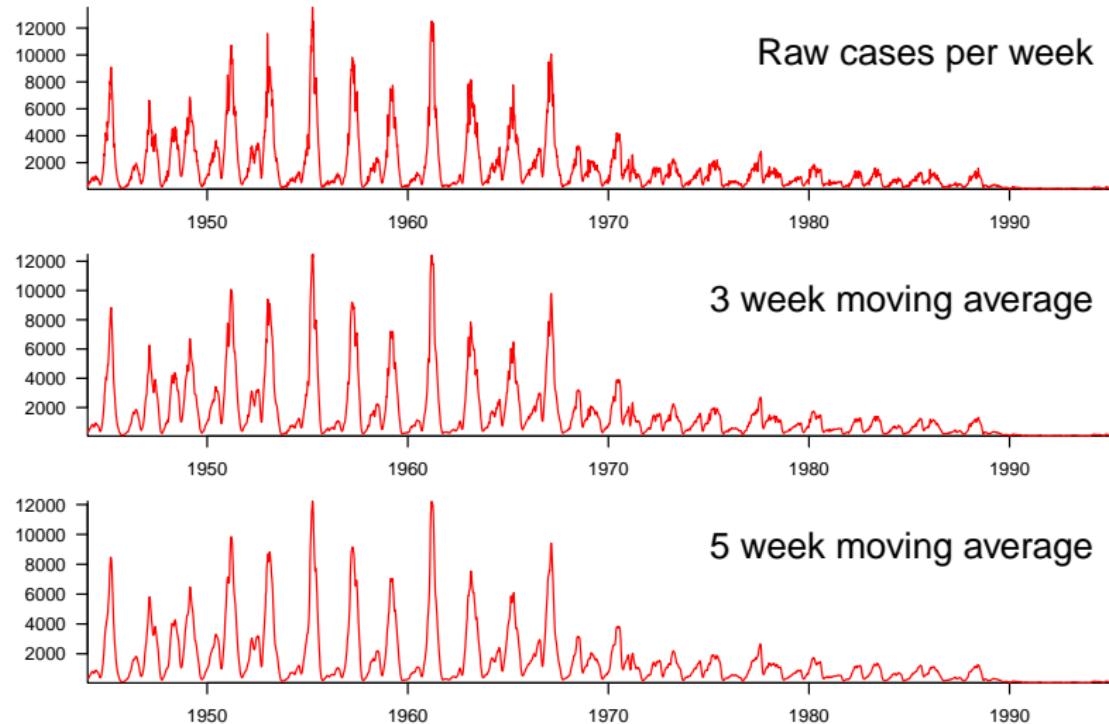
$$x_t \rightarrow \frac{1}{2a+1} \sum_{i=-a}^a x_{t+i}$$

- Replace original data points x_t with averages of nearby points.
- *Linear filter:*

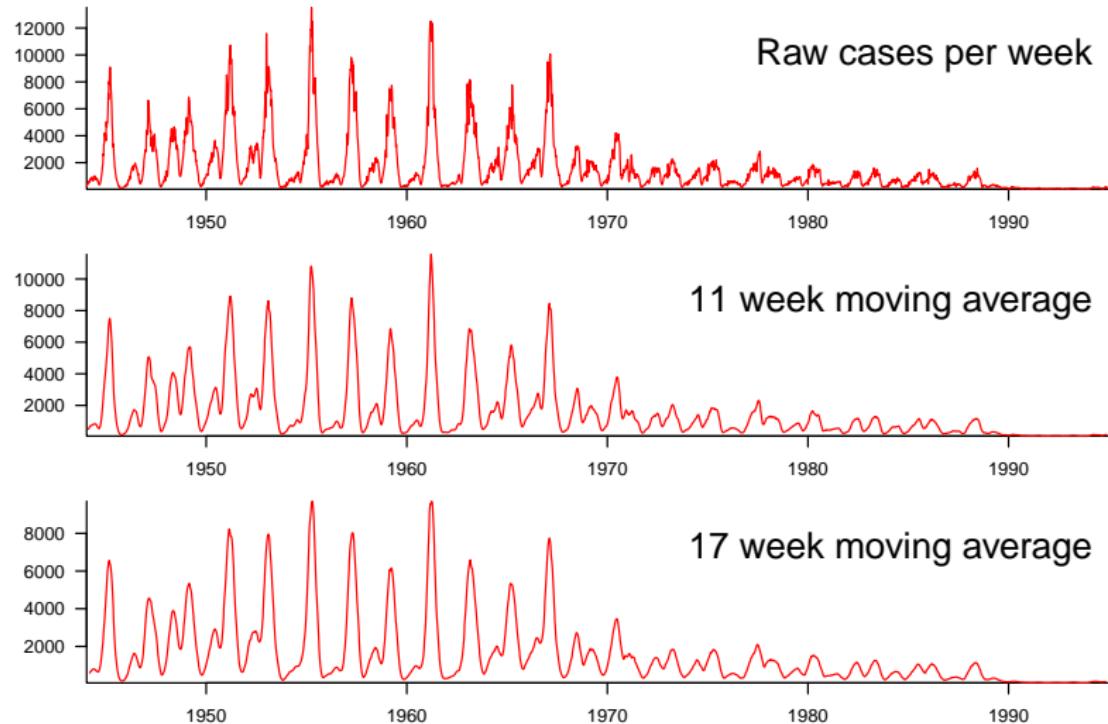
$$x_t \rightarrow \sum_{i=-\infty}^{\infty} \lambda_i x_{t+i}$$

- Generalization of moving average.
- Weights λ_i can be nonlinear functions of i .

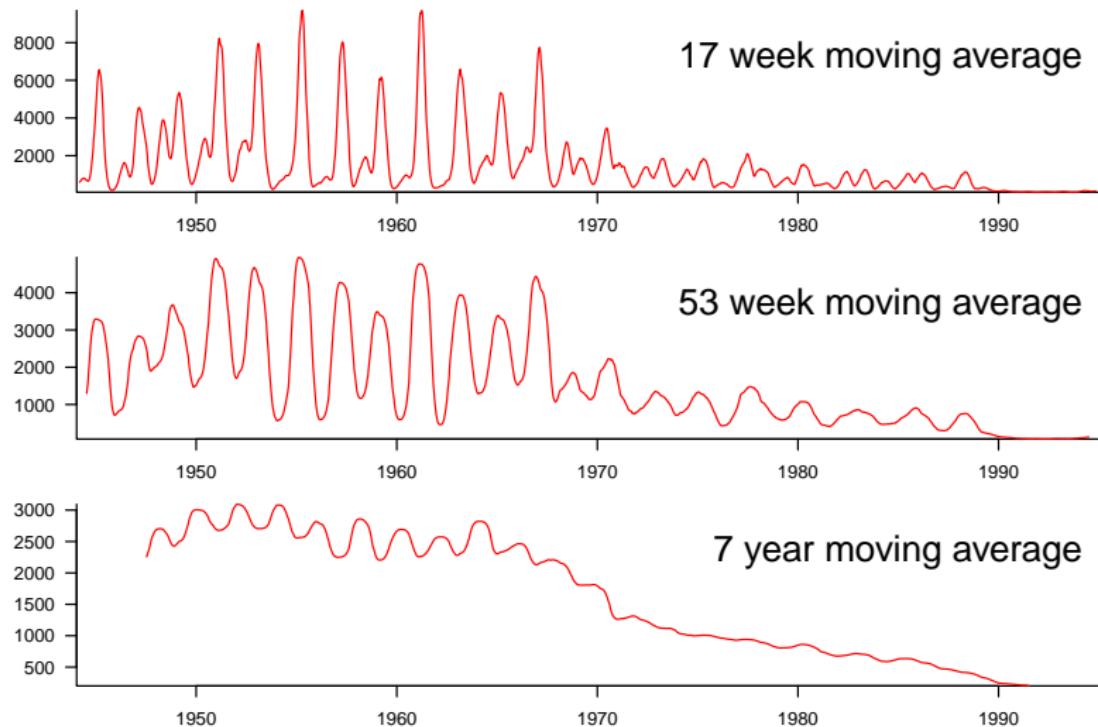
Times Plots of Smoothed Data



Times Plots of Smoothed Data



Times Plots of Smoothed Data



Correlation

- Recurrent epidemics \implies number of cases now is correlated with number of cases in the past and the future.
- Given N pairs of observations of different quantities, $\{(x_i, y_i) : i = 1, \dots, N\}$, the *correlation coefficient* is defined to be

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}}$$

where \bar{x} and \bar{y} are the means of $\{x_i\}$ and $\{y_i\}$, respectively.

Correlation

Properties of the correlation coefficient:

- $-1 \leq r \leq 1$ (Proof? Cauchy-Schwarz inequality)
- $r = 1 \iff$ all points lie on a line with positive slope ("complete positive correlation")
- $r = -1 \iff$ all points lie on a line with negative slope ("complete negative correlation")
- $r \simeq 0 \implies$ "uncorrelated"
- *Interpretation:* r^2 is the proportion of the variance in y explained by a linear function of x .

Derivations and discussions:

- [MathWorld on \$r^2\$](#) , [Wikipedia on \$r^2\$](#)
- [Wikipedia on general coefficient of determination](#)

Autocorrelation

- Given a single sequence of observations $\{x_t : t = 1, \dots, N\}$, we can compute the correlation of each observation with the observation k time steps in the future.
- Thus, we consider the pairs of observations $\{(x_t, x_{k+t}) : t = 1, \dots, N - k\}$ and define the *autocorrelation coefficient at lag k* to be

$$r_k = \frac{\sum_{t=1}^{N-k} (x_t - \bar{x}_{1,N-k})(x_{k+t} - \bar{x}_{k+1,N})}{\sqrt{\sum_{t=1}^{N-k} (x_t - \bar{x}_{1,N-k})^2 \sum_{t=1}^{N-k} (x_{k+t} - \bar{x}_{k+1,N})^2}}$$

where $\bar{x}_{1,N-k}$ and $\bar{x}_{k+1,N}$ are the means of first and last $N - k$ observations, respectively.

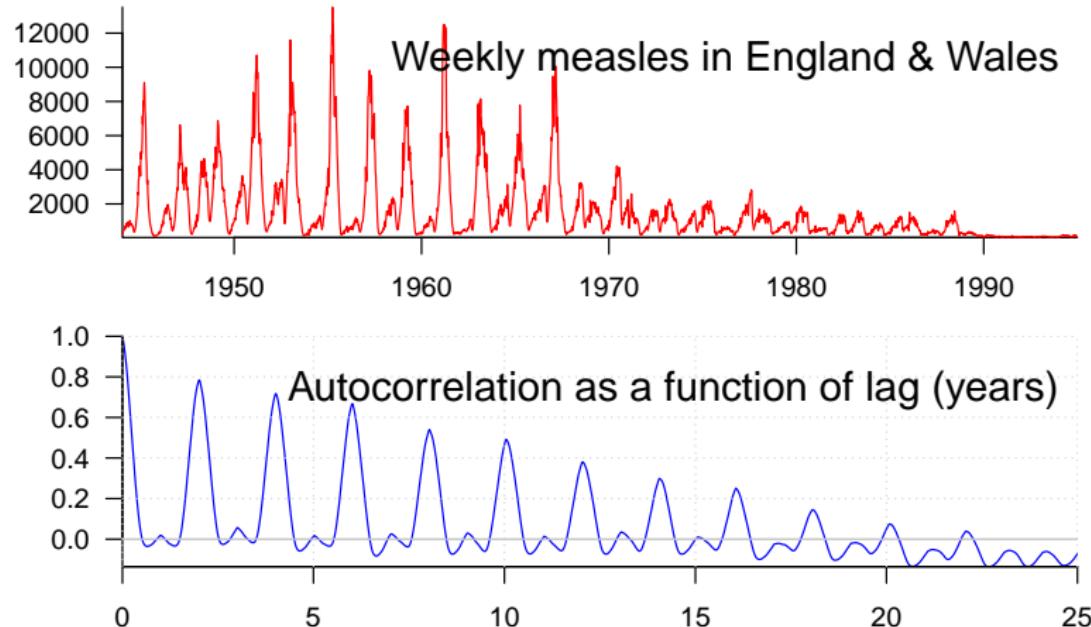
Autocorrelation

- If number of observations N is large and lag $k \ll N$ then

$$r_k \simeq \frac{\sum_{t=1}^{N-k} (x_t - \bar{x})(x_{k+t} - \bar{x})}{\sum_{t=1}^N (x_t - \bar{x})^2}$$

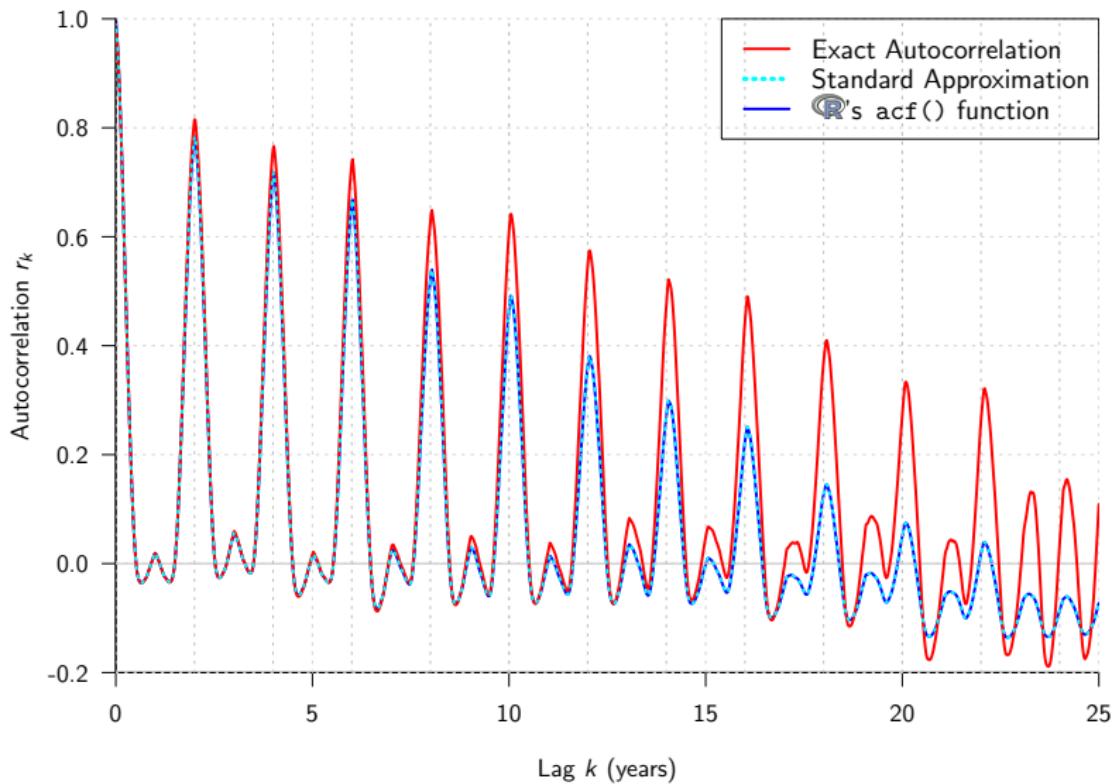
- Approximation of r_k is worse for larger lags k
- Plot of autocorrelation r_k as a function of lag k is called the *correlogram*.

Correlogram



- Peaks in correlogram \implies periodicities in original time series.
- Correlograms of temporal segments are often informative.

Correlogram: exact vs. approximate r_k



Spectral Density

- Can we compute the dominant periods in the time series?
(Rather than estimating them by eye from the [correlogram](#).)
- Express the time series as a [Fourier series](#):

$$x_t = a_0 + \left(\sum_{p=1}^{(N/2)-1} (a_p \cos \omega_p t + b_p \sin \omega_p t) \right) + a_{N/2} \cos \pi t,$$

where $\omega_p = 2\pi p/N$.

- Compute the [Fourier coefficients](#) $\{a_p\}$, $\{b_p\}$ by taking inner products with $\cos \omega_p t$ and $\sin \omega_p t$.

Spectral Density

- Fourier coefficients of x_t are:

$$a_0 = \bar{x} = \frac{1}{N} \sum_t x_t ,$$

$$a_p = \frac{2}{N} \sum_t x_t \cos \omega_p t , \quad b_p = \frac{2}{N} \sum_t x_t \sin \omega_p t ,$$

$$a_{N/2} = \frac{1}{N} \sum_t (-1)^t x_t ,$$

where sum is over observation times.

- Estimated power spectral density (PSD) at frequency ω_p is^{*}:

$$I(\omega_p) = \frac{N}{4\pi} (a_p^2 + b_p^2)$$

^{*}The normalization by $N/4\pi$ is the convention chosen by Chatfield (2004, "Analysis of Time Series: An Introduction"). Other normalization conventions are also in common use.



Mathematics
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 11
Epidemic Data Tools
Wednesday 30 Jan 2019

Announcements

■ Assignment 2:

Due Monday 4 February 2019 in class (and by e-mail) at 9:30am.

■ Midterm test:

- *Date:* Monday 11 March 2019
- *Time:* 9:30am–11:20am
- *Location:* Hamilton Hall 410

Please consider...

5 minute Student Respiratory Illness Survey:

<https://surveys.mcmaster.ca/limesurvey2/index.php/893454>

Please complete this anonymous survey to help us monitor the patterns of respiratory illness, over-the-counter drug use, and social contact within the McMaster community. There are no risks to filling out this survey, and your participation is voluntary. You do not need to answer any questions that make you uncomfortable, and all information provided will be kept strictly confidential. Thanks for participating.

–Dr. Marek Smieja (Infectious Diseases)

Last time...

- Statistical description of time series:
time plot, moving average
- Correlation coefficient: properties
- Autocorrelation
- Correlogram
- Exact vs. approximate autocorrelation
- Power spectral density (PSD)

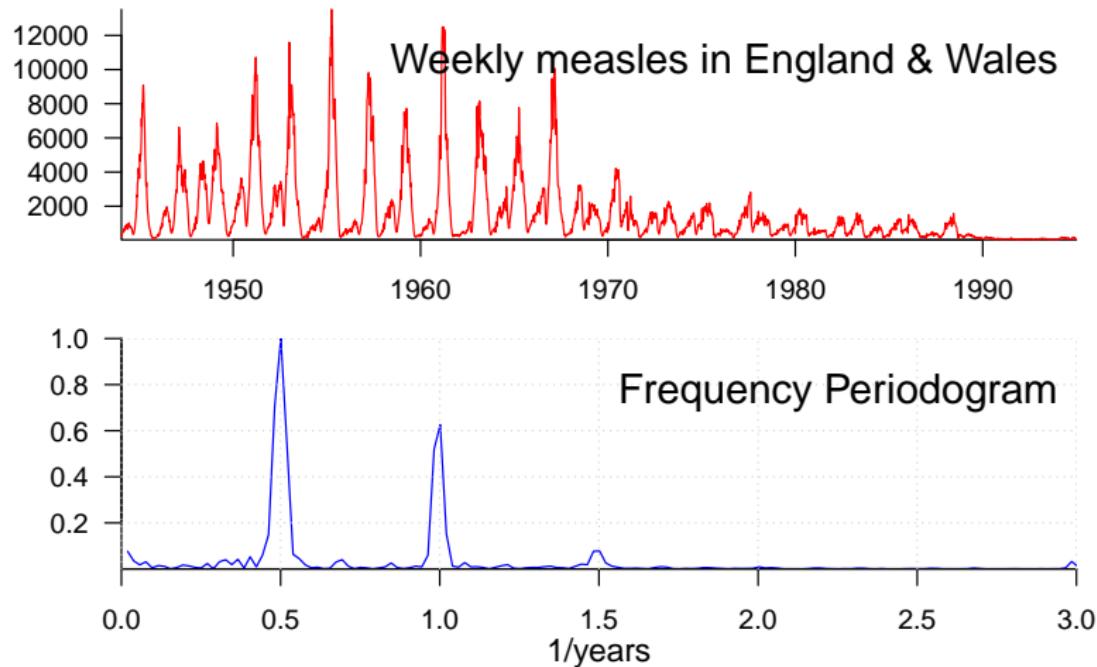
Spectral Density

- There are many different ways to express the **power spectral density** (aka *power spectrum*).
- Most common/useful equivalence is that the power spectrum is the **discrete Fourier transform** of the **correlogram**:

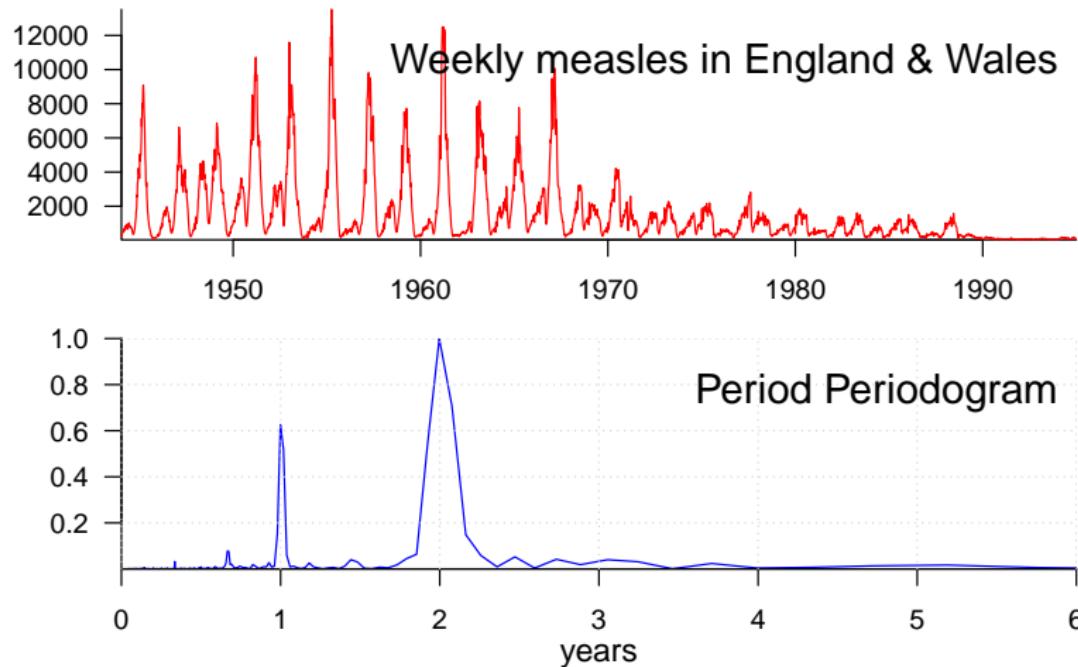
$$I(\omega_p) = \frac{1}{\pi} \left(r_0 + 2 \sum_{k=1}^{N-1} r_k \cos \omega_p k \right)$$

- Plot of estimated power spectrum as a function of frequency ω_p is called the ***frequency periodogram*** or just the ***periodogram***.

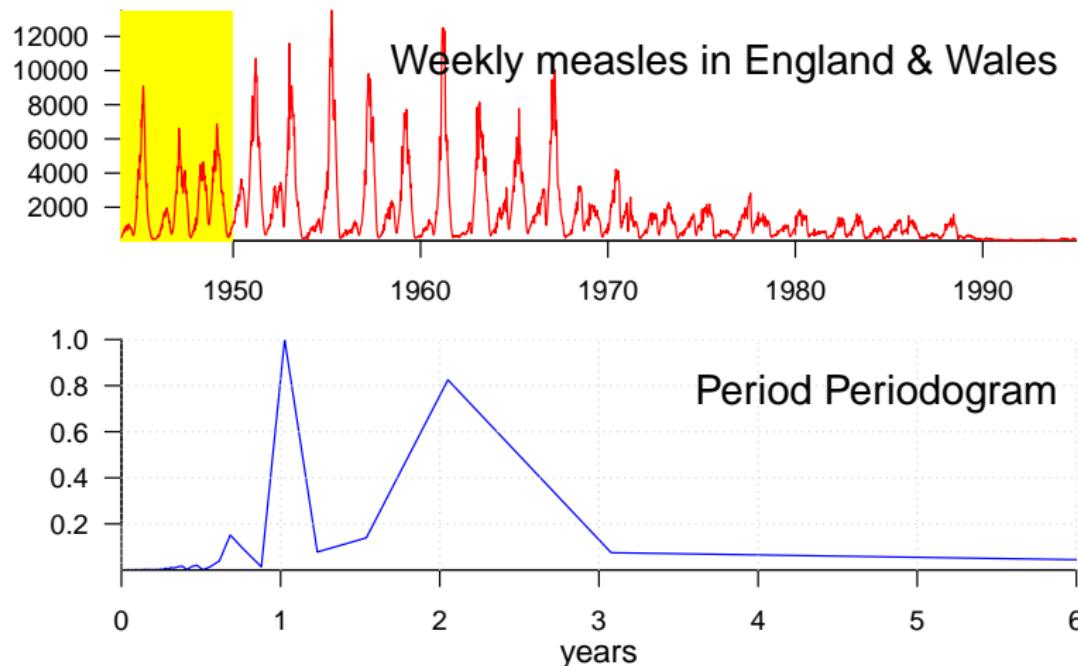
Spectral Density



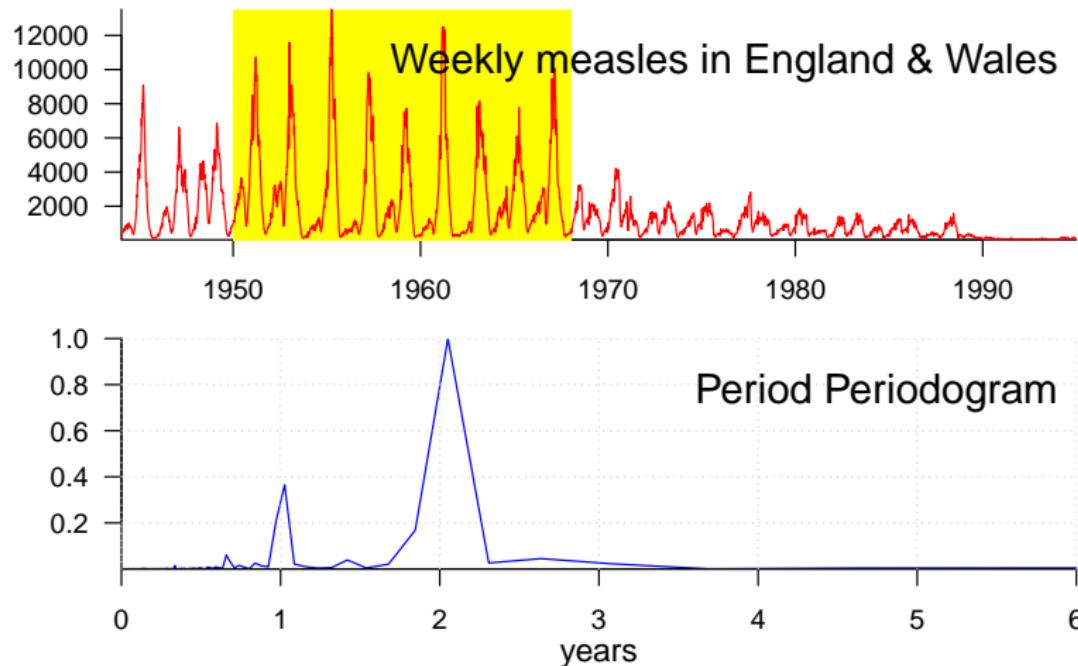
Spectral Density



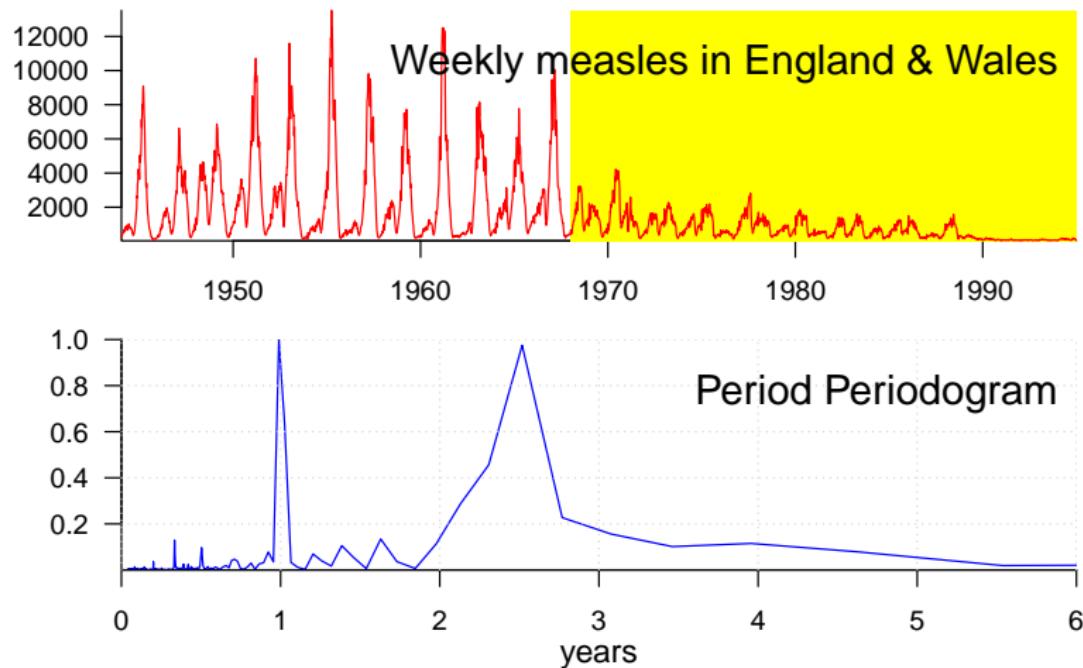
Spectral Density of Temporal Segments



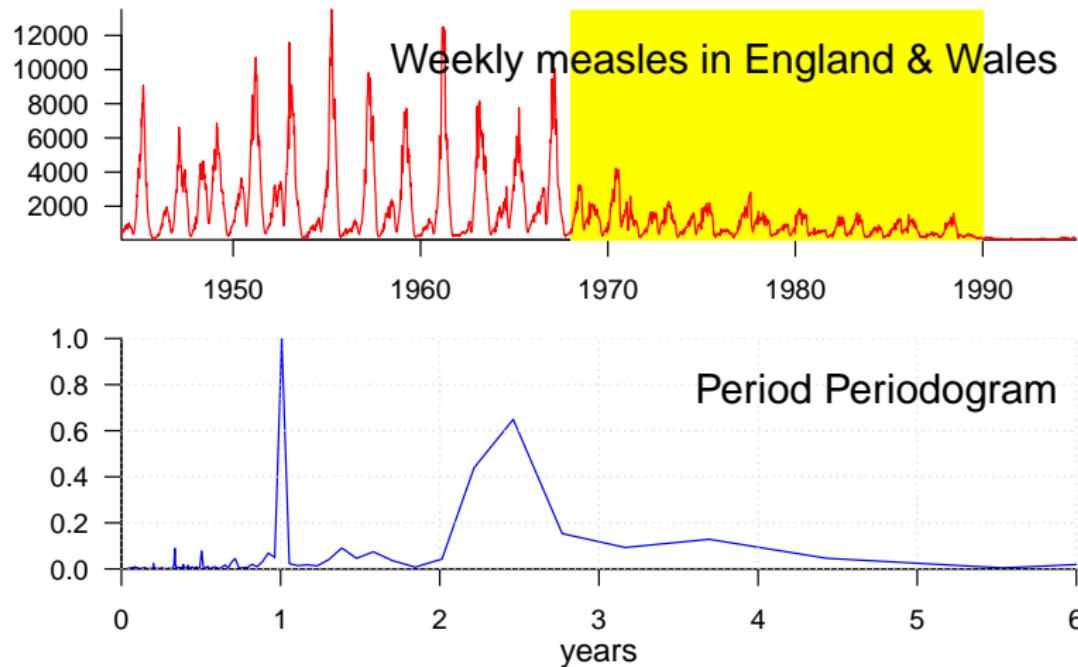
Spectral Density of Temporal Segments



Spectral Density of Temporal Segments



Spectral Density of Temporal Segments

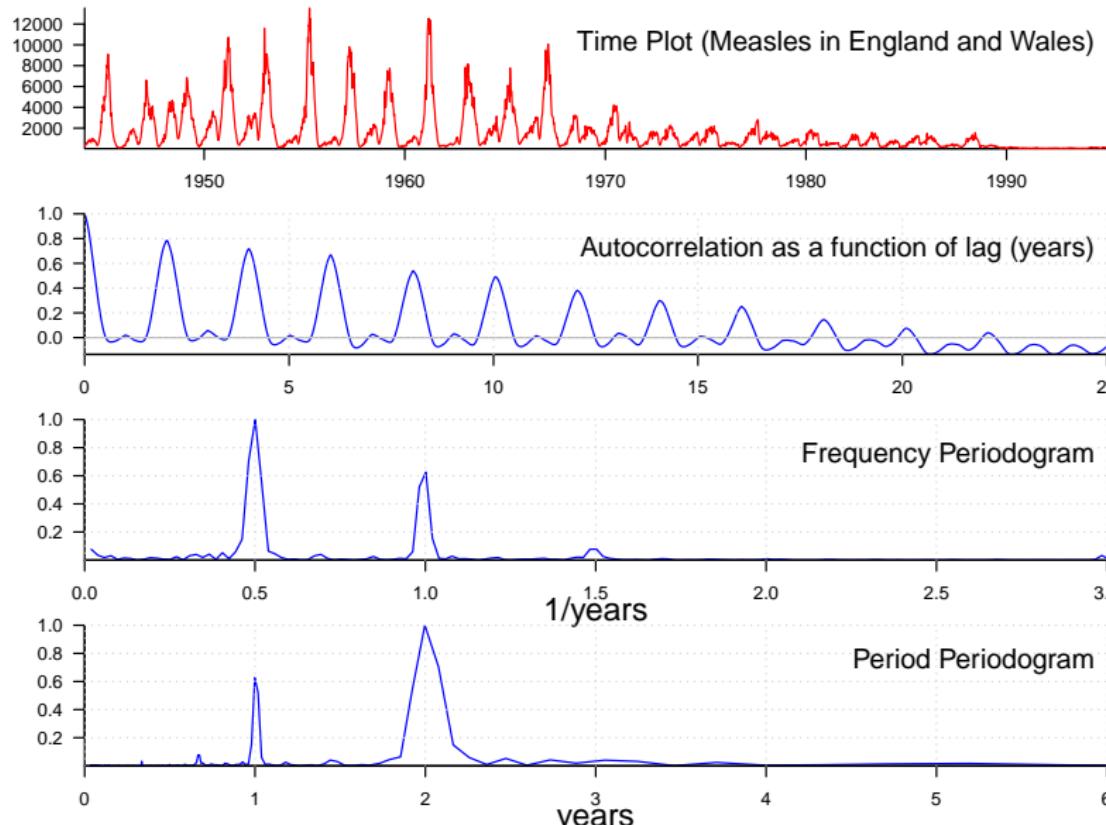


Spectral Density Properties

- Periodogram is discrete Fourier transform of correlogram
- Same information in correlogram and periodogram
- Periodogram usually easier to interpret
- In , calculate power spectrum with `spectrum()`
- The power spectrum $I(\omega_p)$ partitions the variance in the time series with respect to frequency ω_p .
 - Parseval's theorem implies $\frac{1}{N} \sum_t (x_t - \bar{x})^2 = \frac{1}{2\pi N} \sum_{p>0} I(\omega_p)$.
But $\frac{1}{N} \sum_t (x_t - \bar{x})^2 = \text{Var}\{x_t\}$, hence $I(\omega_p)/(2\pi N)$ is the proportion of the variance in the time series associated with period $2\pi/\omega_p$.

[For details, see Chatfield (2004).]

Basic Time Series Analysis of Epidemic Data



Spectral Density of Temporal Segments

- Pre-war measles
- Post-war pre-vaccination measles
- Vaccination era measles
- Vaccination era measles until 1990

Time series analysis functions



has built-in tools for time series analysis:

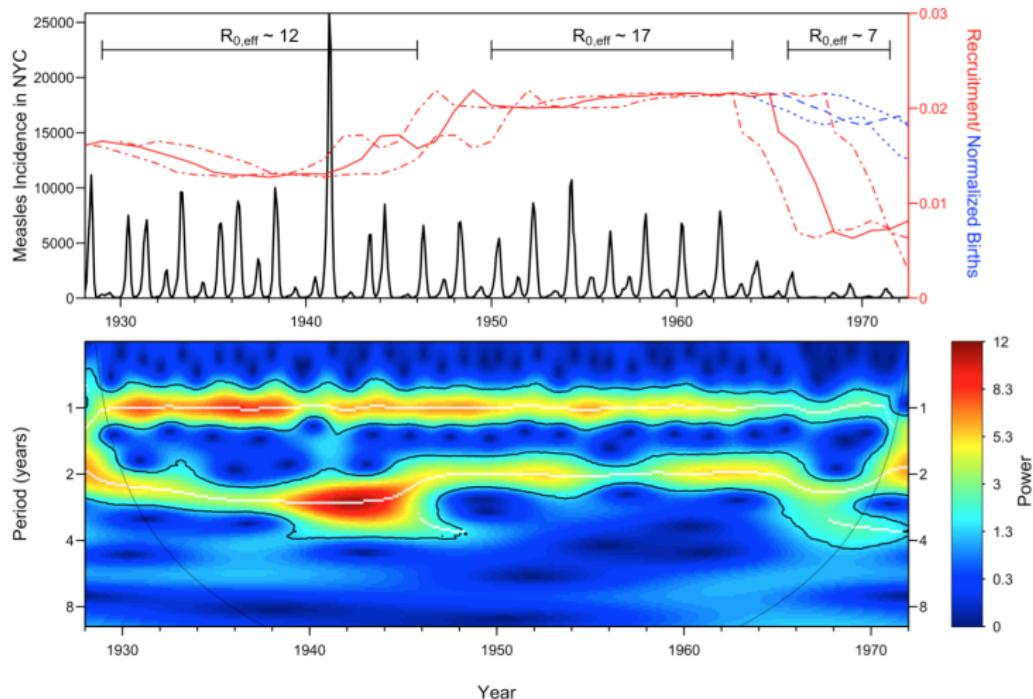
- Time plot: `plot()` etc.
- Linear filter (e.g., moving average): `filter()`
- Correlogram (auto-correlation function): `acf()`
- Periodogram (power spectrum): `spectrum()`

You will use all of these functions in **Assignment 4**.

More sophisticated spectral method

- Traditional power spectrum measures frequency content of entire time series.
- Wavelet decomposition is local in time.
 - Reveals changes in the spectrum over time without having to identify distinct temporal segments yourself.
 - Nice intro to wavelet analysis of time series:
Torrence and Compo (1998) "A Practical Guide to Wavelet Analysis" *Bulletin of the American Meteorological Society* **79**, 61–78
 - $\exists \text{ } \text{R}$ packages for wavelet analysis of time series (e.g., `WaveletComp`, `wavelets`), and at least one book on wavelet methods in 

Wavelet Spectrum of Monthly Measles in New York City



Krylova & Earn 2013, *J. R. Soc. Interface* **10**, 20130098

Wavelet Spectrum of Weekly Measles in New York City

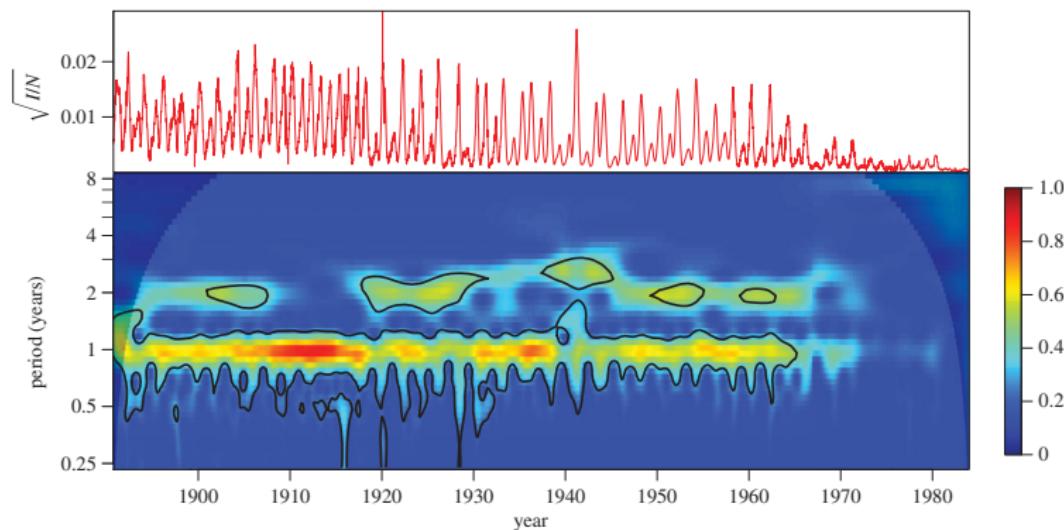


Figure 5. Observed measles dynamics in NYC from 1891 to 1984. (a) Square root of measles case reports, normalized by total concurrent population. (b) Colour depth plot of a continuous wavelet transform of the square root of normalized observed NYC measles cases (colour warmth scales with spectral power and 95% significance contours are shown in black). Shaded regions in the upper left and right indicate the cone of influence.

Hempel & Earn 2015, *J. R. Soc. Interface* 12, 20150024

Statistical Modelling of Time Series

Statistical Modelling of Time Series

- Imagine time series $\{X_t\}$ is generated by random processes.
- Simplest case: X_t (number of cases at time t) is simply a random variable with a known distribution,

$$X_t = \mu + Z_t \quad (*)$$

where μ = time average number of cases
and $\{Z_t\}$ = sequence of random variables with zero mean.

- Might be a reasonable model for importation of new, infectious individuals into a focal community.
- Bad model for epidemics: ignores transmission from one individual to another.
 - There must be a correlation between the number of individuals in the focal community who are infected now and the number who will be infected in the near future.

Statistical Modelling of Time Series: AR and MA

- So, imagine that successive data points in $\{X_t\}$ are correlated.
- For example, perhaps the data are generated by an *autoregressive (AR) process*:

$$X_t - \mu = \alpha_1(X_{t-1} - \mu) + \alpha_2(X_{t-2} - \mu) + \cdots + \alpha_p(X_{t-p} - \mu) + Z_t,$$

where the α_i are constants that determine the degree of correlation along the time series.

- Alternatively, the data might be generated by a *moving average (MA) process*:

$$X_t - \mu = \beta_0 Z_t + \beta_1 Z_{t-1} + \cdots + \beta_q Z_{t-q},$$

where the β_i are constants that define a weighted average.

Statistical Modelling of Time Series: ARMA

- More generally, the data might be generated by an *autoregressive moving average “ARMA(p, q)” process:*

$$\begin{aligned} X_t - \mu = & \alpha_1(X_{t-1} - \mu) + \alpha_2(X_{t-2} - \mu) + \cdots + \alpha_p(X_{t-p} - \mu) \\ & + \beta_0 Z_t + \beta_1 Z_{t-1} + \cdots + \beta_q Z_{t-q}. \end{aligned}$$

Statistical Modelling of Time Series: ARIMA

- Finally, an *autoregressive integrated moving average “ARIMA(p, d, q)” model* includes weighted differences of the time series:

$$\begin{aligned} X_t - \mu = & \alpha_1(X_{t-1} - \mu) + \alpha_2(X_{t-2} - \mu) + \cdots + \alpha_p(X_{t-p} - \mu) \\ & + \gamma_1(X_{t-1} - X_{t-2}) + \gamma_2(X_{t-2} - X_{t-3}) + \cdots \\ & + \beta_0 Z_t + \beta_1 Z_{t-1} + \cdots + \beta_q Z_{t-q}. \end{aligned}$$

- The “I” in ARIMA refers to the original time series X_t , which is an “integrated” version of the differenced time series.
- Technically, an ARIMA model is just an ARMA model with differently labelled coefficients, but explicit differences are often helpful conceptually (e.g., they can “stationarize” a time series).

What kind of process generated our data?

- *How can we tell if our data were generated by such a process?
Can we identify an AR(p), MA(q) or ARMA(p, q) process?*

- Compare time plots of these processes with time plot of our data? (Comparison by eye often challenging/unreliable.)
- Compare autocorrelation functions (correlograms) of these processes with correlogram of our data? (Better.)
- Compare power spectra (periodograms) of these processes with periodogram of our data? (Even better.)
- Compare wavelet spectra of these processes with wavelet spectrum of our data? (Better yet.)

Statistical Modelling of Time Series: ARMA fitting

- Looking at the power spectra of ARMA models would be instructive.
- But is there a better approach to discovering if an ARMA model could explain our data?
- Find the *best fit* ARMA parameters by minimizing the residual sum of squares. e.g., for an AR model, minimize:

$$S = \sum_{t=p+1}^N [(x_t - \mu) - \alpha_1(x_{t-1} - \mu) - \cdots - \alpha_p(x_{t-p} - \mu)]^2.$$

- More generally, we can find the best fit parameters of an ARIMA(p, d, q) model
 - Non-trivial, but there are standard methods
- Compare models with **Akaike Information Criterion (AIC)**, which penalizes models that have more parameters
 - See [Earn \(2009\)](#) review article for more discussion of this.