Quiz 1, STATS/DATASCI 531/631 W25

In class on 2/17

This document produces different random quizzes each time the source code generating it is run. The actual quiz will be a realization generated by this random process, or something similar.

This version lists all the questions currently in the quiz generator. The actual quiz will have one question sampled from each of the 6 question categories.

Instructions. You have a time allowance of 30 minutes. The quiz may be ended early if everyone is done. The quiz is closed book, and you are not allowed access to any notes. Any electronic devices in your possession must be turned off and remain in a bag on the floor.

For each question, circle one letter answer and provide some supporting reasoning.

Q1. Stationarity and unit roots.

Q1-01.

Suppose that a dataset $y^*_{1:N}$ is well described by the statistical model

$$Y_n = a + bn + \epsilon_n,$$

where ϵ_n is white noise and $b \neq 0$. Which of the following is the best approach to time series modeling of $y^*_{1:N}$?

A. The data are best modeled as non-stationary, so we should take differences. The differenced data are well described by a stationary ARMA model.

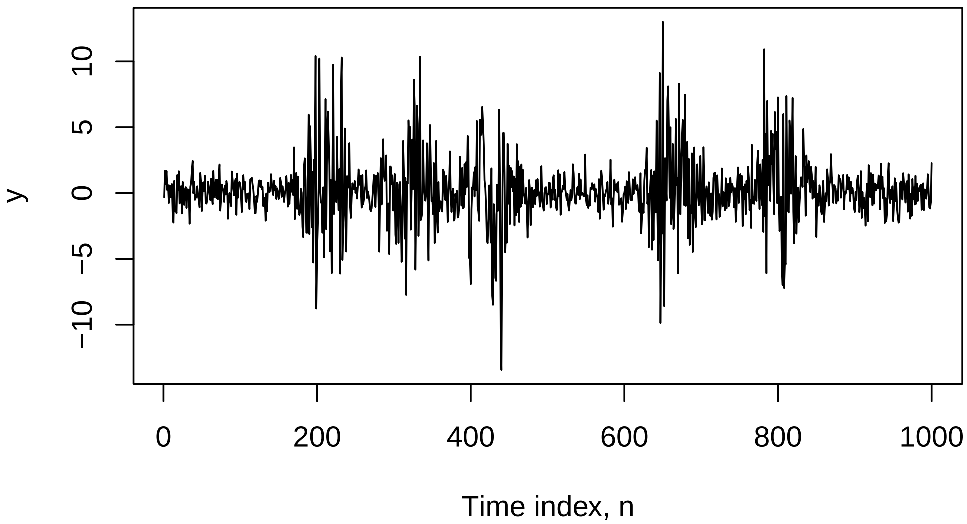
B. The data are best modeled as non-stationary, and we should use a trend plus ARMA noise model.

C. The data are best modeled as non-stationary. It does not matter if we difference or model as trend plus ARMA noise since these are both linear time series models which become equivalent when we estimate their parameters from the data.

D. We should be cautious about doing any of A, B or C because the data may have nonstationary sample variance in which case it may require a transformation before it is appropriate to fit any ARMA model.

Solution. B.
It does matter whether we take differences. For example, the differenced model is non-causal (has an MA root on the unit circle) so cannot be fitted by usual ARMA methods. D is not relevant since we are told that the data are well described by a model that rules out this possibility.

Q1-02.



Consider the time series plotted above. Which of the below is the most accurate statement about stationarity?

A. The plot shows that the data are clearly non-stationary. We could make a formal hypothesis test to confirm that, but it would not be insightful. To describe the data using a statistical model, we will need to develop a model with non-constant variance.

B. The sample variance is evidently different in different time intervals. However, we should not conclude that the underlying data generating mechanism is non-stationary before making a formal statistical test of equality of variances between the time regions that have lower sample variance and the regions that have higher sample variance. Visual impressions without a formal hypothesis test can be deceptive.

C. A model with randomly changing variance looks appropriate for these data. Since the variance for such a model is time-varying, the model must be non-stationary.

D. A model with randomly changing variance looks appropriate for these data. Despite the variance for such a model being time-varying, the model is stationary.

E. The sample variance is evidently different in different time intervals. An appropriate next step to investigate stationary would be to plot the sample autocorrelation function for different intervals to see if the dependence between time points is also time-varying.

Solution. D.
This is a subtle question, so let's discuss each option. The plotted time series is a realization of a stationary model:

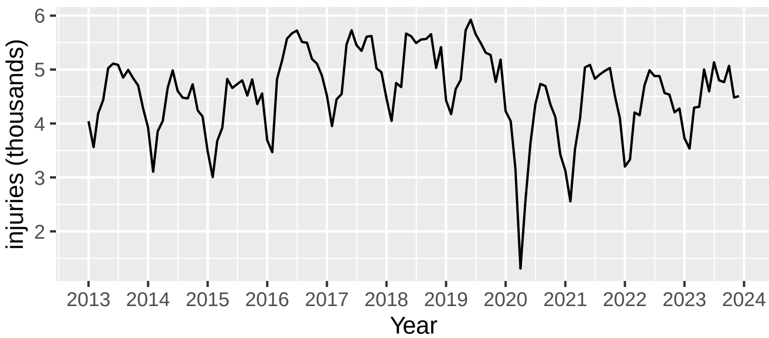
```
N <- 1000
sd1 <- rep(1,N)
events <- runif(N) < 5/N
sigma <- 20
amplitude <- 10
sd2 <- sd1 + filter(events,
  dnorm(seq(from=-2.5*sigma,to=2.5*sigma,length=5*sigma),sd=sigma)*sigma*amplitude,
  circular=T)
Y <- rnorm(n=N,mean=0,sd=sd2)
```

Hopefully, this suggests that it should not be clearly non-stationarity, ruling out A. B and E acknowledge the variation in sample variance but do not provide useful ways to assess whther this variable sample variance comes about via a stationary stochastic conditional variance model or via a non-stationary model.

C and D contain a value judgement, "looks appropriate" which is hard to quantify but is (in this case) correct! "Randomly changing variance" is an informal description of a model with stochastic conditional variance.

The sample variance estimates the variance conditional on the realization of the conditional variance. The actual variance is an expectation over posible values of the conditional variance. So, between C and D, only D can be correct.

Q1-03.



Above are monthly injuries from motor vehicle collisions in New York City. An augmented Dickey-Fuller test, `tseries::adf.test(injuries)`, gives a p-value of 0.01. Which is the best way to proceed:

A: The time plot indicates a non-constant mean function describing a major dip due to the COVID-19 pandemic and an increasing trend at other times. The ADF test does not support or refute that model.

B: The ADF test suggests the series is stationary, supporting a decision to fit a SARMA model.

C: The ADF test suggests the series is non-stationary; it should be differenced before fitting a SARMA.

D: The ADF test indicates that the series is non-stationary, supporting the use of a non-constant mean function to describe a major dip due to the COVID-19 pandemic and an increasing trend at other times.

Solution. A.
The ADF test has a null hypothesis of a unit root linear model and an alternative of a stationary linear model, so neither of these describes a nonlinear trend. Here, the role of the COVID-19 pandemic is large enough that it does not make much sense to build a model that omits it, or describes it as a large perturbation of a stationary process. The conventional interpretation of the ADF test is option B (we reject the unit root hypothesis, and so we are invited to fit a stationary model). Here, a nonlinear trend (which is neither a unit root nor a stationary model) makes sense.

Q2. Calculations for ARMA models

Q2-01.

Let $Y_n = \phi Y_{n-1} + \epsilon_n$ for $n = 1, 2, ...$ with $\epsilon_n \sim \text{iid}N[0, \sigma^2]$ and $Y_0 = 0$. The covariance of Y_n with Y_{n+k} for $k \geq 0$ is

A. $\sigma^2\phi^k/(1-\phi^2)$

B. $\sigma^2\phi^{2k}/(1-\phi^2)$

C. $\sigma^2\phi^k/(1-\phi)$

D. $\sigma^2\phi^{2k}/(1-\phi)$

E. None of the above.

Solution. E.
This model is not started in its stationary distribution, leading to a covariance that is not shift invariant.

The exact calculation is not needed, but it is as follows.

$$\begin{aligned}
\text{Cov}(Y_n, Y_k) &= \text{Cov}\left(\sum_{i=1}^{n} \phi^{n-i}\epsilon_i, \sum_{j=1}^{n+k} \phi^{n+k-j}\epsilon_j\right) \\
&= \sum_{i=1}^{n} \sum_{j=1}^{n+k} \text{Cov}(\epsilon_i, \epsilon_j) \\
&= \sum_{i=1}^{n} \sigma^2 \phi^{k+2(n-i)} = \phi^k \frac{\sigma^2(1-\sigma)^{2n}}{1-\sigma^2}
\end{aligned}$$

If you didn't see this, you may feel you were tricked. However, it is a common mistake in practical data analysis to pay insufficient attention to initial conditions, so it is worth bringing this to your attention.

Q2-02.

Let Y_n be an ARMA model solving the difference equation

$$Y_n = (1/4)Y_{n-2} + \epsilon_n + (1/2)\epsilon_{n-1}.$$

This is equivalent to which of the following:

A. $Y_n = (1/2)Y_{n-1} + \epsilon_n$

B. $Y_n = -(1/2)Y_{n-1} + \epsilon_n$

C. $Y_n = (1/2)Y_{n-2} - (1/16)Y_{n-4} + \epsilon_n + \epsilon_{n-1} + (1/4)\epsilon_{n-2}$

D. $Y_n = -(1/2)Y_{n-2} - (1/16)Y_{n-4} + \epsilon_n + \epsilon_{n-1} + (1/4)\epsilon_{n-2}$

E. None of the above

Solution. A.
Writing the model in terms of the lag operator, L, we get

$$(1 - (1/2)L)(1 + (1/2)L)Y_n = (1 + (1/2)L)\epsilon_n.$$

Canceling out a factor of $(1 + (1/2)L)$, we obtain

$$(1 - (1/2)L)Y_n = \epsilon_n.$$

Q2-03.

Is it possible for an $AR(2)$ model to have a finite moving average representation, so that it is equivalent to some $MA(q)$ model for $q < \infty$?

A. No. Any moving average representation of any $AR(2)$ model is $MA(\infty)$

B. Yes. Although it is not true for any $AR(2)$ process, it is possible to find particular choices of the autoregressive coefficients, p_1 and p_2, that lead to a finite $MA(q)$ representation.

C. It is not possible for any real-valued p_1 and p_2, but it is possible if you permit p_1 and p_2 to be complex-valued.

Solution. A.
For any $AR(p)$ model with $p \geq 1$, an $MA(q)$ representation always has $q = \infty$. One way to see this is to argue by contradiction, by supposing there is a value of $q < \infty$. Then, setting $\phi(x)$ and $\psi(x)$ as the AR and MA polynomials, we can write

$$\frac{1}{\phi(B)} = \psi(B)$$

Thus, $\phi(x)\psi(x) = 1$. But $\phi(x)\psi(x)$ has a nonzero x^{p+q} coefficient so it cannot equal 1. This argument applies for either real-valued or complex-valued coefficients.

Q3. Likelihood-based inference for ARMA models

Q3-01.

The following table of AIC values results from fitting ARMA(p,q) models to a time series $y_{1:415}$ where y_n is the time, in miliseconds, between the nth and $(n+1)$th firing event for a monkey neuron. The experimental details are irrelevant here. You are asked to check how many adjacent pairs of AIC values in this table are inconsistent, such that they could mathematically arise only from a numerical error? Adjacent pairs of models are those directly above or below or left or right of each other in the table.

	MA0	MA1	MA2	MA3
AR0	3966.0	3961.5	3962.7	3964.7
AR1	3961.1	3962.6	3964.6	3966.6
AR2	3962.7	3960.5	3959.8	3961.7
AR3	3964.6	3965.5	3962.6	3968.4

A: 0, so the table is mathematically plausible.

B: 1

C: 2

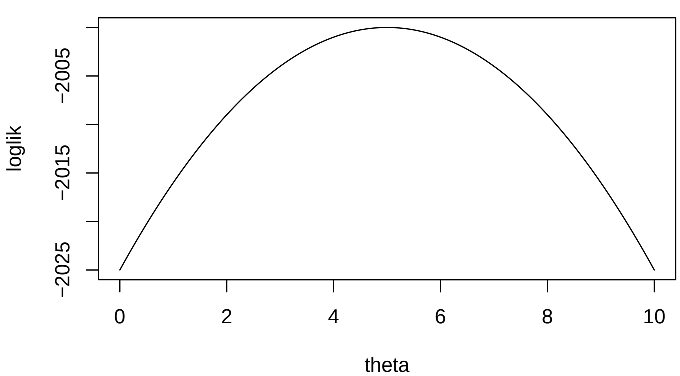
D: 3

E: 4 or more

Solution. E.
Adding one parameter in a nested model cannot decrease the maximized log-likelihood, so it can increase the AIC by at most 2 units. Adjacent pairs $\{(p,q),(p',q')\}$ inconsistent with this are $\{(3,2),(3,3)\}$, $\{(2,3),(3,3)\}$, $\{(2,1),(3,1)\}$, $\{(2,2),(3,2)\}$.

Q3-02.

The R function `arima()` provides standard errors calculated using observed Fisher information. This question tests your understanding of what that means. Suppose a parametric model has a single parameter, θ, and the log-likelihood function when fitting this model to dataset is as follows:



What is the observed Fisher information (I_{obs}) for θ?

Hint 1. The observed Fisher information is accumulated over the whole dataset, not calculated per observation, so we don't have to know the number of observations, N.

Hint 2. Observations in time series models are usually not independent. Thus, the log-likelihood is not the sum of the log-likelihood for each observation. Its calculation will involve consideration of the dependence, and usually the job of calculating the log-likelihood is left to a computer.

Hint 3. The usual variance estimate for the maximum likelihood estimate, $\hat{\theta}$, is $\mathrm{Var}(\hat{\theta}) \approx 1/I_{obs}$.

A: $I_{obs} = 2$

B: $I_{obs} = 1$

C: $I_{obs} = 1/2$

D: $I_{obs} = 1/4$

E: None of the above

Solution. A.
The log-likelihood here is a quadratic function. We can see by inspection that this quadratic is given by

$$\ell(\theta) = -2000 - (\theta - 5)^2.$$

The observed Fisher information is the negative of the second derivative of the log-likelihood at the MLE, so $I_{obs} = 2$. Thus, the standard error is $1/\sqrt{2} = 0.707$

Q3-03.

```
##
## Call:
## arima(x = huron_level, order = c(2, 0, 1))
##
## Coefficients:
##          ar1     ar2     ma1  intercept
##       0.3388  0.4092  0.6320   176.4821
## s.e.  0.4646  0.4132  0.4262     0.1039
##
## sigma^2 estimated as 0.04479:  log likelihood = 21.42,  aic = -32.84
```

```
##
## Call:
## arima(x = huron_level, order = c(2, 0, 2))
##
## Coefficients:
##           ar1     ar2     ma1     ma2  intercept
##       -0.1223  0.7646  1.1310  0.1310   176.4815
## s.e.   0.0682  0.0550  0.1084  0.1004     0.1004
##
## sigma^2 estimated as 0.04364:  log likelihood = 22.64,  aic = -33.28
```

The R output above uses `stats::arima` to fit ARMA(2,1) and ARMA(2,2) models to the January level (in meters above sea level) of Lake Huron from 1860 to 2024. Residual diagnostics (not shown) show no major violation of model assumptions. We aim to choose one of these as a null hypothesis of no trend for later comparison with models including a trend.

Which is the best conclusion from the available evidence:

A: The ARMA(2,2) model has a lower AIC so it should be preferred.

B: We cannot reject the null hypothesis of ARMA(2,1) since the ARMA(2,2) model has a likelihood less than 1.92 log units higher than ARMA(2,1). Since there is not sufficient evidence to the contrary, it is better to select the simpler ARMA(2,1) model.

C: Since the comparison of AIC values and the likelihood ratio test come to different conclusions in this case, it is more-or-less equally reasonable to use either model.

D: When the results are borderline, numerical errors in the `stats::arima` optimization may become relevant. We should check using optimization searches from multiple starting points in parameter space, for example, using `arima2::arima`.

Solution. D.
All the answers are fairly reasonable here! Perhaps the most unreasonable thing would be to be sure there's only one reasonable answer.

However, a more careful optimization using `arima2::arima` shows us that ARMA(2,1) actually has a higher AIC than ARMA(2,2) so all lines of evidence suggest ARMA(2,1) is a better choice. The differences are small, so the choice is unlikely to be highly consequential.

```
##
## Call:
## arima2::arima(x = huron_level, order = c(2, 0, 1), max_iters = 200, max_repeats = 20)
##
## Coefficients:
##           ar1     ar2     ma1  intercept
##       -0.0674  0.7781  1.0000   176.4860
## s.e.   0.0517  0.0518  0.0541     0.1095
##
## sigma^2 estimated as 0.04401:  log likelihood = 21.82,  aic = -33.63
```

```
##
## Call:
## arima2::arima(x = huron_level, order = c(2, 0, 2), max_iters = 200, max_repeats = 20)
##
## Coefficients:
##           ar1     ar2     ma1     ma2  intercept
##       -0.1223  0.7646  1.1310  0.1310   176.4815
## s.e.   0.0682  0.0550  0.1084  0.1004     0.1004
##
## sigma^2 estimated as 0.04364:  log likelihood = 22.64,  aic = -33.28
```

Sometimes the multiple starts used by `arima2::arima` make a difference, sometimes the results from `stats::arima` are unchanged. In this case, it happens to make a difference.

Q3-04.

Suppose model M_0 is nested within a larger model M_1 which has one additional parameter. Suppose that the AIC for M_1 is 0.5 units lower than the AIC for M_0. Which of the following is a correct expression for the p-value of a likelihood ratio test for M_1 against the null hypothesis M_0, supposing that a Wilks approximation is accurate? Here, χ^2_1 is a chi-square random variable on 1 degree of freedom.

A: $P(\chi^2_1 > 0.5)$

B: $P(\chi^2_1 > 1)$

C: $P(\chi^2_1 > 1.5)$

D: $P(\chi^2_1 > 2)$

E: $P(\chi^2_1 > 2.5)$

F: $P(\chi^2_1 > 3)$

Solution. E.
The AIC for each model $k \in \{0, 1\}$ is $AIC_k = -2\ell_k + 2_{D_k}$, where ℓ_k is the log-likelihood for M_k and D_k is the number of parameters. Thus, $AIC_0 - AIC_1 = 2(\ell_1 - \ell_0) - 2 = 0.5$, and so \$ 2(_1- _0)=2.5\$. Under M_0, according to Wilks' approximation,

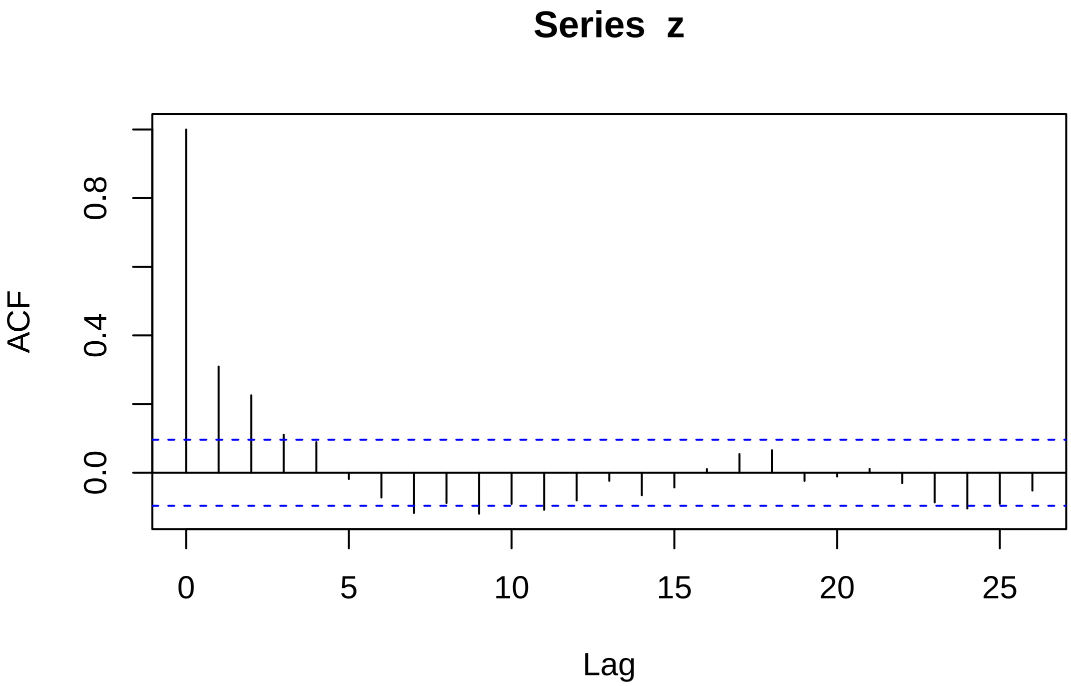
$$2(\ell_1 - \ell_0) \sim \chi^2_1.$$

Therefore, the p-value is $P(\chi^2_1 > 2.5) = 0.11$.

Q4. Interpreting diagnostics

Q4-01.

We consider data $y_{1:415}$ where y_n is the time, in miliseconds, between the nth and $(n+1)$th firing event for a monkey neuron. Let $z_n = \log(y_n)$, with log being the natural logarithm. The sample autocorrelation function of $z_{1:415}$ is shown below.



We are interested about whether it is appropriate to model the time series as a stationary causal ARMA process. Which of the following is the best interpretation of the evidence from these plots:

A. There is clear evidence of a violation of stationarity. We should consider fitting a time series model, such as ARMA, and see if the residuals become stationary.

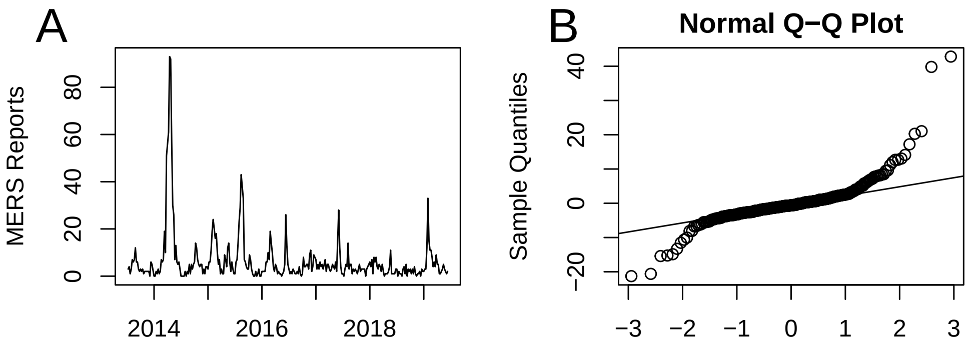
B. This plot suggests there would be no benefit from detrending or differencing the time series before fitting a stationary ARMA model. It does not rule out a sample covariance that varies with time, which is incompatible with ARMA.

C. This plot is enough evidence to demonstrate that a stationary model is reasonable. We should proceed to check for normality, and if the data are also not far from normally distributed then it is reasonable to fit an ARMA model by Gaussian maximum likelihood.

Solution. B.
The usual interpretation of the sample ACF assumes that variance and covariance depend only on lag (i.e., the data are well modeled by a shift-invariant autocovariance) but the plot does not check this.

There is clear evidence that the process is not well modeled by white noise. There is also clear evidence against a trend in the mean, which would show up as a slowly decaying sample ACF.

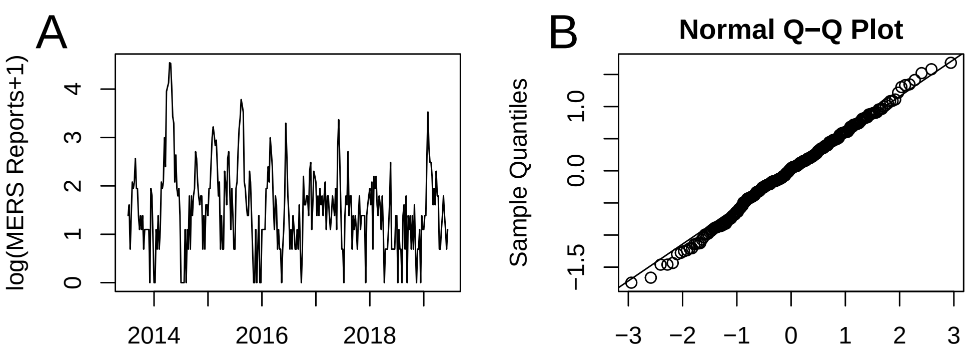
Q4-02.



(A) Weekly cases of Middle East Respiratory Syndome (MERS) in Saudi Arabia. (B) a normal quantile plot of the residuals from fitting an ARMA(2,2) model to these data using `arima()`. What is the best interpretation of (B)?

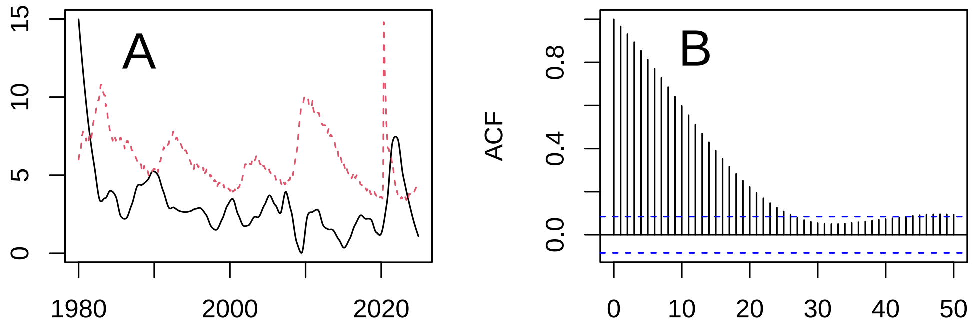
A: We should consider fitting a long-tailed error distribution, such as the t distribution.
B: The model is missing seasonality, which could be critical in this situation.
C: For using ARMA methods, these data should be log-transformed to make a linear Gaussian approximation more appropriate.
D: The normal quantile plot shows a long-tailed distribution, but this is not a major problem. We have over 300 data points, so the central limit theorem should hold for parameter estimates.
E: The normal quantile plot shows long tails, but with the right tail noticeably longer than the left tail. We should consider an asymmetric error distribution.
F: We should not interpret (B) before testing for stationarity. First run `adf.test()` and, if the null hypothesis is not rejected, recalculate (B) when fitting to the differenced data.

Solution. C.
Here's what happens when we take a `log(x+1)` transform, fitting ARMA(2,2) and checking the residuals as before.



It is often a good idea to log-transform non-negative quantities, and failure to do this can show up as long tailed residuals. Fitting long-tailed ARMA models is possible, but non-standard and not necessary here. There is seasonality, but an ARMA(2,2) model can already explain some periodicity so including a seasonal term in the model is not critical. There may be some non-stationarity here, but nothing that resembles the null hypothesis of the Augmented Dickey-Fuller test, so that is not relevant here.

Q4-03.



(A) Inflation (black) and unemployment (red) for the USA, 1980-2024. (B) Sample autocorrelation function of the residuals from a least square regression, 'lm(inflation~unemployment)', with estimated coefficients below. Which is the best interpretation of these graphs and fitted model?

```
##  (Intercept) unemployment
##   2.87056052   0.04543759
```

A: 0.05 is a reasonable estimate for the additional unemployment caused by one percentage point of additional inflation. We should not trust the uncertainty estimate (not shown), since our model does not allow for autocorrelation of the residuals.

B: 0.05 is a reasonable estimate for the association between inflation and unemployment. We should not assume there is a causal relationship. We should not trust the uncertainty estimate (not shown), since our model does not allow for autocorrelation of the residuals.

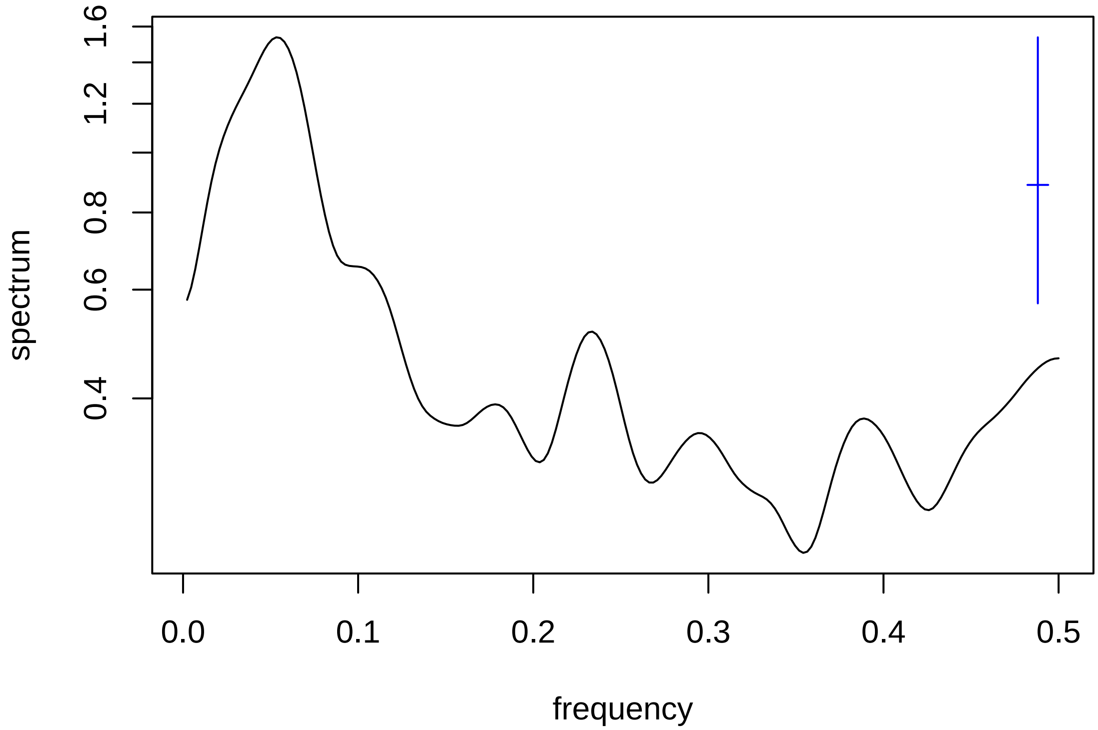
C: 0.05 is a reasonable estimate for the association between inflation and unemployment. We should make an additional assumption that there are no confounding variables, and then we can interpret this association to be causal. We should not trust the uncertainty estimate (not shown), since our model does not allow for autocorrelation of the residuals.

Solution. B.
Association is not causation. Inflation and unemployment are two aspects of a complex system. They may have some direct effect on each other, but they are also both driven by other aspects of the economy such as interest rates, consumer spending, and international trade. Mathematically, we could wish away these confounding variables (as proposed in answer C) but for practical purposes it does not make sense to do so.

Q5. The frequency domain

Q5-01.

We consider data $y_{1:415}$ where y_n is the time interval, in milliseconds, between the nth and $(n+1)$th firing event for a monkey neuron. Let $z_n = \log(y_n)$, with log being the natural logarithm. A smoothed periodogram of $z_{1:415}$ is shown below. Units of frequency are the default value in R, i.e., cycles per unit observation. We see a peak at a frequency of approximately 0.07.



Which if the following is the best inference from this figure

A. Rapid neuron firing events (i.e., short intervals between firing events) come in groups with a typical size of $1/0.07 \approx 14$.

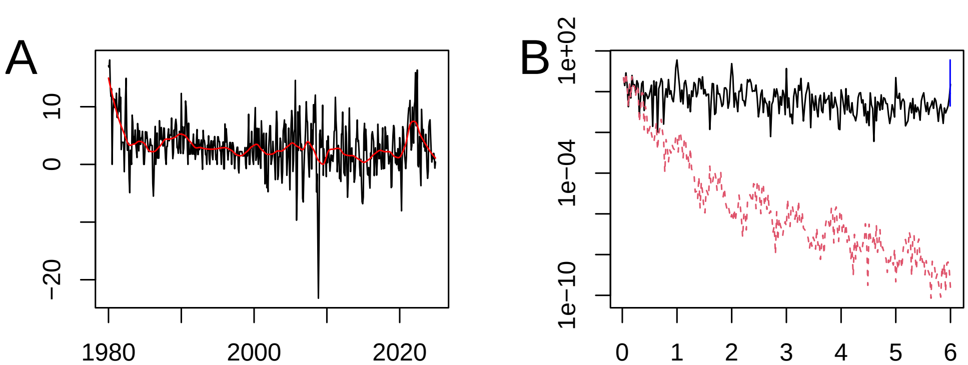
B. The neuron has a characteristic duration between firing events of $1/0.07 \approx 14$ milliseconds.

C. The neuron has a characteristic duration between firing events of $1/\exp(0.07) \approx 0.9$ milliseconds.

Solution. B.
The usual interpretation of the sample ACF assumes that variance and covariance depend only on lag (i.e., the data are well modeled by a shift-invariant autocovariance) but the plot does not check this.

There is clear evidence that the process is not well modeled by white noise. There is also clear evidence against a trend in the mean, which would show up as a slowly decaying sample ACF.

Q5-02.



The monthly US consumer price index (CPI) combines the price of a basket of products, such as eggs and bread and gasoline. (A) Annualized monthly percent inflation, i.e., the difference of log-CPI multiplied by 12×100 (black line); a smooth estimate via local linear regression (red line). (B) The periodogram of inflation and its smooth estimate. Which best characterizes the behavior of the smoother?

A: Cycles longer than 2 months are removed
B: Cycles shorter than 2 months are removed
C: Cycles longer than 2 year are removed
D: Cycles shorter than 2 year are removed
E: Cycles longer than (1/2) year are removed
F: Cycles shorter than (1/2) year are removed

Solution. D.
The units are in cycles per year; if we doubt this, we can tell because the largest peak at 1 corresponds to annual seasonality. At about (1/2) cycle per year, the power in the smooth fit (the red dashed line) rapidly falls several log units below the power in the raw monthly inflation data. (1/2) cycle per year corresponds to cycles of 2 year.

Q6. Scholarship for time series projects

Q6-01.

This question on citing references applies to any statistics report, but it is particularly relevant here since we are learning proper use of sources in order to write open-access midterm and final projects.

Suppose that the midterm project P1 cites a past project, P2, in the reference list. P1 refererences P2 at one point, mentioning that the projects have similarities. When you look at the source code and the writing, you find various points where P1 and P2 are almost identical, though at other points the projects are entirely different. What do you infer?

A: The authors of P1 have done enough to honestly disclose the relationship with P2. After all, there is sufficient information provided for any reader to track down the exact relationship.

B: The authors of P1 have misrepresented the relationship with P2 by appearing to take credit for some original work which was in fact heavily dependent on a source. This is a serious offence which should be reported to Rackham and/or the Associate Chair for Graduate Programs in Statistics as a violation of academic integrity.

C: There is not enough information to tell the actual story for certain. The authors of P2 may or may not have done something wrong, depending on information that is not available to us, but they did cite P2 so they should be given the benefit of the doubt and should not loose any scholarship points.

D: The authors of P1 have misrepresented the relationship with P2 by appearing to take credit for some original work which was in fact heavily dependent on a source. This is a moderately severe offence, partly offset by including P2 in the reference list. A substantial number of scholarship points should be subtracted.

E: P1 evidently has not shown perfect scholarship, but this is a small issue that could easily be an honest mistake given that the authors were not trying to hide the fact that they had studied P2. It is appropriate to substract, say, 1 point for scholarship for this mistake.

Solution. D.
If occurrences such as this were reported to the authorities, this would fill up too much time for the deans and chairs. This is a fairly serious issue, and a responsible student should not usually do this by mistake. It wastes everyone's time if proper credit is not clearly assigned to sources and if the grader has to track down the contribution of the authors.

Q6-02. Four people in a team collaborate on a project. After the project is submitted, a reader identifies that part of the project is adapted from an unreferenced source, i.e., plagiarized. The team worked using git and cooperates on tracking down the issue, and the commit history clearly reveals who wrote the problematic part of the project. What is the most appropriate course of action:

A. The guilty coauthor should be penalized heavily for poor scholarship, and the the other coauthors should have a minor penalty for failing to check their colleague's work.

B. All coauthors should share the same penalty, since this is a team project and all coauthors share equal responsibility for the submitted report.

C. The guilty coauthor should be penalized heavily for poor scholarship. The other coauthors have demonstrated strong scholarship by following good transparent working practices that enabled this issue to get quickly resolved, so they should not receive any penalty.

D. It is necessary to collect more information before coming to a decision. For example, the team may argue that the source is well known to all readers so did not have to be cited.

Solution. A.
Everyone should take responsibility for checking work submitted under their name. However, when it is possible to isolate the misconduct to one individual, and the rest of the team has demonstrated strong scholarship, they have some protection from the heavy scholarship consequences for the serious error.

One can always propose collecting new information, as in D, but in practice you often have to act on the information at hand. Parties can request a regrade if they think the decision is too far from justice.

Q6-03.

You discover that your team-mate is using Google Translate to carry out their share of the writing. The translation looks poorly done, similar in quality to ChatGPT, and does not use technical time series terminology correctly. What is the best course of action among the options below

A. Alert the instructor that you have a team mate adopting questionable scholarship strategies, in order to make sure you are not personally held responsible.

B. Ask ChatGPT to rewrite this problematic section to improve its quality

C. Help your team mate to rewrite the section in their own voice (shared with your voice).

Solution. C.
Different team mates bring different skills to the project, and perhaps you are more fluent at writing in English than one of your team mates. Major team problems can be discussed with the instructor, but this issue is best caught and corrrected early and solved within the team.

Q6-04.

Why is it helpful for a course such as DATASCI/STATS 531, that permits the use of internet resources including GenAI and past solutions, to require students to say explicitly say when they do not use sources?

A. Failure to give credit to sources is against the academic integrity rules of Rackham, the graduate school at University of Michigan.

B. It helps the GSI to grade the homework when they know exactly what sources have been used and for what question.

C. Students whose solution is more dependent on sources than they want to admit are reluctant to explicitly deny using sources.

D. The GSI has the task of evaluating whether the student has demonstrated thought about the homework task beyond collecting material from sources into a solution. This is not an easy task even when the sources are clearly listed and referenced at the point (or points) where they are used.

Solution. C.
The points made in A, B, D are all correct but are not directly relevant to the question. In an ideal world, the absence of a list of sources would be logically equivalent to an explicit statement saying that no sources were used. However, in practice that is not the case. We need a system that is robust against the natural tendency to hide information that could lead us to get a lower grade (because the grader would be able to see that our own contribution was smaller than it might otherwise appear). Most of us realize that explicitly saying we did not consult a source, when in fact we did, is a lie and amounts to academic misconduct. Failure to mention the source sounds like a milder misdemeanor. Therefore, to help the grader distinguish these

things, it is important to be explicit about the lack of sources when indeed you did not need to consult any. It is appropriate for the GSI to award points for turning in solutions that are well-written and easier for the grader to evaluate.
