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Introductory programming at Lincoln: attributes of successful students

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Abstract

In 1994, the introductory programming class at Lincoln University, New Zealand was surveyed, and logistic and ordinal regression models were used to determine the student attributes associated with achievement. Students who intended to major in computing were more likely to achieve than those with other intentions, and older students were more likely to achieve than younger students. Other factors such as gender, previous exposure to computing at a tertiary level, previous tuition in English, experience in programming and experience with computers in general, all had no apparent association with achievement. Female students had a lower pass rate than males but this was because a smaller proportion of females intended to major in computing.

1. Introduction

Many overseas studies have found low and decreasing female participation rates in computer science (Clarke and Chambers 1989, Durndell 1991, Bernstein 1994, Clarke and Teague 1994, Sturm and Moroh 1994). Studies in New Zealand have found similar trends (Toynbee 1993a, Toynbee 1993b, Ryba and Selby 1995, Brown, Andreae, Biddle and Tempero 1996). At Victoria University, women made up only 20% of the introductory programming class in 1994, and only 40% of women in this class (compared with 68% of the men) passed at a level that allowed them to continue on to higher programming classes (Brown *et al* 1996).

We felt that at Lincoln the situation was different. In our 1994 introductory programming class, 44% of the students were women and 57% of these women (compared with 68% of the men) passed at a level that allowed them to take more advanced computing papers (Table 6 in Appendix 1[1]). To learn more about our students, we surveyed the introductory programming class of 1994. We used multivariate statistical methods (logistic regression, proportional odds and loglinear models) to determine the student attributes associated with achievement.

2. Methods

2.1 The class studied

In 1994 introductory programming was taught at Lincoln University in COMP201[2]. Most of the students enrolled in this paper were commerce students. About half of the students enrolled in the paper intended to major in Applied Computing, within a Bachelor of Commerce and Management degree (Table 10 in Appendix 2). The content of COMP201 was similar to that taught at the time in introductory programming papers at other New Zealand universities. Concepts such as assignment statements, conditional statements, loops, procedures and arrays were taught using Turbo Pascal (Appendix 3).

We measured student performance in COMP201 by the student's end of year grade. At Lincoln, those who do not sit the final exam are given a DNS grade, regardless of any marks gained in internal assessment. Lincoln's grade scale has 12 categories. We combined categories to express performance as four levels of achievement:

- DNS - did not sit the final exam;
- F - sat the final but gained such a low grade that they were not allowed to take more advanced computing papers (Grades E, D, C-);
- P - sat the final and gained an 'ordinary' pass (Grades C, C+, B- and B);
- G - sat the final and gained a 'good' pass (Grades B+, A-, A and A+).

In the third week of the semester, COMP201 students were given a questionnaire to complete. Students were free to join or leave the class up until the third week. Of the 105 students on the class list when the questionnaire was given out, 97 completed the questionnaire - a response rate of 92%. Of the eight students who did not complete the questionnaire, seven subsequently failed COMP201 (Table 7 in Appendix 1). This means there may be some bias in our survey results in favour of the sort of student who passes COMP201.

[1] At Lincoln, C- is a restricted pass equivalent to a pass for all purposes <u>except</u> as a prerequisite.

[2] Introductory programming is now taught in a stage one paper, COMP102.

2.2 Survey data

The questionnaire (Appendix 4) collected personal information, reasons for taking the paper and the student's expectations, and previous education and computing experience. In each of our analyses, we looked for associations between achievement and the following variables:

- Age - a discrete variable: values ranged from 17 to 48;
- Gender - a binary variable taking the value one if the student was male;
- Major - a binary variable taking the value one if the student intended to major in computing (Question 2);
- Expect - a binary variable taking the value one if the student expected to get an A or A+ (Question 4);
- COMP101 – a binary variable taking the value one if the student indicated that they had already taken COMP101[3] (Question 5);
- Tertiary – a binary variable taking the value one if the student indicated that they had already taken either COMP101 or some other computing paper at a tertiary institution (Question 5);
- Home - a binary variable taking the value one if the student was planning to make use of a home computer (Question 6);
- Maths – a binary variable taking the value one if the student had enjoyed mathematics at school (Question 9);
- English - a binary variable taking the value one if the student had been taught before in the English language (Question 12);
- School - a binary variable taking the value one if the student had used a computer as part of a course at school (Question 15);
- Score_1 - a score representing previous computing experience; the sum of answers in Question 20 for all rows except the last two.
- Score_2 - a score representing previous programming experience; the sum of answers in Question 20 for rows Pascal, Basic and Other programming languages;

Each of these 'predictor variables' is summarised in Appendix 2 (Tables 8-19), cross-classified by the ordinal 'response variable' Level with the four levels of achievement described in section 2.1. We identified a single outlier using ordinal regression (see section 3.2). We left this student out of the tables in Appendix 2 and out of our analysis of survey data.

2.3 Logistic regression

Logistic regression is a form of regression appropriate for a binary response variable. Consider three steps, each representing a move from one level of achievement to the next. To model the first step, students who did not sit the final exam are coded as a zero and those who did sit are coded as a one. A logistic regression model using this binary response is a way to identify the attributes of those more likely to sit the final exam. The second step concerns just the students who sit the final: those who failed the paper are coded as a zero and those who passed are coded as a one. Of those who sit the final, what are the attributes of those more likely to pass COMP201? The third step concerns just the students who pass the COMP201: those who just pass are coded as a zero and those who pass well are coded as a one. Of those who pass COMP201, what are the attributes of those more likely to pass with good marks? This last step

[3] COMP101, an introductory computing paper, was 'recommended preparation' for COMP201.

excludes students who fail, so there should be no non-response bias in a model for this step.

We used PROC LOGISTIC in SAS to find logistic regression models for each of these three steps. We chose between alternative models using the Wald statistic and changes to the log likelihood ratio statistic (Dobson 1990 p61-62). Both statistics should follow a chi-square distribution, and large values (and small p-values) indicate that a predictor has a significant association with the response variable. Overall goodness-of-fit for a model was assessed using regression diagnostic plots and the Hosmer-Lemeshow statistic (SAS Institute 1996 p425-430). This statistic should also follow a chi-square distribution, and large values (and small p-values) indicate a lack of fit.

2.4 Ordinal regression

The approach in the previous section has a disadvantage - each binary response carries less information than the original ordinal response with its four levels of achievement. A single model for the ordinal response may have more power to detect variables that are associated with higher levels of achievement. An appropriate ordinal regression model is the proportional odds model. We think it reasonable to consider each ordinal response as representing an underlying continuous response - the student's final mark for the paper - but this continuous response cannot be measured if the student does not sit the final exam. If a linear regression model is appropriate for this underlying continuous response and certain predictor variables, then a proportional odds model is appropriate for the ordinal response and these predictors (Anderson and Philips 1981, Agresti 1990 p322-324). This assumption of an underlying linear regression model is called the proportional odds assumption.

We again used PROC LOGISTIC to fit proportional odds models with Level as the ordinal response variable. We chose between alternative models using the Wald statistic and changes to the log likelihood ratio statistic. Overall goodness-of-fit for a model was assessed using plots; the proportional odds assumption was tested using a score statistic (SAS Institute 1996 p415-416). This statistic should follow a chi-squared distribution and large values (and small p-values) indicate that the proportional odds assumption is unlikely. Note that this statistic is not considered particularly reliable if the model includes a quantitative predictor variable such as Age (Peterson and Harrell 1990).

3. Results

3.1 Logistic regression

A logistic regression model for those sitting the final exam (Table 1) implies that those who expect to get a good grade are more likely to sit the final exam. In Table 1, Δ LLR is the decrease in log likelihood ratio when a predictor is added into a model already containing the parameters on rows above it. If Major or School are added to the model, the fitting algorithm cannot converge because of 'sampling zeros' - all students planning to major in computing and all students who did not use a computer at school sat the final exam (see Tables 10 and 17 in Appendix 2). Without convergence parameter, estimates are not to be trusted; however predicted probabilities are usually accurate and the change in the log likelihood ratio is usually reliable (McCullagh and Nelder 1989 p117). The change in the log likelihood ratio suggests that both the variables Major and School are needed in a model for those sitting the final exam; the Hosmer - Lemeshow statistic suggests that the model in Table 1 with three predictor variables is a good fit. Parameter estimates are greater than zero for Major and less than zero for School - this suggests that those who intend to major in computing are more likely to sit the final exam, and those who use a computer at school are less likely to sit the final exam (reflecting the data in Tables 10 and 17).

Table 1 Logistic regression model for sitting the final exam[4]

Parameter	Estimate (SE)	Wald (df)	p-value	Δ LLR (df)	p-value
Intercept	1.5 (0.4)				
Expect	2.0 (1.1)	3.5 (1)	0.06	5.4 (1)	0.02
Major	***	***	***	13.5 (1)	<0.01
School	***	***	***	7.6 (1)	<0.01
Hosmer - Lemeshow statistic = 0.01 (1 df), p-value = 0.94					

The single predictor variable Age seems to provide an adequate model for the second step. For those who sit the final exam, the probability of passing COMP201 increases with increasing age (Table 2).

Table 2 Logistic regression model for passing COMP201[4]

Parameter	Estimate (SE)	Wald (df)	p-value	Δ LLR (df)	p-value
Intercept	-2.2 (1.6)				
Age	0.15 (0.08)	3.8 (1)	0.05	5.9 (1)	0.01
Hosmer - Lemeshow statistic = 5.0 (6 df), p-value = 0.55					

A model for achieving a good pass in COMP201 suggests that students who pass are more likely to achieve a good pass if they're older and aren't planning to make use of a home computer (Table 3).

Table 3 Logistic regression model for a good pass in COMP201[4]

Parameter	Estimate (SE)	Wald (df)	p-value	Δ LLR (df)	p-value
Intercept	-3.2 (1.6)				
Age	0.19 (0.08)	6.4 (1)	0.01	7.4 (1)	0.01
Home	-1.2 (0.6)	3.8 (1)	0.05	4.0 (1)	0.05
Hosmer - Lemeshow statistic = 4.7 (6 df), p-value = 0.59					

3.2 Ordinal regression

Ordinal regression suggests higher levels of achievement are associated with increasing age and with students who intend to major in computing (Table 4). The

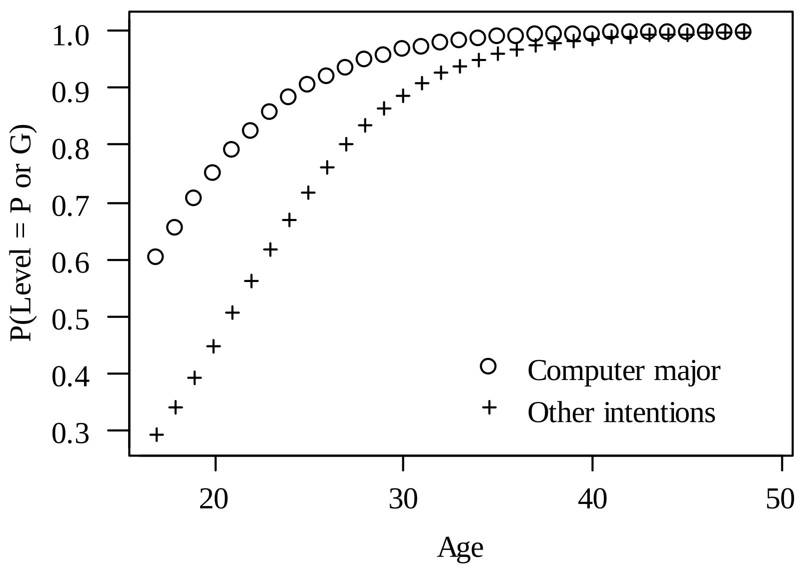
[4] Probabilities can be predicted from the model using equation 4.7 in Agresti (1990).

model in Table 4 can be represented by graphs such as Figure 1. Here the predicted probability of passing (ie Level = P or G) is shown for the range of ages found in the class. The upper curve represents those who intend to major in computing, while the lower curve represents those with other intentions.

Table 4 Proportional odds model for achievement in COMP201[5]

Parameter	Estimate (SE)	Wald (df)	p-value	Δ LLR (df)	p-value
Intercepts	3.4 (1.4)				
	4.8 (1.4)				
	6.0 (1.4)				
Age	0.23 (0.06)	12.7 (1)	<0.01	17.5 (1)	<0.01
Major	1.3 (0.4)	10.1 (1)	<0.01	10.5 (1)	<0.01
Score statistic for proportional odds assumption = 5.8 (4 df), p-value = 0.22					

Figure 1 Probability of passing COMP201 predicted by the proportional odds model



There's no evidence from the score statistic (Table 4) that this proportional odds model is inappropriate. To examine the fit of the model, we looked at plots of predicted probability. For each student, the probability of achieving a good pass under this model is shown in Figure 2. Students who did not sit the final (ie observed Level = DNS) have a low predicted probability of achieving a good pass. We identified an outlier using these plots (Figure 3). This student was one of the oldest in the class and intended to major in computing, but failed the paper. Lecturers attributed the student's poor performance to overconfidence. We've left this student out of the tables in Appendix 2 and out of our analysis of survey data (Tables 1-5).

[5] Probabilities can be predicted from the model using equations 9.10 and 9.12 in Agresti (1990).

Figure 2 Predicted probability of achieving a good pass
(Level = G)

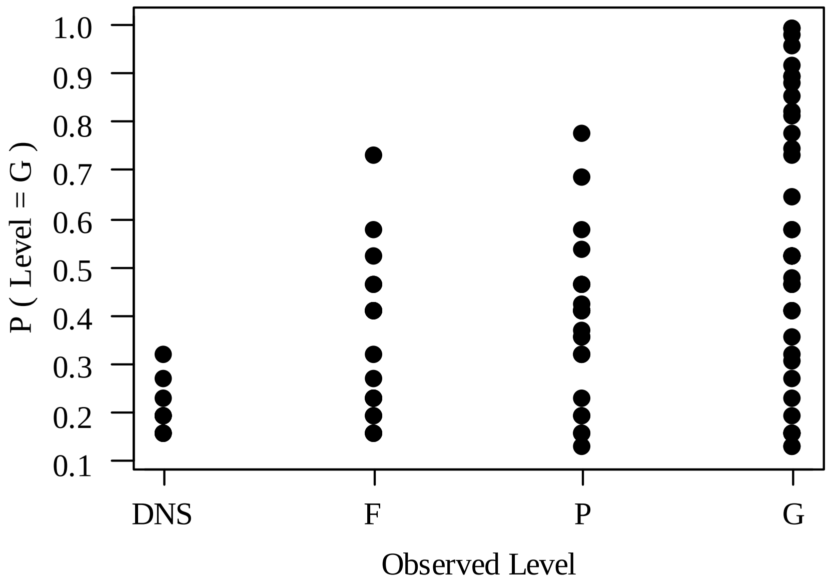
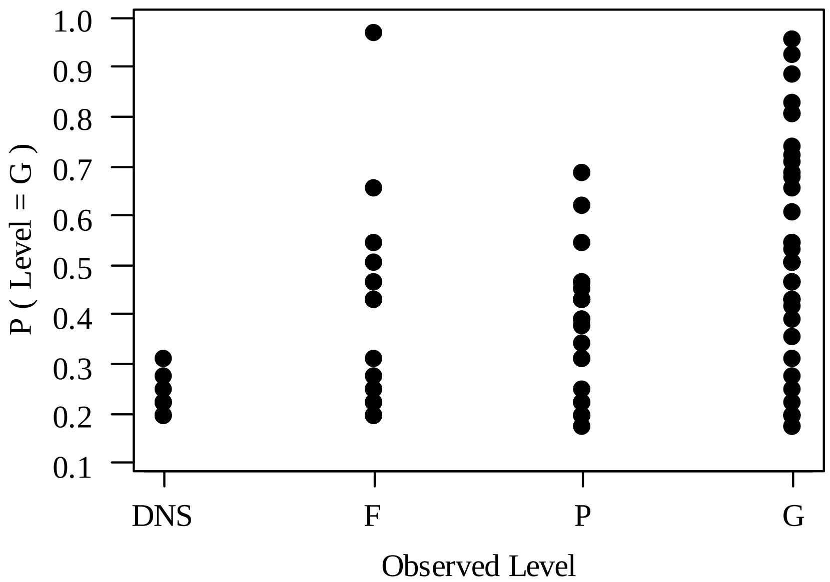


Figure 3 Predicted probability of achieving a good pass
(Level = G) with outlier included



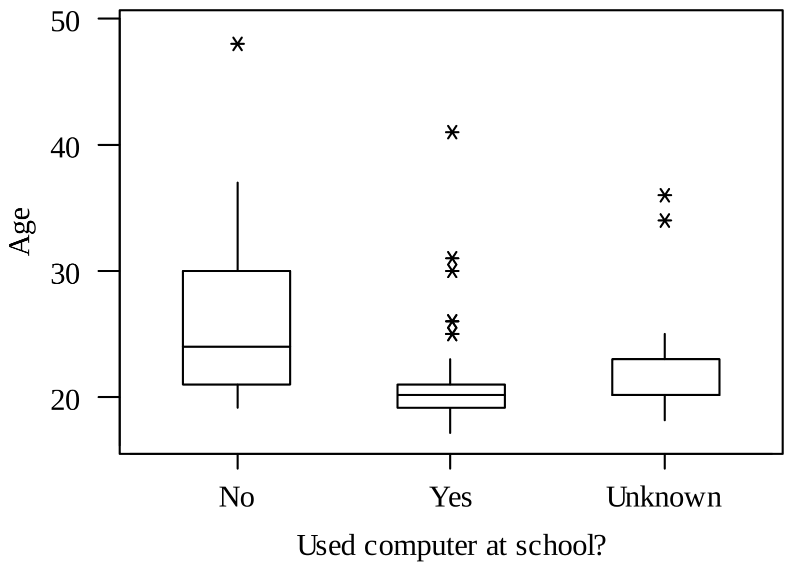
4. Discussion

In each model, the largest decreases in the log likelihood ratio statistic are the result of adding either the predictor variable Age or Major or both. We think the strong associations between each of these two variables and achievement in COMP201 reflects student motivation. Older students and those who intend to major in computing tend to be more motivated, and so are likely to do better.

In contrast, other factors we thought might influence achievement had no apparent association with achievement in COMP201 - factors such as gender, previous exposure to computing at a tertiary level, previous tuition in English, experience in programming and experience with computers in general. Not all students who handed in a questionnaire answered questions about previous tuition in English and about their use of computers at school (see Tables 16 and 17 in Appendix 2) so we are less certain about associations involving these two variables.

Our modeling suggests that students who have used a computer at school are less likely to sit the final exam. We think this association is related to age. Those who have not used a computer at school tend to be older (Figure 4), and older students tend to do better in this paper.

Figure 4 Boxplots for age given past use of computers at school



We are confident that there is no direct association between gender and higher levels of achievement in COMP201. Gender was not an important factor in any of our models, even though 57% of the women in the class passed at a level that allowed them to take more advanced computing papers compared with 68% of the men. The lower 'pass rate' among women can be attributed to a lower proportion of women intending to major in computing (Table 5). A loglinear model for Table 5 (Agresti 1990 p130-149) confirms the presence of a strong association between passing (Level = P or G) and an intention to major in computing; a weak association between an intention to major in computing and gender; and no association between gender and passing.

Table 5	Intend to major in computing?			
	Yes		No	
Level	Women	Men	Women	Men
DNS or F	3	6	13	9
P or G	13	24	13	15
Overall	16	30	26	24

We cannot explain why students who plan to make use of a home computer are less likely to achieve a good pass in COMP201. At least we can reassure our future students that they do not need to have a computer at home nor do they need previous experience with computers to do well at introductory programming. We can reassure older and female students: older students do better than younger students and female students seem to do as well as male students.

Many studies have shown that older students are highly motivated, and that they tend to have better study skills and habits (ie Devlin 1996). Older students typically strive for 'deeper' learning (Richardson 1994, Sadler-Smith 1996) and have higher expectations of completing a paper (Mercer 1993). Other studies have found women doing at least as well as men in computer science papers. Taylor and Mounfield (1994) found similar final grade distributions for men and women, and similar pass rates for native and non-native English speakers. However they found different pass rates for those with and those without prior computing experience. Sturm and Moroh (1994) found that women, many of whom were older students, had significantly higher pass rates than men. Despite this, female enrollment and retention rates were low and falling.

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6. Appendices

6.1 Appendix 1: Summary of the class studied

Table 6		COMP201 students in 1994		
		Female	Male	Overall
Age	Median	20	20	20
	Interquartile range	19-23	19-24	19-23
	Range	17-43	18-48	17-48
Grade	DNS	6	9	15
	E, D, C-	14	10	24
	C, C+, B-, B	9	15	24
	B+, A-, A, A+	17	25	42
Number in class		46	59	105

Table 7	COMP201 students who did not complete a questionnaire	
Grade	Age	Gender
DNS	20	M
DNS	20	M
DNS	23	M
E	18	F
E	20	M
E	23	F
E	25	F
A+	36	M

6.2 Appendix 2: Summary of survey data

Table 8	Age summarised for each Level				
	DNS	F	P	G	Overall
Median	20	20	20	22	20
Interquartile range	19-21	19-22	19-23	19-31	19-23
Range	19-23	18-25	18-27	17-48	17-48
Number of observations	15	23	24	42	104

Table 9	Counts of Gender for each Level				
	DNS	F	P	G	Overall
Female	6	13	9	17	45
Male	9	10	15	25	59

Table 10	Counts of Major for each Level				
	DNS	F	P	G	Overall
Other intentions	10	12	11	17	50
Computer major intended	0	9	13	24	46
Missing	3	4	0	1	8

Table 11	Counts of Expect for each Level				
	DNS	F	P	G	Overall
Other grades expected	10	10	12	21	53
A or A+ expected	2	8	12	20	42
Missing	3	5	0	1	9

Table 12	Counts of COMP101 for each Level				
	DNS	F	P	G	Overall
Haven't sat COMP101	2	2	5	15	24
Have sat COMP101	10	14	18	26	68
Missing	3	7	1	1	12

Table 13	Counts of Tertiary for each Level				
	DNS	F	P	G	Overall
No tertiary computing	1	2	2	7	12
Previous computing paper	11	17	22	34	84
Missing	3	4	0	1	8

Table 14	Counts of Home for each Level				
	DNS	F	P	G	Overall
Won't use home computer	7	14	10	23	54
Will use home computer	5	5	14	18	42
Missing	3	4	0	1	8

Table 15	Counts of Maths for each Level				
	DNS	F	P	G	Overall
Didn't enjoy maths	3	2	9	9	23
Enjoyed maths at school	8	16	15	32	71
Missing	4	5	0	1	10

Table 16	Counts of English for each Level				
	DNS	F	P	G	Overall
Not taught in English	8	18	22	35	83
Taught in English	1	1	2	4	8
Missing	6	4	0	3	13

Table 17	Counts of School for each Level				
	DNS	F	P	G	Overall
Didn't use computers	0	4	6	17	27
Used computers	10	13	17	21	61
Missing	5	6	1	4	16

Table 18	Score_1 summarised for each Level				
	DNS	F	P	G	Overall
Median	19	24	21	20	20
Interquartile range	12-23	14-26	17-31	13-30	14-28
Range	3-32	0-30	12-36	3-38	0-38
Number of observations	12	19	24	41	96
Missing	3	4	0	1	8

Table 19	Score_2 summarised for each Level				
	DNS	F	P	G	Overall
Median	2	3	3	2	3
Interquartile range	1-3	1-4	2-5	1-5	1-4
Range	0-6	0-10	1-8	0-9	0-10
Number of observations	12	19	24	41	96
Missing	3	4	0	1	8

6.3 Appendix 3: Subject outline for COMP201 in 1994

COMP201 Computer Programming

Subject Outline 1994

General:	COMP201 is offered to students in the BCom, BHortSc, BAgrSc and BSc degrees by the Centre for Computing and Biometrics in the first semester.
Examiner:	Theresa McLennan (room H102, ext 8028)
Lecturer:	Debby Hutchison (room H193, ext 8908)
Tutor:	Peter McNaughton, (room H104, ext 8011)
Prescription:	The development of skills and knowledge to solve problems using a computer. The development of a basic understanding of interaction between procedures and data, and algorithm development and programming. Introduction to data structures. Simple file organisation.
Aims:	The aim of this subject is to introduce students to programming in a high level computing language. The language used in the paper is Pascal but the techniques developed will be applicable to problem solving in general.
Objectives:	On completion of this paper, students will be able to: i) design algorithms from real-life problems and present them in pseudocode format. ii) implement these algorithms using Turbo Pascal (version 6.0).
Assessment:	The assessment will be as follows: Labs 10% Project 15% Tests (2) 20% Exam55% The open book tests will be held during normal lecture times on Tuesday 29 March and Tuesday 24 May. The project will be due on Wednesday 1 June but will be accepted up to one week late. Late projects and assignments will have 20% of their total mark value deducted.
Laboratories:	Attendance is strongly advised. A lab manual should be purchased from the Bookshop. The labs are designed primarily to enhance the learning process but will contribute to the final grade as indicated above.
Textbook:	"Turbo Pascal (third edition)" by E.B. Koffman. Students should purchase this text as most of the examples covered in lectures will be taken directly from it.

`	Topics	Labs
1	Introduction to computer programming, Turbo Pascal and the IDE.	-
2	Program structure, assignment statements, input and output, data types, If statements.	1. IDE, simple programs
3	Program style, If statements, loops, case statements.	2. Ifs and loops
4	Math functions, random numbers, problem solving, structure diagrams.	3. Loops and math functions
5	Procedures and parameters.	4. Procedures
6	Procedures and parameters, Test 1.	Catch up
Easter/study break		
7	Using text files, boolean variables.	Catch up
8	Ordinal types and ordinal functions. User-defined functions.	5. Files, booleans
9	Arrays and strings.	6. Ordinal and user-defined functions
10	Subranges and sets, built in units.	7. Arrays and strings
11	Enumerated data types, scope, records.	Project
12	Arrays of records, Test 2.	Project
13	Arrays of records, searching, sorting.	8. Arrays of records
14	Review and revision.	-

6.4 Appendix 4: The questionnaire

COMP 201 Class Survey

Circle the appropriate options or fill in the gaps.

1. <u>General</u>

Student ID : _________ Age : ___ Sex : M / F

Course (eg BCM):_____ Likely Major (eg Accounting):

Year of University study (circle one):
1. 1st
2. 2nd
3. 3rd
4. 4th or more

2. What is/are your main reason/s for enrolling in COMP 201? (circle one or more)

a. I want to major in computing.
b. I thought it sounded interesting.
c. It would be useful to be able to program.
d. I think it might improve my job prospects.
e. I've enjoyed other computing papers.
f. I needed another subject.
g. other ___________________________________

3. How hard do you expect the work to be in COMP 201 ?

a. Same as other subjects
b. Less than other subjects
c. More than other subjects

4. What grade do you expect to achieve in COMP 201 ?

1. A+
2. A
3. B
4. C

5. - Have you sat COMP <u>101</u> ? Yes / No

- If Yes, what was your grade ?

- Are you sitting COMP 101 this semester ? Yes / No

- Have you sat other computing subjects at Lincoln or other tertiary institutes ?

Subject Grade (eg B+)

____

____

____

6. Are you planning to use a computer at home to help you with the assignments in COMP 201 ?

Yes / No

Educational Background

7. What were your three favourite subjects at school ?

____

____

____

8. Which was your least favourite subject at school?

____

9. Rate the following school subjects according to your enthusiasm for them :

(0 = never done, 1 = disliked, 2 = felt neutral, 3 = quite enjoyed, 4 = really loved)

	(circle one)
Maths	0 1 2 3 4
Computing	0 1 2 3 4
English	0 1 2 3 4
Science	0 1 2 3 4
History	0 1 2 3 4

10. List below the subjects you sat at secondary school, and your approximate marks/grades :

(if not sure of your mark, an estimate will do)

6th form or equivalent (age about 16/17 years) : (if applicable)

Year ________

Subject	Mark/Grade	Subject	Mark/Grade

7th form or equivalent (age about 17/18 years) : (if applicable)

Year ________

Subject	Mark/Grade	Subject	Mark/Grade

11. How do you best learn ? (Circle one or more)

a. Formal lectures
b. Set readings
c. Individual assignments
d. Small group discussions/tutorials
e. Whole class discussions
f. Textbooks
g. Group projects
h. Practical exercises and labs
i. Discussion with peers
j. Video/Film
k. Other
l. Other

12. - Did you attend 6th or 7th form in NZ ? Yes / No

- If not, were the school subjects you attended generally taught in English ?

Yes / No

Computing Background

13. How good are your typing skills ?

0 = none
1 = poor
2 = fair
3 = good
4 = excellent

14. - Have you ever lived in a house that had a "home computer" in use ? Yes / No
- If yes, who were the main users ? (circle one or more)

Your :

a.	self	f.	flatmate(s)
b.	brother(s)	g.	husband
c.	sister(s)	h.	wife
d.	mother	i.	son(s)
e.	father	j.	daughter(s)
k.	other _______________		

15. - Were computers available at your school ? Yes / No

- If Yes, what was the maximum number of times you used them in any one year at school:

(circle one)

- as part of your school course work ? 0 1 2 3 4
- outside scheduled class use ? 0 1 2 3 4

0 = never
1 = less than 10 times
2 = 10 to 20 times
3 = nearly every week
4 = nearly every day

16. How much experience have you had with computers (including games etc)?

0 = none
1 = little
2 = some
3 = more than average
4 = a lot

If you answered 0 to question 16, finish here. Many thanks for your help.

17. Have you ever been a member of a computer club (school or other) ? Yes / No

18. Where else (other than home or school) have you used computers ?

19. At approximately what age did you first use a computer ?

20. Rate the amount of experience you have had with the following applications:
(0 = none, 1 = little, 2 = some, 3 = more than average, 4 = a lot)

DOS	0 1 2 3 4
Pascal	0 1 2 3 4
Basic	0 1 2 3 4
other programming languages	0 1 2 3 4
spreadsheets	0 1 2 3 4
word-processors	0 1 2 3 4
desk-top publishing	0 1 2 3 4
database packages	0 1 2 3 4
games	0 1 2 3 4
bulletin boards or news	0 1 2 3 4
mail	0 1 2 3 4
graphics	0 1 2 3 4
accounting software	0 1 2 3 4
other ____________________	0 1 2 3 4
other ____________________	0 1 2 3 4

Many thanks for your help. The information from this survey will be very useful in assessing and improving this subject.

Debby Hutchison
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