

EXAMINERS' REPORT

CS1 - Actuarial Statistics
Core Principles
Paper B

Introduction

The Examiners' Report is written by the Chief Examiner with the aim of helping candidates, both those who are sitting the examination for the first time and using past papers as a revision aid and also those who have previously failed the subject.

The Examiners are charged by Council with examining the published syllabus. The Examiners have access to the Core Reading, which is designed to interpret the syllabus, and will generally base questions around it but are not required to examine the content of Core Reading specifically or exclusively.

For numerical questions the Examiners' preferred approach to the solution is reproduced in this report; other valid approaches are given appropriate credit. For essay-style questions, particularly the open-ended questions in the later subjects, the report may contain more points than the Examiners will expect from a solution that scores full marks.

For some candidates, this may be their first attempt at answering an examination using open books and online. The Examiners expect all candidates to have a good level of knowledge and understanding of the topics and therefore candidates should not be overly dependent on open book materials. In our experience, candidates that spend too long researching answers in their materials will not be successful either because of time management issues or because they do not properly answer the questions.

Many candidates rely on past exam papers and examiner reports. Great caution must be exercised in doing so because each exam question is unique. As with all professional examinations, it is insufficient to repeat points of principle, formula or other text book works. The examinations are designed to test "higher order" thinking including candidates' ability to apply their knowledge to the facts presented in detail, synthesise and analyse their findings, and present conclusions or advice. Successful candidates concentrate on answering the questions asked rather than repeating their knowledge without application.

The report is written based on the legislative and regulatory context pertaining to the date that the examination was set. Candidates should take into account the possibility that circumstances may have changed if using these reports for revision.

Sarah Hutchinson Chair of the Board of Examiners November 2023

A. General comments on the aims of this subject and how it is marked

The aim of the Actuarial Statistics subject is to provide a grounding in statistical techniques that are of particular relevance to actuarial work.

In particular, the CS1B paper is a problem-based examination and focuses on the assessment of computer-based data analysis and statistical modelling skills.

For the CS1B exam candidates are expected to include the R code that they have used to obtain the answers, together with the main R output produced, such as charts or tables.

When a question requires a particular numerical answer or conclusion, this should be explicitly and clearly stated, separately from, and in addition to the R output that may contain the relevant numerical information.

Some of the questions in the examination paper accept alternative solutions from those presented in this report, or different ways in which the provided answer can be determined. In particular, there are variations of the R code presented here, which are valid and can produce the correct output. All mathematically and computationally valid solutions or answers received credit as appropriate.

In cases where the same error was carried forward to later parts of the answer, candidates were given full credit for the later parts.

In questions where comments were required, valid comments that were different from those provided in the solutions also received full credit where appropriate.

In cases where a question is based on simulations, and no seed was specified, all numerical answers provided in this document are examples of possible results. The numerical values presented here will be different if the simulations are repeated.

B. Comments on candidate performance in this diet of the examination.

Overall performance in CS1B was satisfactory. Well prepared candidates were able to score highly.

Comments given alongside the R output were not always clear or adequate. Some candidates failed to provide clear numerical answers as required in the questions. Also, the main R output was missing in some cases.

A number of candidates provided their answers in a layout that was not satisfactory, with input and output being separated and presented with large gaps, and with significant duplications.

C. Pass Mark

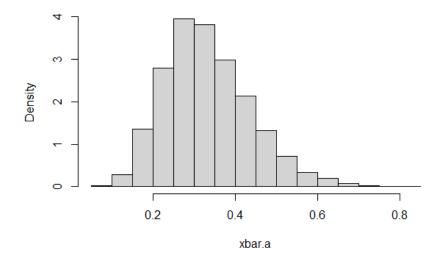
The Pass Mark for this exam was 60. 1508 presented themselves and 730 passed.

Solutions for Subject CS1B - September 2023

(ii)
R Code:
xbar.a = apply(m1,1,mean) [1]

hist(xbar.a,freq=F,main="Sampling distribution of Xbar") [1]

Sampling distribution of Xbar



(iii) Using the CLT, the sampling distribution should be N(1/3, 1/90). [2]

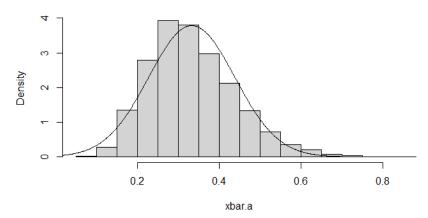
R code:

}

$$x.grid = seq(0,1,length=1000)$$
 [1]
lines(x.grid,dnorm(x.grid,1/3,sqrt(1/90))) [2]

[1]

Sampling distribution of Xbar



The curve shows the exact pdf of the sampling distribution.

(iv) The sampling distribution is relatively asymmetrical compared to the normal. [1] The CLT does not work very well here [1] as the sample size is small (n = 10). [1] [Total 16]

Parts (i)-(iii) were well answered in general. A common error in part (i) was not using properly the inverse transform method as the question asked.

Part (iv) was not well answered, with comments often being vague or not consistent with the graphs plotted earlier.

```
\mathbf{O2}
```

(i)

Simulate samples:

set.seed(12345)
data.A = rbinom(900,1,0.020)
data.B = rbinom(1200,1,0.025)

#data.A; data.B [2]

(ii)
n.A = length(data.A); n.B = length(data.B)
thetahat.A = sum(data.A)/n.A
thetahat.B = sum(data.B)/n.B
thetahat.A; thetahat.B
0.02111111
0.02916667
[2]

[1]

[1]

```
ese.diff = sqrt( thetahat.A*(1-thetahat.A)/n.A +
thetahat.B*(1-thetahat.B)/n.B)
ese.diff
# 0.006823359
                                                                    [1]
ci.theta.diff = (thetahat.A-thetahat.B) + c(-
1,1)*qnorm(0.995)*ese.diff
ci.theta.diff
#[1] -0.025631365 0.009520254
                                                                   [1]
The 99% CI for the difference in proportions is [-0.025631365, 0.009520254]
                                                                   [1]
(iii)
Hypotheses:
                                                                   [1]
H0: theta_A = theta_B v. H1: theta_A < theta_B</pre>
Statistic:
thetahat.common = (sum(data.A)+sum(data.B))/(n.A+n.B)
thetahat.common
# 0.02571429
                                                                    [1]
ese.diff.H0 = sqrt( thetahat.common*(1-thetahat.common) *
(1/n.A + 1/n.B))
ese.diff.H0
# 0.006979562
                                                                    [1]
stat.diff = (thetahat.A-thetahat.B)/ese.diff.H0
stat.diff
# -1.154163
The value of the statistic is -1.154163
                                                                   [1]
P-value:
pvalue.diff =[ pnorm(stat.diff)
pvalue.diff
# 0.1242166
The p-value of the test is 0.1242166
                                                                    [2]
Conclusion:
We do not have evidence against the null hypothesis of equal proportions
                                                                   [1]
at level 12.4%
                                                                   [1]
so we do not reject it.
                                                                   [1]
                                                               [Total 16]
```

Part (i) was well answered in general. A common error was using rbinom(1, n, p), therefore not producing the detailed sample.

In part (ii) there were mixed answers with various errors.

Answers in part (iii) were also mixed, with common errors including not stating correctly, or at all, the hypotheses, parameter errors and not providing a clear conclusion.

```
Q3
#Initialise the dataset.
> data("cars")
> attach(cars)
(i)
                                                              [1]
> model = lm(dist~speed, data = cars)
> model
Call:
lm(formula = dist ~ speed, data = cars)
Coefficients:
(Intercept)
                speed
-17.579
                3.932
                                                              [1]
(ii)
> data predict <- data.frame(speed =</pre>
c(6,7,16,22,28,33,40,42,57,64))
                                                              [2]
> predict(model,newdata=data_predict)
                                                              [2]
           2
                       3
6.015358 9.947766
                    45.339445
                             68.933898
                                        92.528350
                                                    112.190394
                              9
    7
                8
                                       10
139.717255 147.582073 206.568204 234.095066
                                                              [1]
(iii)
> predict(model,newdata=data_predict,
interval="confidence",level=0.90)
                                                              [3]
      fit
                   lwr
                              upr
1
     6.015358
                -1.482803
                            13.51352
2
                3.050136 16.84540
     9.947766
3
    45.339445 41.667593
                            49.01130
4
    68.933898 63.063300
                           74.80450
5
    92.528350 83.019704 102.03700
```

112.190394 99.393826 124.98696

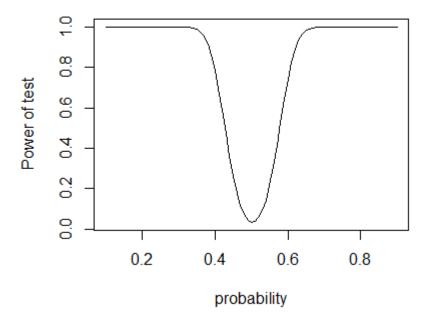
```
139.717255 122.189498 157.24501
7
    147.582073 128.688793 166.47535
    206.568204 177.348219 235.78819
10 234.095066 200.029446 268.16069
                                                                                  [1]
(iv)(a)
The CI is constructed such that with repeated sampling, 90% of the obtained intervals
will contain the true unknown mean stopping distance of cars travelling at 64 mph.
                                                                                  [1]
(b)
For speed 6mph the model gives a CI with negative lower endpoint.
                                                                                  [\frac{1}{2}]
A linear model, predicting negative stopping distance values, may not be
appropriate.
                                                                                  [\frac{1}{2}]
                                                                            [Total 13]
 Parts (i)-(iii) were very well answered in general.
 The answers in part (iv) varied, with a number of candidates giving unclear comments.
Q4
(i)(a)
The probability of heads or tail for a fair coin is 0.5.
                                                                                  [1/2]
round(1 - pbinom(115,200,0.5) + pbinom(84,200,0.5),2)
                                                                                  [4]
# Answer is 0.03
                                                                                  [\frac{1}{2}]
The probability of rejecting the hypothesis of fair coin when it is actually correct is
0.03.
(b)
As the sample size n is large, the binomial distribution can be approximated by the
normal distribution with mean np and variance np(1-p) using CLT.
                                                                                  [1]
Applying continuity correction, the probability of rejecting the hypothesis of fair
coin when it is actually correct, is calculated as:
round(1 - pnorm((115.5 - 100)/sqrt(50)) + pnorm((84.5-
100)/sqrt(50)), 2)
                                                                                 [3\frac{1}{2}]
Answer is: 0.03
                                                                                  [\frac{1}{2}]
(c)
We obtain the same answer and conclude the approximation works well.
                                                                                  [1]
(ii)
A coin is judged fair if in a single sample of 200 tosses, between 85 and 115
(inclusive) heads occur, with p = 0.7 here:
```

round(pbinom(115, 200, 0.7) - pbinom(84, 200, 0.7),4)

[3]

(iii)
p = seq(0.1, 0.9, 0.01)
pow = round(1 - (pbinom(115, 200, p) - pbinom(84, 200, p)),4)

[3]



[1]

(v)
The power of the test increases as we get away from the fair coin probability. [1]
This is consistent with the definition of the power of a test since the ability to reject the null hypothesis of coin being fair should be higher when the hypothesis should be rejected. [1]

[Total 24]

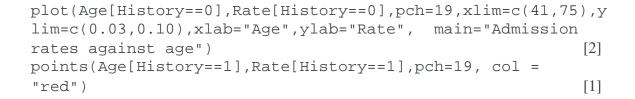
Parts (i)-(iv) were answered reasonably well, with common errors including incorrect parameterisations for the binomial distributions involved.

Part (v) was not well answered with a number of candidates not attempting it.

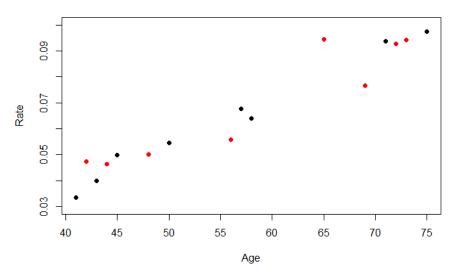
Q5

(i)

R code:

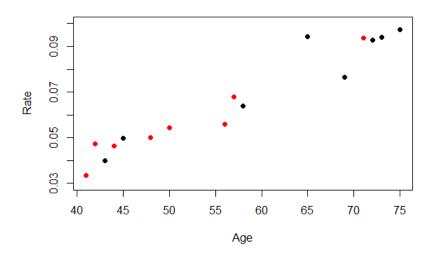


Admission rates against age



Black bullets: History = 0; red bullets: History = 1. [2]

(ii)
R code:
plot(Age[Operation==0],Rate[Operation==0],pch=19,xlim=c(41,
75),ylim=c(0.03, 0.10),xlab="Age",ylab="Rate") [2]



```
Black bullets: Operation = 0; red bullets: operation = 1.
                                                              [2]
(iii)
Age seems to have a clear increasing effect on rates.
                                                              [1]
The effects of History and Operation are not clear.
                                                              [1]
(iv)
R code:
m1 = glm(Rate ~ History + Operation + Age, family =
gaussian(link="log"))
                                                              [2]
summary(m1)
#Call:
#glm(formula = Rate ~ History + Operation + Age, family =
gaussian(link = "log"))
#Deviance Residuals:
     Min
                   10
                           Median
                                              30
                                                         Max
#-0.0096278 -0.0027215
                           -0.0004823
                                         0.0030534
                                                      0.0165070
#Coefficients:
              Estimate Std. Error t value Pr(>|t|)
0.008975
                         0.051115 0.176
                                                 0.864
#History1
             0.010137 0.061309 0.165
#Operation1
                                                 0.871
#Age
               0.025690 0.002616 9.822 4.35e-07 ***
#---
#Signif. codes:
                  0 \***' 0.001 \**' 0.01 \*' 0.05 \.' 0.1 \
#(Dispersion parameter for gaussian family taken to be
4.6878e-05)
     Null deviance: 0.00738638
                                          degrees of freedom
                                  on 15
#Residual deviance: 0.00056253
                                  on 12
                                          degrees of freedom
#AIC: -108.68
                                                              [1]
(v)
History does not have a significant impact since p-value is large (0.864).
                                                              [\frac{1}{2}]
Operation does not have a significant impact since p-value is large (0.871).
                                                              [\frac{1}{2}]
Age has a highly significant
                                                              [1]
positive effect since p-value is very small, 4.35e-07.
                                                              [1]
(vi)
R code:
m2 = glm(Rate ~ History + Operation + Age + Comorbidity,
family = gaussian(link="log"))
                                                              [2]
summary(m2)
```

```
#Call:
#glm(formula = Rate ~ History + Operation + Age +
Comorbidity,
     family = gaussian(link = "log"))
#
##
#Deviance Residuals:
       Min
                              Median
                      10
                                                30
                                                           Max
                                        0.002753
#-0.005923 -0.002551
                          -0.001152
                                                     0.006639
#Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
                              0.151308 -27.781 4.93e-10 ***
#(Intercept) -4.203456
                                           0.124
#History1
                 0.005103
                              0.041287
                                                    0.9044
#Operation1
                 0.006746
                              0.050478
                                           0.134
                                                    0.8966
                 0.027170
                              0.002302 11.803 8.86e-07 ***
#Age
#Comorbidity2 -0.182506
                              0.058996 - 3.094
                                                    0.0129 *
                              0.059872
#Comorbidity3 -0.149206
                                         -2.492
                                                    0.0343 *
#Comorbidity4 -0.125286
                              0.059462
                                          -2.107
                                                    0.0644 .
#---
#Signif. codes: 0 \***' 0.001 \**' 0.01 \*' 0.05 \.' 0.1 \
1
#(Dispersion parameter for gaussian family taken to be
2.927809e-05)
     Null deviance: 0.0073864
                                    on 15
                                            degrees of freedom
#Residual deviance: 0.0002635
                                    on 9
                                            degrees of freedom
#AIC: -114.82
                                                                   [1]
(vii)
As before, History and Operation do not have a significant impact, while age still
has a highly significant positive effect.
                                                                  [1\frac{1}{2}]
Comorbidity has significant impact,
                                                                   [1]
with levels 2-3 (comorbidities B-C) having a significant reducing effect as
compared to level 1 (baseline, comorbidity A)
                                                                   [1]
and level 4 (comorbidity D) having a marginally (non-)significant negative impact.
                                                                   [\frac{1}{2}]
(viii)
The model with the 4 covariates in part (vi) should be preferred,
                                                                   [1]
as it has smaller AIC.
                                                                   [1]
(ix)
Predicted link function value is:
- 4.203456 - 0.182506 + 0.027170 * 62
  -2.701422
                                                                   [1]
and predicted value is:
\exp(-2.701422) = 0.06711001
                                                                   [1]
```

(x) The used GLM has a logarithmic link, which implies that predicted rates can be above 1.

[2] **[Total 31]**

In parts (i)-(iii) answers were mixed, with many candidates failing to distinguish between the different history and operation levels.

Parts (iv)-(viii) were generally well answered. Common errors included failing to use a logarithmic function as specified in the question and comments often being limited or vague.

Answers in part (ix) were mixed, with a number of candidates failing to use the correct link function.

Part (x) was not well answered, with many candidates not attempting it.

[Paper Total 100]

END OF EXAMINERS' REPORT



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