THE ANALYSIS OF PRE-ACCIDENT SEQUENCES

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1.0 INTRODUCTION

1.1 THE STUDY OF BEHAVIOURAL ANTECEDENTS OF ROAD ACCIDENTS

1.1.1 The "traditional" approach

Effective behavioural studies of road accidents have proved to be very difficult to carry out. Despite the abundance of data on most conceivable aspects of the accident process, knowledge about the dynamic relationships between events within the accident situation is still very limited.

The main reasons for this lack of progress seem to be practical. As it is not possible to carry out observational studies on accidents owing to their unpredictable and infrequent nature, behavioural research has typically been done by comparing statistics taken from large databases, such as Stats 19 in the UK, with appropriate exposure data obtained through transport censuses and surveys. From these two sources the involvement rate of a specified category of road user (e.g., young males) in a certain type of road accident (e.g., motorway accidents) can be determined. Where over- or under-involvement is found, behavioural causes are then generally inferred from the study of the normal driving behaviour of that category of road user.

1.1.2 The in-depth approach and its failings

This "traditional" model of research has had some success in improving our understanding of the behavioural antecedents of road accidents, but by the late 1960s its limitations were recognised (Wolf and Fralish, 1969). Causal links are merely inferred rather than identified directly while police reports are often inaccurate and data relevant to particular research questions omitted. In an attempt to overcome these problems, the U.S. established Multidisciplinary Accident Investigation (MDAI) teams in the early 1970s to carry out in-depth investigations of a few accidents, and investigate a larger number of accidents in intermediate depth. Since these initial studies many other in-depth investigations have been carried out in a number of different countries (see Grayson and Hakkert, 1987). However, despite all the effort and expense, to date the results have proved disappointing. Grayson and Hakkert in their review of in-depth accident studies conclude:

"in spite of the tremendous amount of information collected in this type of study, the definitive conclusions reached on the crash process are very limited. ....In the human behaviour and road design aspects, not many firm conclusions for policy implementations were reached." (p.42)

This failure has meant that governments are reluctant to fund in-depth studies and that the "traditional" method still predominates. This raises the issue of whether in-depth studies could, with improvements, work or whether the in-depth approach is doomed to failure. First, let us examine the pessimistic view that in-depth research cannot improve on nomothetic methods.

The advantage of nomothetic methods is that they are relatively cheap and therefore data on a large number of accidents can be collected. In-depth research on the other hand is expensive so few accidents are covered, its supposed strength lying in its detailed coverage of each accident making it a better approximation to what actually happened. If greater understanding is hidden in this extra detail then the in-depth approach will be useful, however it is also possible that the critical details are of a sort that cannot be
obtained even a short time after the accident. Three sources of unreliability must be taken into account:

(i) Inaccessibility to verbal report. Over-learned behaviour, such as driving, often becomes automatic and therefore inaccessible to verbal report. So it may be that the driver was never consciously aware of the critical actions.

(ii) Interference and forgetting. The memory of the witnesses of road accidents is very vulnerable to subsequent (retroactive) interference and so critical information may have simply been forgotten or modified by the time an interview is conducted. For instance, Elizabeth Loftus (1979) found that witnesses testimonies concerning a road accident were affected by the nature of the probe question. Subjects’ mean judgements of the speed of a car involved in an impact ranged from 31.8 mph when 'contacted' was used in a question probing for speed, up to 40.8 mph when 'smashed', was used.

(iii) Covering up of critical information. The driver’s own vested interest may mean that he, or she, may simply not want to tell anyone, or may lie about, what happened, especially if culpability is an issue.

If information critical to the understanding of the crash process is lost in these three ways than it may be that an in-depth approach is bound to be disappointing. However, it is by no means certain that this is the case - according to the optimistic view the failure of previous in-depth studies may be due merely to flaws in their design. This is the stance of Grayson and Hakkert (1987), some of whose criticisms are included in the list below.

(i) Heterogeneity of accidents studied. Typically there has been no sampling of specific accident types. This has led to the existence of large differences within the sample studied and an unsurprising difficulty in finding meaningful patterns in the data.

(ii) On-the-spot investigation. Grayson and Hakkert suggest that far from this being a strength, on-the-spot investigation (so-called “ambulance-chasing”) can cause biases in the data towards injury accidents and certain times of day. The former because of the notification methods used often involve hospitals and the latter because teams are not usually on-call 24 hours a day. These problems disappear if the necessity for an immediate response is removed.

(iii) Multidisciplinary teams. Again, an apparent strength may be counter-productive. These teams are not only expensive but can lead to different interpretations of the contributory factors which may obscure the actual events.

(iv) Data analysis. To date, studies have typically aggregated over cases at a very early stage in the analysis which means that a lot of the structure of the data which has been so expensive to collect is lost. From that point onwards, one of the main advantages over nomothetic approaches is gone but the disadvantage of generally smaller sample sizes remains.

1.2 THE PRESENT STUDY

The main aim of this study was to carry out an in-depth investigation which would not be subject to the above objections, and many of the other criticisms of in-depth studies. It was hoped that after these improvements the utility of the in-depth approach would be increased.
1.2.1 The type of accident

It was decided that the basic source of data would be Nottinghamshire Constabulary records for 1988, as it was expected that the new methods would prove successful on police accident files, thus making a colossal new data base available for accident research in general. This decision was taken despite the well-documented problems involved in the use of police accident records as data for research (Agran and Dunkle, 1985; Hakkert and Hauer, 1987). However, in recognition of these problems police reports were checked whenever apparent inconsistencies or ambiguities arose, by contacting those involved including witnesses of the accidents, reporting officers, and site visits to the location of accidents.

Following the recommendations of Grayson and Hakkert a specific type of accident was targeted in order to cut down the heterogeneity of the sample and thus improve the chances of obtaining meaningful results. The type of accident chosen was the right-turning accident either onto or off a larger road. These were selected because they met the criteria we had set in advance, namely:

(1) they occurred with sufficient frequency in Nottinghamshire within the calendar year of 1988 to give a large enough pool of accidents from which to select the cases for the study;

(2) there was a reasonably long chain of separable events leading up to the accident. As sequence analysis was to be one of the main methods we used (see below) longer chains were desirable to increase the scope for the discovery of meaningful patterns;

(3) the class of accident studied needed to be of particular interest to accident researchers. It seemed that right-turning accidents fitted this criterion because of previous findings that older drivers are over-represented in this class of accident (Moore, Sedgley and Sabey, 1982; Viano, Culver, Evans and Frick, 1990). With the ageing population and the greater susceptibility from side impacts (Viano et al., 1990), it seems that the human and financial cost of this category will increase with time just as the incidence of other types of accident is decreasing.

1.2.2 Data analysis

As mentioned above, the problems of in-depth studies do not stop when the data collection is complete. Even when the mass of data has been assembled, its analysis is still non-trivial. Methods used in other in-depth studies could be criticised for not being powerful or sophisticated enough to do justice to their data. This study aimed to overcome some of the difficulties in analysis by drawing upon a variety of methods from other areas of the behavioural sciences, as well as more conventional statistical analyses.

Sequence Analysis

Previous multiple case studies have typically collected large amounts of data then analysed them with respect to occurrence, or non-occurrence, or certain features and events. However, this method loses a lot of potentially critical information, such as the order of events and other relations between them. It assumes that the same events will have the same effects regardless of the stage of the accident at which they occur.

Sequence analysis on the other hand is a technique which preserves the temporal structure of the data and enables the effects of the order of events to be examined, so it may be
possible to detect chains of events which are especially likely to result in accidents. Such findings would be of special value, because drivers could take appropriate action early enough to be effective if they could recognise such occurrences at an early enough stage. In other words sequence analysis seems a strong candidate to produce results which would suggest behavioural interventions.

The utility of this approach has already been demonstrated by Malaterre at INRETS in France (Malaterre, 1990). He identified fifteen categories of accident each with its own pattern of causation. For example one category consisted of cases where the driver has to evaluate a distance, a speed, or a gap, before making a decision. The point is that these categories are non-arbitrary, and so there may be corresponding types of preventative or remedial measures suitable for the accidents within each category, precisely because the categories are based systematically on the different accident processes which have been found to occur.

Rule-finding

The primary 'rule-finder' we used belongs to a class of computer programs called genetic algorithms because they are based on evolutionary principles. An (initially arbitrary) set of predictive rules is repeatedly put through a cyclical process in which each rule is evaluated for the accuracy with which it can discriminate selected subsets of the data; the worst rules are discarded; the best predictors are retained and 'bred' (that is new versions are produced by modification and combination of two 'parent' rules) and the cycle repeated (Forsyth and Rada, 1986). The rule-finder continues this process up to a specified maximum number of iterations. The power of rule-finding is that it is not only quick and straightforward to carry out but it also tends to converge rapidly on near optimal sets of rules with most kinds of data, capturing linear and non-linear relationships in and between the sequential and the static data, in a way that is impossible with other statistical techniques.

In addition, a second, complementary, method of rule finding - based on Quinlan's ID3 algorithm (Quinlan, 1986) - was employed to generate decision trees.

Other methods of analysis

Other more conventional methods were used such as cluster analysis, prototyping (cf Malaterre, 1989), analysis of variance and other parametric and non-parametric analyses. These methods were used to complement the above techniques because they are better at quantifying certain aspects of the data.

1.2.3 Additional studies

In addition to the main in-depth study a subsidiary study was carried out where a sample of experienced drivers were asked to write an account of a right-turning accident as they envisaged it and a safe right turn (that is one that does not result in an accident). These hypothetical accounts were compared with each other using the same methods as for the real data, and looking for differences in their sequential structure. This was to identify behaviour which is seen as safe and behaviour which is seen as dangerous by the driver sample. Further, differences between real accidents and hypothetical accidents were examined for indications of whether drivers are taking inappropriate precautions by overrating the danger of certain actions or conditions and underrating the danger of others.
2.0 METHOD

The main data collection involved obtaining and coding police reports on actual right turn accidents ("real accidents"). There was also the elicitation of "hypothetical accidents" and "hypothetical safe transits". As real and hypothetical data were collected using very different methods, these methods will be described separately.

2.1 REAL ACCIDENTS

2.1.1 Selection

Two hundred police reports on right-turning accidents were randomly selected from Nottingham Constabulary's records for 1988 (to include 100 right turns off a main road and 100 right turns onto a main road). Of these, 185 were coded by one or other of the two coders with 15 failing at least on one of the following exclusion criteria:

(a) the accident occurred at a roundabout (these were excluded to reduce the heterogeneity of our sample),

(b) there was insufficient data on the police report to allow the accident to be reliably coded,

(c) the accident had obviously been mis-classified as a right turn.

2.1.2 Coding

Among other things included on the coding proforma both 'static features' (such as weather and road conditions, time of day, carriageway type, and so on) and the sequence of events were coded. The static features were unproblematic, but it was necessary to devise a special coding scheme to cope with the sequential information, TRAAL (Traffic-Related Action Analysis Language).

TRAAL

Most road accidents involve at least two participants, who act independently for part of the time. This creates problems for the usual methods of sequential coding because without direct observation it is not possible to interweave the actions of the various participants into a simple event sequence reliably. Therefore, TRAAL is used to code only the actions of the right-turner, and any other relevant actions and events occurring in known relation to that.

TRAAL was created in order to be easily intelligible with only the minimum amount of training. It was hoped that this would improve both intro- and inter-coder reliability, facilitate checking, and make coded accidents easier to explain to untrained readers. Therefore, despite greater problems in computability it was decided to use a structured linguistic representation for coding accident sequences in TRAAL as opposed to an atomistic representation.

---

1 The shorthand for drivers turning onto and off the larger road will be 'Turners Onto' and 'Turners Off' respectively from now on. The vehicle or pedestrian they hit will be referred to as the 'Collider'. Safe transits will be called 'safes'
Each action is coded using a verb, or verb phrase, which may be modified by adverbs or adverbial phrases. Each verb has only a limited number of allowable modifiers, these are defined within TRAAL and are separated from the verb they modify by a slash, e.g. Fails to notice vehicle /left /moving. This allows the accident to be analysed in varying degrees of detail. An example of the sequential coding of a single accident is shown below.

TRAAL coding of the sequential features of a single right-turning accident.

RAIMA
approaches junction
indicates /right
slows
stops
view obstructed by vehicle /right /static
fails to notice vehicle /right /moving
starts right turn
impact /at y10 * /on front /by nearside
stops

[*y10 is a location code specifying the part of the intersection where the accident occurred]

2.1.3 Checking

After the initial coding each coded accident was independently checked by the other coder. This was to check for errors and discrepancies in coding technique. Where these arose the coders discussed the case before making changes. When disagreements occurred these were settled by consulting a third coder. Through this process TRAAL was also further refined and the meaning of terms made more concrete.

After all the data collection and conventions for dealing with missing data were complete a final check of inter-coder reliability was carried out. This was done by setting the rule-finder to find rules that predicted which accidents were coded by which coder. Where the rule-finder was able to find such rules this not only indicated an inter-coder discrepancy but also described its nature. The first time the rule-finder was used some predictive rules were found, so all accidents were checked by both coders jointly and altered where necessary. After this the rule-finder was used again and failed to find any good predictive rules (which is as it should be). If biases had still existed then further iterations of this process could have been made.

2.1.4 Missing data

Where the data contained in the police report appeared to be incomplete or contradictory the original coder entered a query in the ‘Questions’ section of the coding proforma and these, where possible, were checked using one of, or a combination of, the following methods:

(i) writing to participants and witnesses and asking for an account of the accident and questions relating to the specific item of missing information.

RAIMA is the code in TRAAL for a vehicle moving along without any remarkable incident occurring. It is how most of the action sequences begin.
(ii) contacting the reporting police officer to see if she, or he, remembered the accident or, more likely, had relevant notes.

(iii) visiting the site to ascertain the exact nature of the junction.

Using these three checks some, but not all, of the missing data were found, and one further accident was discovered to fail exclusion criterion (c) leaving 184 on which the final analyses were carried out, of which 90 were turning onto, and 94 were turning off, a major road.

2.2 HYPOTHETICAL ACCIDENTS AND SAFE TRANSITS

2.2.1 Subjects

One hundred drivers, 52 males and 48 females, with a mean age of 40.7 years were paid a small honorarium to take part in this experiment. They were recruited through advertisements in the local press and shop windows, and by word of mouth.

2.2.2 Design and procedure

Each subject was taken to a quiet room where they completed two questionnaires. The first asked them to imagine a right-turning accident, write a free form description of how it occurred and then to fill in background details; these details corresponded to the information contained in the police reports of real accidents. The second questionnaire related to a safe right turn (one which did not end in an accident), and again subjects were asked to imagine (or remember) a suitable episode then answer questions which provided the same types of information as those contained in police accident report forms (where this was appropriate). As the safe right turn is such a common manoeuvre for experienced drivers, there seemed to be no point in asking for a hypothetical example to be invented in any sense which would be clearly different from reporting a specific or generic memory.

Although subjects worked in a room alone they had an internal telephone to contact the experimenters if they had any questions. On completion of both questionnaires an experimenter went over the subject's answers with him/her to check for misunderstandings. The subject was then debriefed and paid.

2.2.3 Checking and missing data

The hypothetical accident and safe transit data did not pose the same problems of missing detail as the real accident data, so the methods used for dealing with missing real data were not necessary. However, the same checks as for the real data were carried out on the hypothetical accidents and safe transit descriptions.
3.0 RESULTS

As the present project was intended, at least in part, to test the applicability of a number of novel analytic methods in the field of road-accident research, this section is organized by method of analysis rather than by substantive results. (In section 4 the results from these various techniques are integrated by topic.)

Our main analytic techniques have been grouped under four headings:

- rule finding
- analysis using decision trees
- sequential analyses
- conventional statistics

3.1 RULE FINDING

Several runs of the BEAGLE evolutionary machine-learning system (Forsyth & Rada, 1986) have been conducted. This software attempts to generate logical rules that discriminate between subclasses in a data-set on the basis of predictive attributes or features, using a genetic algorithm. Some of these runs are discussed below.

3.1.1 Injury versus noninjury accidents

An obvious dichotomy, of great practical importance, is that between accidents that result in injury and those that do not. So one of our first BEAGLE runs attempted to discover rules for distinguishing between these two classes.

Given a training set of 107 randomly selected right-turning accidents, the system produced the following pair of rules:

\[
(PULLOVER \ | \ (VEHICLE2 < 2.88)) \\
(FAILSTN > (TYPE > WEATHER)).
\]

The first rule means roughly "the right-turner changes lane from left to right prior to the turning manoeuvre OR the colliding vehicle has less than four wheels". The second is less easy to interpret but is true if and only if:

The Turner fails to notice a vehicle or pedestrian
AND
the Turner is turning Off a larger road
OR
the Turner is turning Onto a larger road in poor weather.

Together these rules can be seen as making a 3-way prediction: Injury if both rules are true, Damage-only if both are false, and uncertain if the rules conflict. Applied to a test set of 77 cases (previously unseen by the rule-generator) the results were as tabulated in Table 1 below.
<table>
<thead>
<tr>
<th>Rule Status</th>
<th>Injury</th>
<th>Damage-only</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Both True</td>
<td>9 (82%)</td>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>Mixed</td>
<td>11 (48%)</td>
<td>12</td>
<td>23</td>
</tr>
<tr>
<td>Both False</td>
<td>8 (19%)</td>
<td>35</td>
<td>43</td>
</tr>
<tr>
<td>All cases:</td>
<td>28 (36%)</td>
<td>49</td>
<td>77</td>
</tr>
</tbody>
</table>

*Table 1*

The Chi-squared value for this crosstabulation is 16.99, with 2 degrees of freedom ($p < 0.001$). It is also worth noting that 3 of the 11 cases when both rules were true were serious-injury accidents, whereas only 1 of the 43 cases with both rules false was a serious accident.

Between them these two rules illustrate many of the features of rule finding by computer. The first rule is simple and obvious, and might be dismissed for that reason. In its defence it should be noted that many equally obvious rules, such as

$$((BREATHT1 > 2) \lor ((SEX1 = 2) \land (AGE1 < 28)))$$

"young male driver or turner fails breath-test"

and

$$((SURFACE > 1) \land (VIEWOBST > SLOWS))$$

"turner fails to slow on wet road surface with view obstructed"

have been tried and have failed.

The second machine-generated rule is slightly less obvious. It exploits an interaction effect between the action of the Turner, the road layout and the weather conditions prevailing. Such a relationship might well be missed by a human investigator. Certainly it cannot be accepted as it stands, but it is valuable so long as we realize that the computer has given us not an answer but a question.

The same analysis was repeated with a different random split of test (84 cases) and training data (100 cases) and a slightly different coding for the variables, which included the presence or absence of certain pairs of action-terms.

The two best rules produced in this second run are listed below.

$$(LITTLE2 \lor (CONFAIL \lor SLOWFAIL))$$

$$(!((OLD1 > SLOWSTOP) \lor (SLOWSTOP > WINTER))$$

The first rule can be interpreted as: "EITHER the Collider is a 2-wheeler or Pedestrian OR the Turner continues through a green light and then fails to notice another vehicle OR the Turner slows down then fails to notice another vehicle". The second rule requires a certain amount of rearrangement. It is true only if:

In Winter (Dec, Jan, Feb):

EITHER

The Turner is 60 or over
OR

The Turner is under 60 but does not slow down then stop

In Other Seasons (March to November):

The Turner is 60 or more but does not slow down then stop.

These two rules together were tried on 84 unseen cases in the same manner as before, with the following outcome.

<table>
<thead>
<tr>
<th>Rule status</th>
<th>Injury</th>
<th>Damage-only</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Both True</td>
<td>15 (75%)</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>Mixed</td>
<td>19 (38%)</td>
<td>31</td>
<td>50</td>
</tr>
<tr>
<td>Both False</td>
<td>1 (7%)</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td><strong>All Cases:</strong></td>
<td>35 (42%)</td>
<td>49</td>
<td>84</td>
</tr>
</tbody>
</table>

Table 2

The Chi-squared of this tabulation is 16.28 (with 2 degrees of freedom) which is significant at the p < 0.001 level. Four of the 20 cases where both rules were true were serious injuries but none of the 14 cases where both rules were false.

Once again the size of the colliding vehicle appears in the most important rule. Indeed the size of the colliding vehicle turns out to be the main single discriminator between injury and non-injury accidents. This is hardly a surprise, so the rule-finding process was repeated without using information about the site of the collider's vehicle.

The two best rules obtained under these conditions were:

\[(\text{BREATH1} = (\text{WEATHER} < > (\text{TYPE} < > \text{FAILSTNV})))\]
\[(\text{FAILSTN} > = \text{SLOWDOWN})\] .

The first rule is true only when

The Turner passes the breath-test AND
EITHER
it is not fine weather
OR ELSE
it is fine and the turn is Off a larger road
AND
the Turner fails to notice another vehicle.

The second rule is true when the Turner either fails to notice another road user (possibly a vehicle) or does not slow down prior to the junction.

Taking these rules together in the same way as above, we can calculate the effect of using them to predict the severity of 77 unseen cases.
Here the Chi-Squared is slightly lower, at 12.82 with 2 degrees of freedom, but still significant at the \( p < 0.005 \) level. The problem is that, interpreted literally, the first rule suggests that passing the breath-test is a risk factor. In fact, what the program has found is that drivers involved in injury accidents are more likely to be breathalyzed but that most of them pass. For less serious accidents, the police are much less likely to breathalyze the participants. To this extent the finding is spurious. It is a reminder that the rule-finding process may uncover artefacts of the recording process as well as causal links.

The previous analyses were performed on our entire accident data-set, but we know that accidents turning onto a larger road (Onto accidents) differ from those where the Turner turns off a larger road (Off accidents), so we applied the rule-finder again to distinguish injury-accidents from damage-only accidents within these subgroups. For Onto accidents the rules were not very successful when judged by their performance on unseen data: but for Off accidents the two best rules

\[(\text{LITTLE2} \not\leftrightarrow \text{SLOWFAIL})\]
\[(\text{FAILSTN} \mid (\text{PULLOVER} > (\text{MISINTERP} < \text{AJSLOWS})))\]

predicted the unseen cases quite well, as shown below.

<table>
<thead>
<tr>
<th>Rule Status</th>
<th>Injury</th>
<th>Damage-only</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Both True</td>
<td>7 (78%)</td>
<td>2</td>
<td>9</td>
</tr>
<tr>
<td>Mixed</td>
<td>2 (12%)</td>
<td>15</td>
<td>17</td>
</tr>
<tr>
<td>Both False</td>
<td>1 (17%)</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td><strong>All cases</strong></td>
<td><strong>10 (30%)</strong></td>
<td><strong>23</strong></td>
<td><strong>33</strong></td>
</tr>
</tbody>
</table>

Here the Chi-squared value is 13.22 with 2 degrees of freedom, significant at the \( p < 0.005 \) level. In addition, all the three serious accidents in this unseen subset had both rules true.

We also applied the rule-finder to those 61 cases in our overall data-set where the Turner was turning Off an A or B road. Thirty-four of these (56%) were injury-accidents, making it one of the most dangerous natural categories in our sample. Here there were too few cases to split into training and test sets, so the rule-finder was used purely descriptively. The rules that emerged were:

\[(\text{LITTLE2} \mid \text{LITTLE1})\]

and

\[(\text{SUMMER} > \text{SLOWSTOP}).\]
This indicates that when Turning Off the most dangerous form of right turn occurs

when either the Turner or Collider is driving a 2-wheeler (or the Collider is a pedestrian),
OR
in the summer months (Jun, Jul, Aug) when the Turner does not slow and then stop at the junction.

Of the 11 cases where both rules were true, all resulted in injury.

3.1.2 Real versus \textit{hypothetical} accidents

Another illuminating comparison is that between the serious accidents in our sample coded from police records ($n = 24$) and the hypothetical serious and fatal accidents described by our sample of informants ($n = 26$).

By looking at the variables that best separate these two categories we get some idea of the difference between what a serious accident is like and what people tend to imagine it to be like.

\textit{As might be} expected, the real accidents – even those involving serious injury – are less dramatic than the imaginary ones. In particular, a real serious right-turning accident is much more common

- at a simple T junction (not a complex crossroads),
- on a minor road,
- involving a 2-wheeled collider,
- at a low speed limit,
- in fine weather, on a dry road surface

than people seem to imagine. It is also more likely to be a result of a simple failure to notice another road user than our informants seem to suppose.

Applying the BEAGLE rule-finder to the task of separating the real from the hypothetical serious-injury accident records, produced the two rules shown below.

\begin{align*}
\text{(WEATHER} & \leq (\text{BREATH2} < 1.875)) \\
\text{(JUNCTION} & \leq \text{ROADTYPE}) \geq \text{SLOWDOWN})
\end{align*}

The first rule is true in fine weather when the Collider either passes the breath-test or does not provide a breath-test. The second is true when the Turner fails to slow down or is at a simple junction (with less than four arms) on a minor road.

Due to the small size of the sample, the rules cannot be used predictively here but only descriptively. Having said that, they provide effective discriminators on the training data: of the 24 real accidents only two had both rules false; of the 26 hypothetical cases none had both rules true and only three had either rule true. (Using a 3-way tabulation as used in the previous section would yield a Chi-squared value of 33.18 with 2 degrees of freedom.)

These rules do not of course imply that fine weather \textit{is} a risk factor or that simple junctions are more dangerous than complex ones, still less that the sobriety of other road users presents a hazard to right-turners. What they do suggest is that our informants
tended to produce relatively dramatic accident descriptions in which the risks posed by poor weather, complex intersections and intoxicated drivers were especially exaggerated.

One could account for such a finding by arguing that people tend to assume that 'ordinary' situations are safer than they really are, and obviously dangerous ones more hazardous. Whether this is a tenable conclusion will be deferred till section 4, after we have looked at some other pieces of evidence.

3.1.3 Turning Onto versus Off a larger road

The rule-finder was also applied to look for systematic differences between Off and Onto accidents. Its first rule-set was 97% correct on unseen cases; but that used variables such as whether there was a road straight ahead and/or a road leading away to the left of the Turner. When such 'cheating' variables were eliminated, the two best rules were simple.

\[
\begin{align*}
\text{(CONGREEN = DANGERB)} \\
\text{(SLOWSTOP | DANGERR)}
\end{align*}
\]

The first is true when the Turner does not continue through a green light without stopping first AND there is no danger from behind (but usually from another direction). The second rule is true EITHER when the Turner slows then stops at the junction OR when the direction of danger is from the right, or both.

The performance of these rules on a random subset of 84 cases (unseen during the rule-generation phase) was as follows.

<table>
<thead>
<tr>
<th>Rule-status</th>
<th>Onto</th>
<th>Off</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Both True</td>
<td>32 (86%)</td>
<td>5</td>
<td>37</td>
</tr>
<tr>
<td>Mixed</td>
<td>10 (40%)</td>
<td>15</td>
<td>25</td>
</tr>
<tr>
<td>Both False</td>
<td>2 (9%)</td>
<td>20</td>
<td>22</td>
</tr>
<tr>
<td><strong>All cases:</strong></td>
<td><strong>44 (52%)</strong></td>
<td><strong>40</strong></td>
<td><strong>84</strong></td>
</tr>
</tbody>
</table>

Table 5

Here the Chi-squared is 35.32 with two degrees of freedom (p < 0.001), indicating that the system has found a compact way of characterizing the difference between accidents turning right Onto a larger road and those turning right Off a larger road.

Typically an Onto accident does not involve danger from behind nor continuing through a green light without stopping; it does tend to involve danger from the right or slowing down followed by stopping at a junction (or both). This is not very startling, with hindsight, since if traffic lights are present they will show green to drivers on the bigger road for longer periods and if they are absent drivers on the smaller road will have to give way. None the less it does gives us a brief, machine-generated description which combines behavioural and topological elements into a simple, unified summary.

3.1.4 Age effects

Another rule-finding analysis concerned age differences. Here accidents with drivers of unknown ages were excluded and the best rules found for discriminating (1) Turners under 25 from the rest and (2) Turners 60 and over from the rest.
The best rules for picking young-driver accidents are listed below.

\[
\begin{align*}
\text{ROADTYPE} & > \text{LIGHTING} \\
((\text{VEHICLE1} \leq 3.48) & > \text{SURFACE}) \\
((\text{SEX1} = 1) & \land (\text{MONTH} < 9.5))
\end{align*}
\]

These indicate that young drivers tend to be overrepresented as Turners in accidents:

1. on B, C or Unclassified roads in any lighting conditions or on A roads after dark;
2. driving two-wheelers on a dry surface;
3. where the Turner is female or driving during the first 9 months of the year (i.e. not males during October, November or December).

Elderly drivers (60 years old or more) tend to be characterized by the following conditions.

\[
\begin{align*}
((\text{SPEEDLIM} > 40) & \land \text{WAITS}) \\
((\text{AGE2} > 73.5) & \land (\text{HOUR} < 15))
\end{align*}
\]

Thus the older drivers are overrepresented in right-turning accidents where

1. there is a high speed limit and the Turner waits for a gap in traffic (i.e. busy main roads);
2. the Collider is also old and the time is before 3 p.m.

Once again these two subgroups were too small (with 65 young drivers and 21 elderly ones in our full database) for a proper unseen test, so these results can only be suggestive. We will attempt to tie them in with other findings in section 4.

### 3.1.5 Coder discrepancy

We have also used BEAGLE as part of the process of validating our coding scheme, by setting it the task of finding rules that discriminate between the two people who encoded the data. Gratifyingly enough, it performed rather poorly at this task, even before the final validation stage. However, the best rule found prior to our final data check

\[
! ((\text{CONTINUES} + \text{FAILSTNV}) & \land \text{SLOWDOWN})
\]

helped to alert us to the terms which we were initially using with low consistency. Thus it guided us towards specific aspects of our coding which needed attention during the final phase of data-validation. In this novel method of consistency checking the present project appears to have broken new ground.

After the final data checking, PC/BEAGLE was unable to find rules that could discriminate the two coders with better than chance accuracy on unseen data. Indeed only one of 63 individual variables differed significantly between the two encoders, namely SEX2 (the sex of the Collider). Having looked again at the raw data, we believe this to be simply a chance occurrence.

### 3.1.6 Other dichotomies

We also applied the rule-finder to some other dichotomies, without much success. Negative results of this type are more than usually suspect (since they may be due to poor performance of the software as well as to many other extraneous factors) but it is perhaps
worth noting that the system was unable to find effective rules for distinguishing

- male from female Turners [real data]
- male from female informants [hypothetical accidents]
- young and old Turners combined from middle-aged (25 to 59 year-old) Turners [real data].

Although the system discovered effective rules for discriminating safe-transit descriptions from descriptions of hypothetical accidents, and for discriminating accidents on major roads (A and B) from accidents on minor roads (C or Unclassified), they were all trivial. When the 'cheating' variables were removed, good rules were no longer found.

3.2 ANALYSES USING DECISION TREES

This section describes the results of applying a modified version of one of the better known machine-learning algorithms (Quinlan, 1986) to the data set of right-turning accidents in Nottinghamshire. We chose Quinlan's ID3 algorithm as the basis for a second induction program to compare against the PC/Beagle rule-finder, since it is computationally efficient and expresses its output in the form of decision trees. Decision trees - unless they are very complex - are relatively easy to understand, even by untrained users.

3.2.1 Decision trees as data descriptors

A decision tree consists of nodes and arcs (or branches). Each node in the tree represents a test on an attribute, and there are outgoing branches from that node for each possible outcome of the test. In the present study only binary attributes were used, so each node could have no more than two branches.

Using Decision Trees

To classify an example case, using a decision tree, a path from the root of the tree to a leaf node must be followed. (A leaf node is one without branches.) At each internal node the branch corresponding to the result of the test at that node is taken. When a leaf (or terminal) node is reached, the class label found there is a prediction of the class membership of the current case. An example decision tree, derived from a small zoological database, is shown in Figure 1. Classifying a particular animal, such as a rabbit, with this decision tree, would result in the following steps. First we would ask: does it breathe air? It does, so we follow the Yes branch from the root to the second test, which is: does it have fins? Here the answer is No, so we follow the No branch to the third question and ask: Does it lay eggs? Rabbits give birth to live young, so we take the No branch. This leads to a leaf node, so the classification of a rabbit is Non-Aquatic.

Creating Decision Trees

To construct a decision tree from data the ID3 procedure starts by creating a root node containing all the training instances. Unless these examples all belong to the same class, the procedure will grow branches from that node which test an attribute and sort the cases into subsets corresponding to the values of that attribute. Attributes which sort the examples into homogenous groups, i.e., groups with examples mainly or exclusively from a single class, are preferred. ID3 uses an entropy measure as a heuristic for evaluating potential attributes - the lower the entropy, the better the test at sorting the examples into homogenous subgroups.
Figure 1 — Example Decision tree: Aquatic versus Non-Aquatic Animals
Having evaluated all possible tests at a node, **ID3** puts the test with the lowest entropy score at the node being examined, attaches branches to that node corresponding to the values of the attribute tested, and splits the data into subsets according to those values. Then each of the leaf nodes is examined in turn. If all the examples at a leaf node are of the same class, that node needs no further attention: it is labelled with the appropriate class label. If it contains examples of more than one class, it must be expanded in the same way as the root node. The procedure continues expanding unfinished nodes until no more need expanding.

**3.2.2 The problem of overfitting**

**ID3** is one of the most popular machine-learning algorithms, but when applied to noisy data it tends to generate large, complex discrimination trees that fit the training instances well but generalize poorly to unseen cases. This problem — not unique to **ID3** — is known as overfitting.

To guard against this problem, modern versions of **ID3**, and similar algorithms, generally incorporate **tree-pruning** or simplification mechanisms (Quinlan, 1987). Simplification can be achieved either by halting the tree-growing process early (**pre-pruning**) or by growing the decision tree to its full extent and then cutting off branches which cover too few training instances to be statistically reliable (**post-pruning**). It is generally found that post-pruning is preferable to pre-pruning (Breiman et al., 1984; Niblett, 1987), since it partly compensates for the fact that the **ID3** algorithm does no explicit look-ahead.

In general, a pruned tree will have leaf nodes with a mixture of example types, and hence will not perfectly classify the training data. However, once over-fitting has been eliminated, the resultant decision tree represents a more economical description of the relationship between the measured attributes of the data and their class membership than an unpruned tree. In addition, it is typically found that pruned decision trees are more accurate than unpruned ones on unseen data.

The learning system used in this section (**BID3/TREEMIN**) employs a method of post-pruning based on information theory which has been described elsewhere (Forsyth, Clarke & Wright, 1991). Essentially, we view the decision tree as an encoding scheme, following Wolff (1982, 1991), and compute its cost as the sum of its own size and the size of the encoded outcome data. Both the site of the tree and the size of the encoded data are measured in a ‘common currency’, namely information-theoretic bits (Shannon & Weaver, 1949; Abramson, 1963; Edwards, 1964).

It is worth noting that we also tested an alternative pruning method, based on cutting back from leaf nodes till a Chi-squared value significant at the 99% confidence level was reached, and obtained similar (often identical) trees to those quoted in this report. Thus the precise nature of tree-pruning method used here is less important than the fact that precautions were taken against overfitting.

**3.2.3 Injury versus non-injury** accidents

The most important feature of an accident is its severity. To look at relationships bearing on the severity of right-turning accidents, we first segregated the Onto from the Off accidents (since we already knew these categories to have significantly different causal structures), and then applied the **BID3** program to both subsets separately.
Onto Accidents

The Onto sample of 90 accidents contained 32 that resulted in injury to at least one of the participants and 58 that resulted in damage only. When given the task of growing (and pruning) a decision tree to classify accident records as either injury or damage-only accidents the program produced the decision tree shown as Figure 2.

We can amplify the 'message' of this tree by taking the three terminal nodes with more than 10 cases and re-expressing them as IF/THEN rules.

IF  
THEN  Collider on a 2-wheeler or on foot  Injurious  (83% injury accidents).

IF  
AND  Collider is NOT 2-wheeler nor pedestrian  
AND  Season is Winter (Dec, Jan, Feb)  
AND  Turner fails to notice another road user  
THEN  Injurious  (59% injury accidents).

IF  
AND  Collider NOT 2-wheeler nor pedestrian  
AND  Season is NOT Winter  
AND  Junction has less than 4 arms  
THEN  Mild  (14% injury accidents).

To sum up: the main problems with our Onto turns appear from this analysis to be colliding with an unprotected road user or failure to notice another road user in winter.

Off Accidents

A similar procedure was applied to Off accidents, of which 47 resulted in injury and the same number, 47, resulted only in damage.

The full tree for discriminating injury from damage-only Off accidents had 16 terminal nodes; the pruned tree has only 6, but still predicts over 42% of the redundancy in the outcome data, which is essentially equivalent to accounting for 42% of the variance in a binary dependent variable. This tree is reproduced as Figure 3. Here, once again, the most important variable is the vehicle-size of the Collider, with pedestrians and 2-wheelers being implicated in more than half the injury accidents. Translation of the whole tree into a rule-based notation is slightly less simple in this case, but rules for the two largest terminal nodes (covering 73 out of the 94 cases) are given below:

IF  
AND  Collider is on 2 wheels or on foot  
AND  Collider is NOT approaching from behind  
THEN  Injurious  (95% injury accidents).

IF  
AND  Collider is NOT on 2 wheels nor on foot  
AND  Turner does NOT pull over from an inner to an outer lane just prior to the turn  
AND  Turner is NOT on 2 wheels  
THEN  Mild  (23% injury accidents).
Figure 2 -- Onto Accidents: Injury versus Non-Injury
Figure 3 -- Off Accidents: Injury versus Non-Injury
3.2.4 Severity in 'model' accidents

This takes us tantalizingly close to being able to offer safety recommendations, but not quite close enough. In an attempt to get closer to this goal, we extracted from the Onto cases a subset intended to serve as model exemplars for the tree-growing process. For this we used collateral information from our own and other studies, in particular the fact that middle-aged drivers are safer than either young or old drivers.

To be specific our selection consisted of two contrasting subtypes:

1. Injury accidents where the Turner was under 25 years of age or over 59 years of age; versus
2. Non-injury accidents where the Turner was aged 35 to 55.

The former category we will label, for the purposes of this report, goats and the latter as sheep. (It will be apparent that we are trying to make up for the lack of baseline data by treating the sheep as instances of almost-safe behaviour, i.e. surrogate safe turns, and the goats as presumptive high-risk behaviour; it will equally be apparent that there are pitfalls in such an identification: these will be addressed in Section 4.)

Onto Accidents

When required to separate the 12 sheep from the 19 goats in the Onto accidents, the BID3 program produced the decision tree given as Figure 4. Here it is an easy matter to translate the tree into a set of conditional rules. By doing so we get slightly closer to our goal of safety recommendations:

IF Season is Winter (Dec, Jan, Feb)
THEN High Risk (91% injury accidents)
ELSE IF Collider on 2 wheels or on foot
THEN High Risk (100% injury accidents)
ELSE IF Turner fails to slow down prior to turn
THEN High Risk (80% injury accidents)
ELSE Low Risk (17% injury accidents).

In a nutshell, the program has highlighted three main risk factors when turning right Onto a road with right of way: whether it is winter, whether the (potential) Collider is inside an enclosed metal shell, and whether the driver slows before the turning manoeuvre. Only one, slowing down, is fully under the control of the Turner, though increased vigilance for 2-wheelers and reluctance to drive during the winter might also be recommended as appropriate behavioural responses.

Off Accidents

An even simpler picture emerges from looking at the tree for discriminating 'sheep' (13 cases) from 'goats' (18 cases) among the Off accidents. The resulting tree is given as Figure 5. This tree can be summed up in a nutshell as stating that if the Turner is in a vehicle with more than 2 wheels and correctly appreciates the situation ahead then there is unlikely to be an injury as a result of the turn. Note that here it is the size of the Turner's vehicle that matters.
Figure 4 — Onto Accidents: Sheep versus Goats
Figure 5 -- Off Accidents: Sheep versus Goats
To the extent that the sheep and goats exemplify better and worse driving behaviour, we are justified in saying: to reduce your risk when turning right Off a road with right of way, do NOT drive a 2-wheeler and be especially attentive to oncoming traffic. A corollary of this is that rear and side-on collisions tend to be less severe than accidents involving a Collider approaching from ahead of the Turner.

3.2.5 Young male drivers versus the rest

Another division we investigated with this method was that between young male drivers and the rest. Numerous studies (e.g. Parker, 1991; Manstead et al., 1991) have highlighted the importance of this particular distinction in road safety research.

Onto Accidents

Of the 78 Onto accidents where the age and sex of the Turner could be reliably ascertained, 25 involved drivers who were male and under the age of 25 (known from national statistics to be a group with a high proportion of 'problem' road users). The BID3 program produced a decision tree for separating this group from the rest which is shown as Figure 6.

After pruning, this tree contained only four leaf nodes, yet still accounted for over 40% of the redundancy in the outcome data. The most important single variable was the complexity of the junction. Of the 13 cases at a junction with 4 or more arms, none involved a young male turner:

- IF Junction has 4 or more arms
  THEN NOT Young Male (0/13 young males).

- IF Junction has only 3 arms
  AND Turner does NOT wait
  AND Turner does NOT slow down prior to manoeuvre
  THEN Young Male (8/9 young males).

Off Accidents

Of the 92 Off accidents where the age and sex of the Turner were known, 23 involved male drivers under the age of 25. The pruned tree for discriminating this group from older and/or female drivers is given as Figure 7.

The picture here is less clear than in the previous cases, though it seems that if an accident arises when the Turner gets an invitation to proceed by another road user and does NOT involve a failure to notice another road user by the Turner and does NOT take place in the evening (6 p.m. to 11:59 p.m.) then it is highly unlikely to involve a young male driver. In fact, young males tend to have their right turning accidents on 2-wheelers or on urban roads, though the pruned tree does not show this very well.

To Stop or not to Stop

The tree-growing program was also applied to a behavioural factor which we knew to be implicated as a determinant of severity from other parts of the study, namely the question of whether drivers stopped or not prior to turning right Onto a road with right of way, cf. Section 3.4.2. (Overall 54 / 90 = 60% of Turners involved in Onto accidents did stop before turning.)
Figure 6 -- Onto Accidents: Young Males

Junction with 4 or more arms?

Yes

NOT Young Male
0:13

No

Turner waits at junction?

Stop

Yes

NOT Young Male
3:17

No

Turner slows prior to manoeuvre

Yes

NOT Young Male
14:22

No

Young Male
8:1
other road user?

Yes

Time between 6 pm & 11:59 pm?

Yes

Undecided 5:5

No

Turner invited to proceed by other road user?

Yes

Young male 5:0

No

Undecided 2:2

Turner on 2 wheels?

Yes

No

Young male 11:21

NOT young male 0:41

Figure 7 -- Off Accidents: Young Male
The resultant decision tree has 6 leaf nodes and accounts for only 22% of the redundancy in the outcome variable, so it is not given in full; but one node is of interest in identifying a distinctive cluster of 'non-stoppers'. It is expressed below as a conditional rule:

\[
\text{IF} \quad \text{It is Dark} \\
\text{AND} \quad \text{Turner is NOT female (i.e., male driver)} \\
\text{AND} \quad \text{Season is NOT Winter (i.e., month is March to November)} \\
\text{AND} \quad \text{Turner is under 60 years old} \\
\text{THEN} \quad \text{Turner does NOT Stop (12/13 = 92\% Nonstoppers)}. 
\]

This throws some more light, indirectly, on the behaviour of younger male drivers, since this subgroup consists mainly of non-elderly males.

The main contrasting group of 'stoppers' can be described as follows:

\[
\text{IF} \quad \text{It is NOT Dark} \\
\text{AND} \quad \text{Turner does Stop (39/51 = 77\% Stoppers).} \\
\]

It might seem strange that drivers are less inclined to stop prior to turning in the dark than in daylight, but two possible reasons suggest themselves: firstly that drivers may well expect less traffic in darkness and secondly that they may rely on approaching headlights to signal the presence of another vehicle (which they cannot do in the daytime).

3.2.7 Other dichotomies

Various other dichotomies were investigated using this technique. Only one, a comparison of male and female drivers, added fresh information to the results of the rule-finder analyses (section 3.1).

Having segregated Onto from Off accidents we found some evidence for sex differences in the sense that the decision trees appeared to isolate some typically masculine accident types, i.e. accidents without a single female Turner in the selected subgroup. For Onto accidents the masculine accident type can be characterized as follows:

\[
\text{IF} \quad \text{Turner does NOT Stop prior to Turn} \\
\text{AND} \quad \text{Speed limit is less than 35 m.p.h.} \\
\text{AND} \quad \text{Junction is NOT controlled by Traffic Lights} \\
\text{THEN} \quad \text{Turner is Male (25/25 = 100\% male drivers)}. 
\]

For Off accidents there were two masculine subgroups, which we have combined and characterized as follows:

\[
\text{IF} \quad \text{Time is evening, i.e. 6 p.m. to 11:59 p.m.} \\
\text{OR} \quad \text{On a Major Road during Spring (Mar, Apr, May)} \\
\text{THEN} \quad \text{Turner is Male (33/33 = 100\% male drivers)}. 
\]

It may not be wise, however, to place much emphasis on these prima facie sex differences, since the pruned tree for discriminating male from female Turners in Onto accidents accounted for only 30\% of the outcome redundancy and in Off accidents for only 23\%.
3.2.8 Interim conclusions

This aspect of the present study had two main aims:

(1) to demonstrate the feasibility of using inductively derived decision trees as compact descriptors of relations among variables in the field of road accident research;

(2) to elucidate some aspects of the relationship between severity of accident and a selection of putative causal factors in right-turning accidents.

In the first aim we believe we have succeeded. Tree-growing algorithms, provided that appropriate pruning strategies are implemented to guard against the danger of overfitting, represent a useful addition to the researcher's armoury of data-analytic techniques.

Pruned decision trees are typically compact, readily intelligible and suggestive in ways that more conventional techniques such as regression or linear discriminant function analysis are not. We commend their use to fellow researchers.

With regard to the second aim, our claims must be more tentative. We have used a tree-growing program to discover and display simple but meaningful associations between severity and a number of background factors for both Onto and Off accidents. The resultant decision trees tell a story that was not known in advance by the investigators but which has fairly clear safety implications. However, since we have concentrated on the descriptive rather than the predictive usage of decision trees, our specific conclusions can only be regarded as signposts to further research. In particular, our 'sheep-versus-goats' approach, i.e. the use of specially selected subsets for presentation to the learning program, raises important issues that need fuller investigation.

This procedure, which we intended as a kind of 'contrast enhancement', is analogous to presenting hand-picked 'archetypal' cases to a human student to assist the learning process. At present we can only justify it informally, but we believe that this idea of selecting particularly bad accidents and contrasting them with especially minor ones has an important role to play in combatting the bane of accident research — namely the dearth of data on everyday safe driving — even though we recognize that the selection criteria used here (middle-aged drivers in non-injury accidents contrasted with young or old drivers involved in injury accidents) are certainly not ideal.

Further progress with this approach depends on finding a better method for demarcating sheep (surrogate safe turns) from goats (genuinely bad accidents). Any demarcation rule must, of course, be objective -- otherwise the tree-growing program will only pick up and reformulate someone's preconceived notions about safe and dangerous driving. (See also Section 4.)

3.3 SEQUENTIAL ANALYSES

In this subsection we describe some of the results obtained from the sequential data in TRAAL (the coding of event sequences), ignoring the static features.

3.3.1 Stochastic Analysis

One of the first things to do with sequential data is to estimate its degree or order. This is normally done by treating the sequences as Markov chains and using information theory
to compute the redundancy of each symbol given knowledge of varying numbers of preceding symbols, from zero upwards (Attneave, 1959).

Here the issue is whether each event is influenced by the preceding event alone or by combinations of two, three or more events. For this investigation the 48 commonest actions in the TRAAL lexicon were each allotted a single character code and a 49th character ('@') used to mark the place of a rare event. (All 'rare' events occurred less than 3 times in our database.) This gave us an 'alphabet' of 49 symbols.

Thus the event descriptions were transformed into strings of characters, which were analyzed as if they were texts. To give an example, the accident sequence

RAIMA [Driving along]
SLOWS
APPROACHES JUNCTION
CHECKS BEHIND
FAILS 70 NOTICE VEHICLE /BEHIND
INDICATES /RIGHT
STARTS RIGHT TURN
NOTICES VEHICLE /BEHIND
STRAIGHTENS UP
IMPACT /AT 29 /ON BACK /BY FRONT
STOPS
END.

was encoded as the single string below

cgFJSWja@VkP*

for the sequential analyses described in this section. (Here the rare event is STRAIGHTENS UP, but in other sequences the rare-event marker might have another interpretation.)

Most studies of the order of Markov sequences treat the data as a single sample and quote significance values derived from examining that single sample (e.g. Thomas, Roger & Bull, 1983). However, we wrote a program that enabled us to apply the training-set/test-set logic to this task. This was done by randomly dividing the sequences into two subsets, forming an event-transition table on one of these sets, and using this table to estimate the redundancy of the other subset. This procedure does not seem to have been reported in the literature, and the results of the two approaches were - in our case - strikingly different.

We analyzed the real accidents, the hypothetical accidents and the safe transits in this manner - both backwards and forwards. Our main conclusion is that all six modes are best characterized as 2nd-order Markov processes, i.e. that symbol triplets (or longer substrings) do not significantly add to the information provided by pairs.

The results obtained on the real-accident dataset are typical of the other five modes, and are tabulated in Table 6 below.
Accident Data : Self-Test

<table>
<thead>
<tr>
<th>Order</th>
<th>Percentage Correct</th>
<th>Mean Entropy per Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.04%</td>
<td>5.61 (bits/symbol)</td>
</tr>
<tr>
<td>1</td>
<td>6.49%</td>
<td>3.37</td>
</tr>
<tr>
<td>2</td>
<td>54.10%</td>
<td>1.34</td>
</tr>
<tr>
<td>3</td>
<td>65.59%</td>
<td>1.04</td>
</tr>
<tr>
<td>4</td>
<td>72.58%</td>
<td>0.85</td>
</tr>
<tr>
<td>5</td>
<td>79.86%</td>
<td>0.65</td>
</tr>
<tr>
<td>6</td>
<td>85.75%</td>
<td>0.48</td>
</tr>
<tr>
<td>7</td>
<td>92.44%</td>
<td>0.37</td>
</tr>
<tr>
<td>8</td>
<td>95.23% (max)</td>
<td>0.31 (min)</td>
</tr>
</tbody>
</table>

Accident Data : Split-half Testing

<table>
<thead>
<tr>
<th>Order</th>
<th>Percentage Correct</th>
<th>Mean Entropy per Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.17%</td>
<td>5.61 (bits/symbol)</td>
</tr>
<tr>
<td>1</td>
<td>6.15%</td>
<td>3.56</td>
</tr>
<tr>
<td>2</td>
<td>55.80% (max)</td>
<td>1.38 (min)</td>
</tr>
<tr>
<td>3</td>
<td>52.70%</td>
<td>1.80</td>
</tr>
<tr>
<td>4</td>
<td>49.83%</td>
<td>2.11</td>
</tr>
<tr>
<td>5</td>
<td>44.15%</td>
<td>2.41</td>
</tr>
</tbody>
</table>

Table 6

The percentage-correct column for order N is calculated by taking the first N-1 symbols and using their commonest successor (Nth symbol) as a prediction of the current successor. If both are the same, the prediction is deemed correct. The mean entropy is obtained using the formula described in Attneave (1959): it measures the improbability of each symbol under various conditions of prior knowledge. For order N (as long as N exceeds 1) this represents the unpredictability of the Nth symbol given the previous N-1. The condition N=0 represents complete ignorance: all 49 symbols are assumed to be equally frequent. With N = 1 the relative frequency of each symbol on its own is known but no knowledge of transitional probabilities is used.

When the data is treated as a single set, the apparent unpredictability of each symbol continues to drop almost indefinitely as N grows larger, though the biggest fall occurs between 1st and 2nd order. When the data is split into training and test sets, however, the entropy estimate rises after order 2, while the percentage of correct guesses starts to fall. This indicates that knowledge of two previous symbols is no better than knowledge of one predecessor for predicting the next symbol.

This relationship is also presented graphically in Figure 8.

Knowing that most of the sequential information in our data could be - broadly speaking - captured by second-order transitions enabled us to use event-pairs as critical markers in some of the subsequent analyses.

3.3.2 Overlay Analyses

We also wrote an 'overlay' program that allowed us to build a complete transition tree of all event sequences in our data, backwards or forwards, and another that took two subsets of our sequential data (e.g. injury and non-injury accidents or accidents involving male and female Turners) and pinpointed 'hot-spots' - i.e. transition points where the frequency of alternative branches differed significantly between the two data-sets.
Very little of substance came from this form of analysis, although it did enable us to locate the commonest sequence in various sorts of incident. Three of these are shown below.

Real Accident (7 examples)

RAIMA 171  
APPROACHES JUNCTION 162  
SLOWS 125  
FAILS TO NOTICE VEHICLE 10  
STARTS RIGHT TURN 10  
IMPACT 8  
STOPS 7  
END. 7

Hypothetical Accident (4 examples)

RAIMA 99  
APPROACHES JUNCTION 95  
INDICATES 64  
SLOWS 59  
STOPS 40  
VIEW OBSTRUCTED 11  
FAILS TO NOTICE VEHICLE 7  
STARTS RIGHT TURN 6  
IMPACT 4  
STOPS 4  
END. 4

Safe Transits (5 examples)

RAIMA 90  
APPROACHES JUNCTION 86  
INDICATES 61  
SLOWS 59  
STOPS 44  
WAITS 27  
STARTS RIGHT TURN 7  
CONTINUES 6  
RAIMA 5  
END. 5
Here the numbers at the right give the frequency of the sequence up to that point in the data-set.

The sudden drop in frequency, from 125 to 10, between SLOWS and FAILS TO NOTICE VEHICLE in the real accident sequences indicates that this is a stage at which there are many options open — hence the point of maximum difficulty for the Turner, and the point in the sequence with the highest likelihood of something going wrong. This was not reflected in the hypothetical accident descriptions, where our informants imagined STOPS to follow SLOWS much more often than it does in real life.

Contrasting real with hypothetical sequences, after RAIMA + APPROACHES JUNCTION (the commonest beginning of both types), SLOWS was significantly overrepresented as the next act in the real accidents whereas INDICATES was significantly overrepresented among the hypotheticals. Also after RAIMA + APPROACHES JUNCTION + SLOWS, both STOPS and FAILS TO NOTICE VEHICLE were overrepresented among real accidents; while after RAIMA + APPROACHES JUNCTION + INDICATES SLOWS was overrepresented among the hypothetical sequences.

These differences can be accounted for on the basis of two simple assumptions: (1) the hypothetical accidents are slightly more detailed than the real ones, because the informants have privileged access to their own stories; and (2) the hypothetical accidents describe unrealistically well-behaved Turners, because the informants usually cast themselves in that role and imagined accidents in which they were victims of other elements of the road environment.

3.3.3 Typical sequences

Because the overlay analyses were not particularly revealing, we tried an alternative approach of seeking typical and distinctive sequences, based on a method of sequence comparison known as the Gestalt algorithm. This is a procedure which takes two symbol-strings and returns a value between 0 and 1 that measures their similarity. This measure takes account not only of the elements shared by the two strings but also their relative locations. There are many algorithms for computing string-similarity (see Sankoff & Kruskal, 1983), of which we tested three

- the proximity scan procedure (Rosenthal, 1984)
- Levenshtein's algorithm (Levenshtein, 1965)
- the Gestalt algorithm (Ratcliff & Metzener, 1988).

The latter performed best on trial data, so it has been used for all the analyses quoted herein. To give a simple illustration, some character-strings are listed below along with their similarity score when compared to the target phrase "DESERT ORCHID".
One program (TYPICAL) takes a set of strings and calculates the average similarity between each one and all the rest. The string with the highest score is a typical member of the ensemble. (In our case, the strings represent event sequences, as outlined in 3.3.1.) This sort of similarity analysis has been used previously for comparing bird songs (Bradley & Bradley, 1983), for estimating the evolutionary distance between segments of DNA (Sellers, 1980), for correcting misspellings in text files (Alberga, 1967) and for other purposes. However, we believe ours is the first application of this technique to the field of road-safety research.

A second program (CONTRAST) takes two sets of strings, one designated as positive instances of some type and the other as negative instances, and computes the average similarity of each string to the positive exemplars and to the negative exemplars. Then the string with the largest difference between these two averages is, in a sense, the most distinctive of the positive strings in contrast to the negative ones.

We applied this typicality analysis in six areas:

- sex differences
- age effects
- road type
- turn type
- real versus hypothetical accidents
- severity

Sex Differences: To look at sex differences, we separated the accidents involving a male Turner from those involving a female Turner. According to the TYPICAL program, the most typical male accident was an Off accident which went as follows.

RAIMA
APPROACHES JUNCTION
SLOWS
FAILS TO NOTICE VEHICLE /BEHIND
STARTS RIGHT TURN
IMPACT
STOPS
END.

This sequence is the same as the most typical accident overall, which is not surprising as the majority of the Turners in the sample (75.3%) were male. Somewhat unexpected, however, was the finding that the typical sequence for female Turners (also an Off accident) was just the same. This suggests that male and female drivers behave the same way—at least to the level of detail accessible by the TRAAL coding scheme—when turning right at junctions.

The hypothetical accidents invented by our informants are also quite similar whatever the sex of the informant. The typical sequences given by both sexes start in the same way.
RAIMA
APPROACHES JUNCTION
INDICATES /RIGHT
SLOWS
STOPS

then the sequences diverge slightly

Male Informants
CONTINUES /THROUGH GREEN LIGHT
VIEW OBSTRUCTED /BY VEHICLE
FAILS TO NOTICE VEHICLE

Female Informants
WAITS /FOR GAP IN TRAFFIC
FAILS TO NOTICE VEHICLE

and then continue again in the same way

STARTS RIGHT TURN
IMPACT
STOPS
END.

As it happens, both described accidents turning Onto a larger road which resulted in damage only. So males and females do not imagine accidents which are markedly different in their sequential structure, nor do they seem to have accidents with different sequential structure.

Age Effects: To look at age effects, we extracted accidents where the Turner was under 25 (young drivers) into one data-set and put all the accidents where the Turner was 60 or over into another (elderly drivers). The typical elderly driver's accident, according to the TYPICAL program, is an Off accident and goes as follows.

RAIMA
APPROACHES JUNCTION
SLOWS
INDICATES /RIGHT
STOPS /AT TRAFFIC LIGHTS
WAITS /FOR GREEN LIGHT
FAILS TO NOTICE VEHICLE
STARTS RIGHT TURN
IMPACT
STOPS
END.

The typical young person's accident sequence, on the other hand, comes from an Onto accident, and goes as follows.

RAIMA
APPROACHES JUNCTION
SLOWS
FAILS TO NOTICE VEHICLE
STARTS RIGHT TURN
IMPACT
STOPS
END.
Both sequences start and finish in the same way. In the middle, the elderly Turner (unlike the young Turner) INDICATES, STOPS and WAITS but still crashes. This is consistent with the idea that young people go wrong through not taking precautions while elderly drivers fail more commonly through failure of observation.

Road Type: We also looked at differences between accident sequences on major roads (A or B) and minor roads (C or Unclassified). The typical major-road sequence comes from an Off accident and goes as follows.

RAIMA
APPROACHES JUNCTION
SLOWS
INDICATES /RIGHT
FAILS TO NOTICE VEHICLE /AHEAD
STARTS RIGHT TURN
IMPACT
STOPS
END.

The typical minor-road accident is exactly the same except that the INDICATES /RIGHT is omitted. Thus the typical major and minor road event sequences are much the same, but an application of the CONTRAST program indicates that the most distinctive sequences from each category are rather different.

The most distinctive major-road sequence came from an Off accident which resulted in slight injury:

RAIMA
APPROACHES JUNCTION
SLOWS
INDICATES /RIGHT
STOPS
FAILS TO NOTICE VEHICLE /BEHIND
STARTS RIGHT TURN
IMPACT
STOPS
END.

The most distinctive minor-road sequence came from an Onto accident that resulted in damage only:

RAIMA
APPROACHES JUNCTION
STARTS RIGHT TURN
LOSES CONTROL OF VEHICLE
LEAVES CARRIAGEWAY
IMPACT [hits a road-sign]
REJOINS CARRIAGEWAY
RAIMA [drives off at high speed]
END.

Although the latter is not typical of what happens in right-turning accidents on minor-road junctions, it is the kind of episode that is only found on minor roads in our data.
Presumably, even careless drivers are not this careless on a major road. (It happened at 2245 hours, leading to a strong presumption of alcohol involvement.)

**Turn Type:** Of course road-type is confounded with turn-type, since in our database only 42% of the major-road accidents are Onto whereas 58% of minor-road accidents are Onto, so we also looked for sequences typical of Onto and Off accidents.

The typical event sequence among accidents turning Off a larger road (not always an A or B road) is listed below. (It is the same as the typical major-road sequence shown above.)

- RAIMA
- APPROACHES JUNCTION
- SLOWS
- INDICATES /RIGHT
- FAILS TO NOTICE VEHICLE /AHEAD
- STARTS RIGHT TURN
- IMPACT
- STOPS
- END.

The most typical **sequence** from the Onto accidents is the same as that above, except that (1) INDICATES /RIGHT is missing and (2) FAILS TO NOTICE VEHICLE is qualified by /LEFT rather than /AHEAD – i.e., the direction of danger is from the left not the front.

Applying the CONTRAST program tells a slightly different story. The most distinctive sequences from Off and Onto accidents are listed below.

**Off Sequence**

- RAIMA
- SLOWS
- INDICATES /RIGHT
- APPROACHES JUNCTION
- CONTINUES /THROUGH GREEN LIGHT
- FAILS TO NOTICE PEDESTRIAN /RIGHT
- STARTS RIGHT TURN
- IMPACT
- STOPS
- END.
- *SLI

The distinctive Off accident is a rather ordinary right-turning accident, except that the Turner goes through a green light (more likely when turning Off than Onto a bigger road for obvious reasons) and fails to notice (then hits) a pedestrian rather than a vehicle, causing injury rather than just damage (also commoner among Off than Onto accidents).

**Onto Sequence**

- STARTS FROM PARKED
- APPROACHES JUNCTION
- SLOWS
- VIEW OBSTRUCTED /LEFT
- FAILS TO NOTICE VEHICLE /LEFT
- STARTS RIGHT TURN
- IMPACT
- CONTINUES /TURNING RIGHT
- RAIMA
- END.
- *D/O

The distinctive Onto accident sequence really is distinctive: it is not very like the typical Onto sequence, **but** it is very unlike the typical Off sequence. Starting from a parking place, having view obstructed and continuing after an impact (the second RAIMA) are seldom found in Off sequences.
We also contrasted Off and Onto accident sequences on fast roads only (roads with a speed limit over 35 mph). The typical sequences are almost identical but the most distinctive sequences are not, as shown below.

Fast Road (Off)

RAIMA
APPROACHES JUNCTION
SEES TURN-OFF SIGN LATE
FAILS TO NOTICE VEHICLE /BEHIND
INDICATES /RIGHT
SLOWS
PULLS OVER /TO OUTSIDE LANE
IMPACT
FORCED INTO ONCOMING TRAFFIC
IMPACT
STOPS
END.
*SER

Fast Road (Onto)

STARTS FROM PARKED
APPROACHES JUNCTION
STOPS
WAITS /FOR GAP IN TRAFFIC
FAILS TO NOTICE VEHICLE /RIGHT

Here the program has picked up some genuine distinctive features of accidents turning Off high-speed roads:

(1) late recognition of turn-off;
(2) consequent late indication and slowing;
(3) failure to appreciate danger from behind;
(4) changing lanes from left to right;
(5) double impact.

All these features, while not common in right-turn accidents Off a fast road, are extremely rare in Onto accidents. On the other hand, starting from a parking place is found only in Onto accidents. (The fact that the Off sequence above leads to a serious injury while the Onto sequence leads to a slight injury is also realistic.)

Real versus Hypothetical Accidents: We also looked at typical sequences among hypotheticals, real accidents and safe transits. The typical hypothetical sequence is rather like the typical safe transit.

Hypothetical Accident

RAIMA
APPROACHES JUNCTION
INDICATES /RIGHT
SLOWS
STOPS
STOPS
WAITS /FOR GAP IN TRAFFIC
FAILS TO NOTICE VEHICLE /AHEAD
STARTS RIGHT TURN
IMPACT
STOPS
END.

Safe Transit

RAIMA
APPROACHES JUNCTION
INDICATES /RIGHT
SLOWS
STOPS
STOPS
WAITS /FOR GAP IN TRAFFIC
STARTS RIGHT TURN
CONTINUES /TURNING RIGHT
RAIMA
END.
Thus our informants tend to envisage a prototypical accident as one where the Turner does everything right (i.e., in the same way as in an "idealized" safe turn) until reaching the junction and then goes wrong by failing to observe a hazard. One could argue that this tells us something about our informants' hypotheses on accident causation. In so far as it does, they are right to focus on failure of observation as playing a decisive part in the process, but wrong to assume that indicating, stopping and waiting are normal constituents of the event sequence leading to a right-turning accident.

In real accidents, the typical sequence is shorter and less like the ideal safe turn.

Real Accidents

RAIMA
APPROACHES JUNCTION
SLOWS
FAILS TO NOTICE VEHICLE /LEFT
STARTS RIGHT TURN
IMPACT
STOPS
END.

Severity: Finally, we used this method to look again at the important question of severity, by contrasting injury with non-injury accident sequences. The most typical injury accident sequence is given below. (It happens also to be the typical serious-injury accident sequence.)

RAIMA
APPROACHES JUNCTION
SLOWS
FAILS TO NOTICE VEHICLE /RIGHT
STARTS RIGHT TURN
IMPACT
STOPS
END.

The most typical damage-only accident sequence was exactly the same, except that the vehicle the Turner failed to notice was approaching from behind, not from the right. Both, in fact, are typical accident sequences, so it would appear that injury and damage-only accidents do not differ in sequential structure.

The CONTRAST program found that the distinctive serious-injury sequence (as opposed to damage-only sequence) was as above except that SLOWS was absent and

MISJUDGES SPEED & DISTANCE OF VEHICLE /AHEAD

was inserted in its place, though the measure of discrimination between the two sequence types was very low.

Our overall conclusion from this phase of the analysis is that the sequential structure of serious-injury accidents, slight-injury accidents and damage-only accidents is not markedly different – at least in so far as it can be captured by TRAAL. The three kinds of incidents unfold in a similar pattern, and the factors that determine how serious the result will be are things like the size of the vehicle(s) involved and the speed at which they are travelling.

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3.3.4 Chunking

Another of our sequential analyses employed a program based on an algorithm described by Dawkins (1976), who used it to pick out 'melodies', i.e. frequent sub-sequences, in temporal records of insect behaviour.

On our data this chunking method has not uncovered the kind of hierarchical structures that Dawkins found with his flies, but it has identified some standard sequences that might be called clichés, rather than melodies. Two examples are listed below.

<table>
<thead>
<tr>
<th>Accident Cliché</th>
<th>Safe-Turning Cliché</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAILS TO NOTICE VEHICLE</td>
<td>RAIMA</td>
</tr>
<tr>
<td>STARTS RIGHT TURN</td>
<td>APPROACHES JUNCTION</td>
</tr>
<tr>
<td>IMPACT</td>
<td>INDICATES /RIGHT</td>
</tr>
<tr>
<td>STOPS</td>
<td>SLOWS</td>
</tr>
<tr>
<td>END.</td>
<td>STOPS</td>
</tr>
<tr>
<td>[Damage OR Slight injury]</td>
<td>WAITS</td>
</tr>
</tbody>
</table>

The fragment on the left is found in 38% of the accident sample; that on the right is found in 27% of the descriptions of safe right turns. Interestingly, we find that the accidents typically end with standard sequences while safe transits tend to begin with them. This suggests that accidents start out diverse and then converge onto a similar ending, while safe turns tend to start in similar ways and then diverge.

The following table shows the frequency of the most common 4-step initial sequence and the most common 4-step terminal sequence in real accident descriptions compared to safe-transit descriptions. It tells essentially the same story.

<table>
<thead>
<tr>
<th>Accidents</th>
<th>Safe Turns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>60/184 (33%)</td>
</tr>
<tr>
<td>Terminal</td>
<td>115/184 (63%)</td>
</tr>
</tbody>
</table>

Table 7

Thus accident sequences are more standardized at the end, safe transits at the start.

3.3.5 Sequential Pattern-Detection

We also wrote a new program, based on the ID3 algorithm (Quinlan, 1986) to supplement the analyses described in the foregoing sections.

This program (TEXTREE) uses a modified version of Quinlan's ID3 rule-induction algorithm to build a discrimination tree for distinguishing two kinds of text strings. In our case such strings represent accident sequences, encoded as described in subsection 3.3.1. A discrimination tree can be used to classify unseen cases or read off as a set of rules for separating the two types of string (sequence).

In all the analyses reported below the full data was randomly divided into a training set for forming the rule-trees and a test set for assessing the efficacy of the rules on unseen data. Any significance levels quoted are for the results on unseen data.
Since we knew from our N-gram analyses that act-pairs were the natural sequential units in our data (subsection 3.2.1), we forced the program to seek distinctive pairs of symbols in all the runs reported in this section.

Using only act-pairs, the program did not find a robust rule for discriminating injury from non-injury accidents. It was, however, easy for the program to find a rule-tree that discriminated hypothetical from real accident sequences. This was also based on testing for the presence of particular action couples, and is summarized below.

```
IF  APPROACHES JUNCTION  +  INDICATES
    THEN  Type = Hypothetical
ELSE IF  APPROACHES JUNCTION  +  SEES TURN-OFF SIGN LATE
    THEN  Type = Hypothetical
ELSE IF  VIEW OBSTRUCTED  +  STARTS RIGHT TURN
    THEN  Type = Hypothetical
ELSE IF  FAILS TO NOTICE VEHICLE  +  EDGES FORWARD
    THEN  Type = Hypothetical
ELSE  Type = Real.
```

This was developed on 174 cases and tested on a random selection of 110 other cases. Of the unseen cases classed as Hypothetical by this rule 32 were and 11 were not; of those classed as Real by this rule 57 were and 10 were not. This gives a Chi-squared of 39.27 with 1 degree of freedom, which is significant at the \( p < 0.001 \) level. In addition, a point-biserial correlation of the estimated probability of being a Hypothetical accident sequence with the actual category was computed \( (r = 0.591) \), indicating that the rule accounted for 35% of the variance.

In this case, the system has discovered four couplets that do reliably distinguish hypothetical from real accident sequences.

We also used this procedure to look for consistent differences between the sequences of male and female Turners and between young and elderly drivers. In both cases the rule-trees failed on unseen data.

In addition, we looked for differences between hypothetical accidents and safe-transit sequences. Here the problem was that the system found the task too easy (since pairs involving IMPACT, for instance, were never found in safe turns). Having removed all such 'cheating' couplets from the vocabulary available to the program, we obtained a rule-tree that was still successful at categorizing unseen cases. On unseen data it gave:

- 32 true positives
- 3 false positives
- 12 false negatives
- 39 true negatives

yielding a Chi-squared value of 38.30 with 1 degree of freedom \( (p < 0.001) \).

The rule is rather complex, but can be summed up by stating that safe-transits were marked by

```
STARTS RIGHT TURN
```

immediately followed by one of the three event-codes below.
or by the pair

\[ \text{BRAKES} + \text{CONTINUES /TURNING RIGHT.} \]

This may seem trivial, but it probably does reflect a real tendency on the part of our informants to have good behaviour by other road users (AVOIDED BY VEHICLE), pure good luck (CONTINUES /TURNING RIGHT) or skill at last-minute avoiding action (BRAKES, ACCELERATES) in the forefront of their minds as characteristics of safe right-turns. To put it the other way round: they do seem somewhat disposed to ascribe right-turning accidents to

1. lack of skill/care by other road users; or
2. lack of skill in emergency action by the Turner; or
3. pure bad luck;

rather than to failure of observation by the Turner.

### 3.4 CONVENTIONAL STATISTICS

Some more conventional analyses have also been performed which are briefly reported here.

#### 3.4.1 Attribution of Blame

Informants who gave us the 100 hypothetical accidents were also asked to attribute blame to the parties involved. They were given four choices: Turner, Collider, Both or Neither. As a result it is possible to look at the ways in which the age and sex of the informant and the ages and sexes of the (imaginary) accident participants affect attribution of blame.

One point that emerges clearly is a tendency to blame the younger party. We define AGEDIFF as difference between the Turner's and the Collider's age and BLAMEDIF as 1 if the Turner was blamed and the Collider was not, -1 if the Collider was blamed and the Turner was not, 0 otherwise. The correlation between AGEDIFF and BLAMEDIF is -0.40 ($p < 0.001$).

This relationship held for both male and female informants but it was not constant across all age groups in our sample. If we define GUILTAGE as the difference between the age of the 'blamed' party and the 'innocent' party (0 when neither or both parties are blamed) then we find that older informants are more likely to blame the younger party. The correlation between age of informant and GUILTAGE was -0.275 ($p < 0.01$). This negative correlation is stronger among male informants ($r = -0.429; p < 0.001$) but disappears with females ($r = -0.068; p = 0.645$). The effect was thus mainly produced by the older males in our sample, who 'distanced themselves' from fault by imagining a situation in which a young driver or rider caused an accident to a more mature road user.

To see whether a similar process was operating with respect to the gender of the participants we selected the 24 cases in which (a) blame was unequally allocated and (b) the Turner and the Collider were of different sexes. These are tabulated below by sex of informant.
Sex of Person ‘at fault’

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male Informant</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Female Informant</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>18</strong></td>
<td><strong>6</strong></td>
</tr>
</tbody>
</table>

Table 8

It does seem that there is a slight tendency for female informants to envisage an accident in which an innocent female driver is hit by a rogue male.

Any conclusions must be highly tentative at this stage, but we can be fairly sure of one thing: the public is well aware of the danger posed by young male drivers; in fact, we suspect they may overestimate this danger.

3.4.2 Agegroup Profiling

In this section statistics contained in Table 37 in "Road Accidents in Great Britain 1988: The Casualty Report" will be used as a baseline for our results. In order to make our findings comparable with this table, pedestrians and cyclists in our sample were excluded from all analyses presented in this section.

The first analysis examines whether drivers of different age groups are particularly prone to one of the three types of accident (Turning Off, Turning Onto, or Colliding). For this a Chi-squared test was used as a goodness-of-fit measure: if the observed frequencies in the different age groups were significantly different from expected values calculated using the national statistics for all accidents then it would be possible to conclude that certain age groups were over-represented in our sample relative to their representation in other accident types. Expected values are obtained by first calculating the percentage involvement of each age group for all accidents in 1988. These are shown in Table 9.

<table>
<thead>
<tr>
<th>Age</th>
<th>No. Involved</th>
<th>percentage of total involvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 25</td>
<td>119,443</td>
<td>31.5%</td>
</tr>
<tr>
<td>25-34</td>
<td>99,333</td>
<td>26.2%</td>
</tr>
<tr>
<td>35-54</td>
<td>116,950</td>
<td>30.9%</td>
</tr>
<tr>
<td>55 +</td>
<td>43,013</td>
<td>11.4%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>378,739</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

TABLE 9

---

3 The relevant part of Table 37 is the involvement statistics for all motor vehicle drivers

4 The data have been collapsed across age categories in Table 37 to keep expected values in the analyses above 5 so the assumptions of the Chi-squared test are not violated.

5 This total excludes 25,832 unknown values which will be ignored here.
For each type of accident the number expected in each age group is taken to be the same percentage of the sample as the respective percentages shown in Table 9. For example, 31.5% of people involved in all accidents belong to the 'Under 25' category, therefore the number of this category expected to be in the Collider group if 46.4 (0.315 x 147). The observed and expected frequencies for each age group are shown in Table 10.

<table>
<thead>
<tr>
<th>Age</th>
<th>Onto</th>
<th>Off</th>
<th>Collider</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 25</td>
<td>33 (23.6)</td>
<td>28 (28.4)</td>
<td>47 (46.4)</td>
</tr>
<tr>
<td>25-34</td>
<td>12 (19.7)</td>
<td>24 (23.6)</td>
<td>44 (38.5)</td>
</tr>
<tr>
<td>35-54</td>
<td>17 (23.2)</td>
<td>23 (27.8)</td>
<td>39 (45.4)</td>
</tr>
<tr>
<td>55+</td>
<td>13 (8.5)</td>
<td>15 (10.2)</td>
<td>17 (16.7)</td>
</tr>
<tr>
<td>Total</td>
<td>75 (75)</td>
<td>90 (90)</td>
<td>147 (147)</td>
</tr>
</tbody>
</table>

Using a Chi-squared test it was found that the frequencies in different age groups for Turners Off and Colliders did not differ from what would be expected from the national data (Chi² = 3.10 and 1.70 respectively, df = 3, prob. for both >0.25). However, the distribution of the frequencies for Turning Onto accidents did significantly differ from the expected values (Chi² = 10.79, df = 3, p < 0.025). This seems to be due to the over-representation of the youngest and oldest age groups compared to all accidents.

A potential reason for this over-representation is suggested by Moore et al's (1982) analysis of disobedience of junction controls which found that both young and old drivers were coded as 'disobeying sign/signal' more often than middle-age drivers. This may be an indication that drivers in these categories are failing to stop at junctions when perhaps the situation requires it. As very few of our sample were coded by the police as disobeying sign/signal (only nine, with three of these being either turners or colliders involved in turning off accidents) it is not possible to do a meaningful analysis on this. However we have a more sensitive measure available to us in that from the sequential data it can be determined which Turners Onto did not stop before starting the right turn. This tendency was investigated by counting how many times right turning drivers in each age group (again collapsing across the age groups in Table 37) were and were not coded as stopping before making the right turn. These figures are shown in Table 11.

<table>
<thead>
<tr>
<th>Age</th>
<th>Did not stop</th>
<th>Stopped</th>
<th>(Expected)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 25</td>
<td>13/33 (39%)</td>
<td>20</td>
<td>(6.7)</td>
</tr>
<tr>
<td>25-34</td>
<td>3/12 (25%)</td>
<td>9</td>
<td>(13.9)</td>
</tr>
<tr>
<td>35-54</td>
<td>1/17 (6%)</td>
<td>16</td>
<td>(16.4)</td>
</tr>
<tr>
<td>55-64</td>
<td>5/13 (38%)</td>
<td>8</td>
<td>(6.0)</td>
</tr>
</tbody>
</table>

As can be seen the percentages of the youngest and oldest age groups not stopping are higher than the other two age groups. If a Chi-square analysis is done on the remainder, (i.e. the number who do stop) again calculating the expected from national statistics, a non-significant Chi-square of 4.00 is obtained (df =3, p > 0.25). This suggests that an important cause of the over-representation is that both groups concerned are prone to failing to stop when the situation necessitates it. Of course this may be for very different reasons. (See also Section 3.2.6.)
Another possible explanation of the over-representation of older drivers in right turns onto the major road is given by Moore et al. (1982), on the basis of the finding that older drivers have more accidents on faster rural roads than on slower urban roads. Moore et al. suggest that the slower information processing abilities of older drivers become critical when turning onto a fast major road.

"...on reaching a major road at a junction, particularly at a rural junction without signals, he has to accept the speed of the traffic on the major road and the rapidity with which the whole situation changes. Nothing the older driver can do can modify it and he has to do his best to cross or merge with the traffic, but his best might not be good enough." (p21)

So it may be that even when older drivers do stop before turning they may be still more prone to accidents due to misjudgements. If they do have this problem then, using age as the dependent variable, there should be an interaction between the speed limit of the road and type of turn. This is because, if an information processing account is correct, a smaller effect of speed of road may be expected when making the less demanding turnings off major road. A two-way 'type (on/off) x speed limit (low/high)' analysis of variance was carried out to test this. A 'high' speed limit being defined as greater than 30mph and 'low' as 30mph or below. The means for this are shown in Table 12.

<table>
<thead>
<tr>
<th>Type</th>
<th>Speed Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Onto</td>
<td>34.1</td>
</tr>
<tr>
<td>Off</td>
<td>32.9</td>
</tr>
</tbody>
</table>

TABLE 12

No significant effect of type of turn was found, however the main effect of speed limit was significant (F = 6.64, df = 1,161, p < 0.05) as was the type x speed-limit interaction (F = 4.13, df = 1,161, p < 0.05). Surprisingly this was in the opposite direction to that which might be expected from the analysis of Moore et al. It seems that the mean age for the right turners is higher on roads with high speed limits due to the apparent difficulty of older drivers turning off fast roads and not onto, as was expected.
4.0 DISCUSSION

4.1 REVIEW OF MAIN FINDINGS

In this section we attempt to integrate the results obtained from various analytic techniques under four main topic headings:

- sex differences
- age effects
- risk factors (severity)
- driver preconceptions.

4.1.1 Sex differences

On the whole, our data provide little evidence that male and female drivers have different kinds of right-turning accidents at junctions. The rule-finding system, the sequential analysis and the sequential pattern-detector all failed to reveal consistent differences between male and female Turners. The decision-tree analyses (Section 3.2) did find some apparent sex differences, though these were weak effects.

Most conveniently, part of TRRL's 1990 seat-belt survey (which involved stopping vehicles randomly between the hours of 8 a.m. and 6 p.m. at selected sites - mostly traffic signals) was conducted in Nottinghamshire. The number of male and female drivers found by the seat belt survey matches remarkably well with our accident figures when time of day is taken into account, as shown in Table 13 below.

<table>
<thead>
<tr>
<th></th>
<th>Turners in right-turn accidents</th>
<th>SBS Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekdays (0800-1800 hrs)</td>
<td>32.56%</td>
<td>31.54%</td>
</tr>
<tr>
<td>Weekends (0800-1800 hrs)</td>
<td>25.93%</td>
<td>25.04%</td>
</tr>
</tbody>
</table>

Table 13

Hence neither sex appears especially prone to right-turning accidents.

However, we did find a lower proportion of females among Colliders than among Turners \((z = 1.99; \ p < 0.05)\) and a slight tendency for female Turners to collide with other females, as shown in the frequency table below, in which only cases where the sex of both Turner and Collider was known are counted.

<table>
<thead>
<tr>
<th></th>
<th>Female</th>
<th>Male</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turn: Turner:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>9</td>
<td>33</td>
</tr>
<tr>
<td>Male</td>
<td>14</td>
<td>103</td>
</tr>
<tr>
<td>Collider:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>103</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>136</td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>117</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>136</td>
</tr>
<tr>
<td></td>
<td>159</td>
<td></td>
</tr>
</tbody>
</table>

Table 14
It does seem that: (1) males are over-represented as Colliders; but (2) that female Turners tend to hit other females more often than might be expected. We believe that point (1) can be accounted for on the assumption that women drive more slowly and thus present a lesser hazard to other road users, and that point (2) is a result of the fact that women drive less at night, and more during the day. Thus women have accidents when there is a higher than usual proportion of female drivers on the road. Conversely males drive more during the hours of darkness when there are very few women drivers to collide with. (The National Travel Survey of 1985-86 shows that women do a significantly higher proportion of their travelling between 0700 and 1759 than men.)

The data also showed that a higher proportion of females than males (79% versus 53%) stopped prior to an Onto accident, \( \chi^2 = 3.98, \text{df.} = 1; p < 0.05 \).

Overall, we conclude that male and female drivers do not differ greatly in their susceptibility to right-turning accidents; and hence that though there are detectable differences in driving style between the sexes both sexes can be targeted by the same safety advice.

4.1.2 Age effects

We did find significant differences between age-groups, however. In the first place, we found that young drivers (aged 16 to 24) accounted for more than their fair share of accidents. The table below divides the Turners of known age into three age groups and compares the proportion found in each group with the proportion expected according to mileage driven (estimated from the National Travel Survey 1985-86).

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Expected Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 25</td>
<td>66/1170</td>
<td>39%</td>
<td>12%</td>
</tr>
<tr>
<td>25 to 59</td>
<td>83/170</td>
<td>49%</td>
<td>77%</td>
</tr>
<tr>
<td>60+</td>
<td>21/170</td>
<td>12%</td>
<td>11%</td>
</tr>
</tbody>
</table>

Table 15

It can be seen from Table 15 that Turners in the youngest age-group are more than three times as numerous as mileage alone would lead us to expect. Middle-aged drivers appear to be the safest group. This replicates the findings of Rabbitt (1991) among others. The inductive analysis enables us to give a concise ‘thumbnail sketch’ of the main distinguishing characteristics of young and old Turners. Typically the young Turners (under 25) are found in right-turn accidents on minor roads or after dark, riding two-wheelers on a dry road surface.

Elderly drivers (60 and over) are most commonly found in accidents where there is a high speed limit and the Turner has to wait for a gap in traffic (i.e. on busy fast roads).

The sequential analysis confirms this by indicating that sequences involving elderly drivers are more likely to have the events

**INDICATES, STOPS, WAITS**

(in that order) before the turn.
The picture is completed by our conventional statistical analyses, which show that although elderly drivers are more likely than middle-aged ones to stop and wait before turning right Off a larger road, they are (like the youngest age-group) somewhat less likely to stop prior to turning Onto a larger road than drivers in intermediate age-groups.

To recapitulate, the youngest group is more likely than other age-groups to have right-turning accidents

- riding a **2-wheeler**, in darkness, on a minor road,
- at a T-junction turning with no road ahead, and
- to misjudge the speed & distance of another vehicle,

and less likely

- to slow down prior to the junction,
- to fail to notice another road user,
- to be hit from behind.

Elderly Turners are more likely than others

- to indicate, stop and wait,
- on a fast road (speed limit over **30 mph**),
- in daylight,
- at the weekend,
- to be hit from ahead when turning Off,
- to be hit from the right when turning Onto.

In summary, our analyses show that both the youngest and the oldest drivers are more prone to accidents turning right Onto a larger road than they are to other types of accident (as computed from the National statistics). An important reason for this seems to be that they do not stop before executing the right turn when perhaps the situation requires it.

Additionally, we have found that older drivers are over-involved in accidents on faster rural roads. The explanation of Moore et al. (1982) for this is that the older drivers experience difficulties turning Onto fast roads due to their comparatively poor information-processing abilities. This was not substantiated by our data, where the over-representation of older drivers seems to be due to an excess of Off rather than Onto accidents.

The overall picture that emerges is of elderly drivers who are perhaps over-cautious and of young drivers who are not cautious enough. Even so, Turners under 25 and over 55 are significantly less common among injury-accidents as compared with damage-only accidents in our database.

### 4.1.3 Severity

The contrast between injury and damage-only accidents does not reveal any 'hidden secrets'. Our investigations show that the key risk factors are:

- pulling over to an outside lane just prior to the turn,
- colliding with a 2-wheeler or pedestrian,
- failing to notice another road user when turning Off,
- failing to notice another road user in poor weather when turning Onto a larger road.
Most of this just reinforces conventional wisdom on road safety, although it has not previously been noted (1) that poor weather conditions have a more pronounced effect turning Onto than Off a larger road, or (2) that failure of observation is so commonly implicated in injury accidents (compared, for instance, with intentional violation or lack of skill).

Of our codes

FAILS TO NOTICE [vehicle / pedestrian]
MISJUDGES SPEED & DISTANCE OF VEHICLE
MISINTERPRETS INTENT OF [driver / pedestrian]
FAILS TO GIVE WAY

only the last would be categorized as a violation according to the typology used by Reason et al. (1990) and Rasmussen (1987), while the others would count as errors. It has previously been supposed that errors were on the whole less dangerous than violations (e.g. Manstead et al., 1991). Our findings suggest otherwise in the case of this particular type of accident.

Unfortunately failures of observation (or vigilance) are notoriously unsusceptible to training.

4.1.4 Driver preconceptions

The comparisons of real serious-injury accidents with hypothetical serious-injury accidents revealed some systematic differences which we believe have implications for driver education.

The most distinctive serious-injury accident, i.e. the case with most in common with other real serious accidents and least in common with the hypothetical ones, is listed (in slightly abridged form) below.

<table>
<thead>
<tr>
<th>TYPE</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHEN</td>
<td>WEDNESDAY, 14-12-88, 2235</td>
</tr>
<tr>
<td>ROADTYPE</td>
<td>U/C</td>
</tr>
<tr>
<td>SPEEDLIM</td>
<td>30</td>
</tr>
<tr>
<td>URBANITY</td>
<td>URBAN</td>
</tr>
<tr>
<td>CARRIAGEWAY-TYPE</td>
<td>SINGLE</td>
</tr>
<tr>
<td>JUNCTION-TYPE</td>
<td>PRIVATE DRIVE</td>
</tr>
<tr>
<td>JUNCTION-CONTROL</td>
<td>NONE</td>
</tr>
<tr>
<td>WEATHER</td>
<td>FINE</td>
</tr>
<tr>
<td>SURFACE</td>
<td>DRY</td>
</tr>
<tr>
<td>LIGHTING</td>
<td>DARK</td>
</tr>
<tr>
<td>AGE-OF-DRIVER</td>
<td>19, 11</td>
</tr>
<tr>
<td>SEX-OF-DRIVER</td>
<td>M, M</td>
</tr>
<tr>
<td>SEATBELTS</td>
<td>IN USE, N/A</td>
</tr>
<tr>
<td>BREATH-TEST</td>
<td>NOT REQ., N/A</td>
</tr>
<tr>
<td>VEHICLE-TYPE</td>
<td>CAR, PEDESTRIAN</td>
</tr>
</tbody>
</table>

RAIMA
APPROACHES JUNCTION
SLOWS
FAILS TO NOTICE PEDESTRIAN /RIGHT /MOVING
STARTS RIGHT TURN
This case illustrates most of the features that differentiate between real and imaginary serious-injury accidents.

More likely in **Real** Serious Accidents
Collider on 2-wheeler or on foot
fine weather, urban road
Time-of-day **P.M.**
Danger from behind

More likely in **Hypotheticals**
Turner **INDICATES** then **SLOWS** then **STOPS**
Accident on Major road with fast speed limit
Turner **EDGES FORWARD** to gain better view
Collider fails breath-test

Our informants gave us descriptions that were unrealistic in two main respects (1) they were over-dramatic, with a large number of risk factors added together, and (2) they portrayed the prime actor (the Turner) as being unlucky or **unskilful** rather than careless.

Part of this contrast can be explained by the implied demand-characteristics of the experimental situation; but we believe that is not the whole story. Our results appear to replicate the tendency (found in several areas of psychological research) of people to perceive safe situations as safer than they really are and risky ones as more dangerous. (cf. Howarth, 1987.)

### 4.2 REVIEW OF ANALYTIC TECHNIQUES

In this section we summarize our evaluation of the analytic techniques employed during the present study, for the benefit of other researchers who might wish to employ similar techniques.

#### 4.2.1 Rule finding

One of our original hopes was that rule-finding software — either pre-written (e.g. PC/BEAGLE) or developed specifically for the project (e.g. BID3 TEXTREE) — would help to reveal regularities in the data which were simply undetectable by other means.

The rule-finders did provide some surprises (e.g. the excess of elderly males in accidents during the last 3 months of the year), but overall they generated more questions than answers. There is nothing wrong in this, as long as it is anticipated. It means that, in order to benefit from the strong points of such systems, one must be prepared to deal with their weaknesses, which are:

1. tendency to pick up artifactual associations, unless carefully constrained;
2. tendency to produce results that are hard to interpret.
Even more serious is the lack of a code of good practice governing their use. In this respect, machine induction is still a relatively immature technology, whereas statisticians have had nearly a century to develop a methodology covering the mainstream statistical techniques, such as analysis of variance, regression and factor analysis. If (or when) such a methodology is developed for machine learning, it will lessen the force of the objections listed above. In the meantime, it is necessary to stress a fairly obvious point (but one that is not usually emphasized by vendors of such software): using a rule-finder or inductive package does not remove the need for human inspection, evaluation and interpretation of the data; in fact, it increases this need.

We have no fully worked-out methodology to offer, only some informal guidelines, of which the most important are:

- use rule-finding alongside, rather than instead of, conventional analytic techniques;
- use rule-finding early rather than late.

Our initial attitude was to regard the rule finders as black boxes which would reveal 'hidden secrets towards the end of our data analysis. This turned out to be mistaken. In fact, their most valuable role proved to be in suggesting questions for further analysis by other methods.

Rule finders frequently do discover unexpected associations (sometimes nonlinear) which a human analyst might well miss. Many of these turn out to be spurious or trivial, but some deserve further investigation. Used as part of the early data-screening process such programs have a valuable role to play especially in early data-screening, but they should not be treated as oracles.

4.2.2 Sequential analyses

Another aim of this project was to test the applicability of sequential analysis in the area of road-accident research. In this context, the results obtained in section 3.3 were somewhat disappointing, especially in proportion to the effort involved in obtaining them. It must be said that the purely sequential information in our data was not able to bear the emphasis we wanted to place on it.

This somewhat negative conclusion seems to have two major sources. In the first place the police records describe events at a level of granularity which does not permit us to establish the ordering of certain high-speed events with any great confidence. Secondly, it would appear that right-turning accidents simply do not have a particularly complex sequential structure. Although driving is a temporal process, giving rise to long chains of behaviour, we have not found significant dependencies between acts separated by more than a few other acts. The analogy with syntax does not appear to be very fruitful in this case.

In so far as accidents have a 'grammar' it is a very simple and rather inflexible one in which the omission of a key element at a fixed point in the sequence (such as failing to notice an approaching vehicle just prior to starting the turn) renders an otherwise valid 'sentence' completely invalid. To be more concrete: the boundary between low-risk and high-risk situations is sharp and can be crossed in a moment by a single act (or omission).

Nevertheless, the fact that a serious and thorough attempt to explore the linguistic analogy has been made in this field, and has come up with a broadly negative result, is worth putting on record.
4.2.3 Data-coding from Police records

The fact that our data turned out to be, to put it crudely, less sequential than we expected, has implications for TRAAL and for future attempts to code from local police records (rather than nationally aggregated statistics).

TRAAL has aroused interest in the USA and in France, but it is clearly far from perfect. A better version of the language (TRAAL-2 perhaps) could easily be developed, once the emphasis on exhaustive sequential coding has been reduced. A major improvement could be obtained by 'checklisting' the main action terms. This would entail dividing the episode under scrutiny into two or three phases which are reliably identifiable from the police records, and recording the presence or absence of acts or short sequences of acts rather than attempting to specify the detailed sequence of events. Such an approach would fit the coding scheme better to the data on which it is based and would have several advantages: each case would take less time to encode; it would be easier to cross-check between coders; and, above all, it would enable recording the acts of the Collider (if any) on the same basis as those of the Turner. It could also be used on other kinds of manoeuvre than right turns.

Our experience with Nottinghamshire Constabulary traffic records leads us to believe that police accident records, although unsuitable for detailed moment-by-moment coding, do contain useful information that is not exploited for the purposes of road accident research. Such records give behavioural information which is lost by the time the national statistics are aggregated. TRAAL can be seen as a first step in the evolution of coding practices that will enable more productive usage of this under-utilized data resource.

4.2.4 Other considerations

The present study attempted to employ an exploratory approach to accident analysis. We went back to the 'Baconian' methodology which most philosophers of science regard as obsolete. Our rationale was that this data-driven approach has been given a new lease of life by recent advances in inductive software.

In practice the Baconian method was less productive than we hoped, even with advanced software. Many of our results were obtained using less sophisticated techniques. We conclude that the quality of the data (more precisely, the aptness of the data to the techniques being used on it) is a more important determinant of the quality of the results than the sophistication of the analytic software.

There is also the problem of novelty. Some of our findings merely replicate familiar relationships. This is inevitable with inductive methods that cannot be set to induce only novel results in the way that hypothesis-testing methods can be set to test only novel hypotheses.

To that extent our neo-Baconian methodology would have to be modified in any future study - essentially relegated to a supporting role in the preliminary screening phase of a predominantly hypothesis-driven investigation.
4.3 CONCLUSIONS

In this section we make brief (tentative) recommendations in two distinct areas: (1) research methodology; (2) practical matters.

4.3.1 Methodological matters

One part of our approach that we believe should definitely be copied in future is the decision to concentrate on a relatively homogenous class of accidents. If we had taken a random sample of accidents (as some early 'in-depth' studies did) we would have discovered almost nothing. Indeed it was when we examined quite specific subsets from our total database (such as drivers over 55 Turning Off a fast rural road) that a coherent picture began to emerge.

We conclude that one of the most valuable outcomes of this research is a better idea of what counts as a natural grouping of accidents for the purposes of causal analysis, and of the level of detail at which accident types can be reliably differentiated.

Two further methodological conclusions arise out of the decision-tree study (section 3.2), as summarized below.

(1) Decision-tree growing is a viable exploratory method in road-accident data analysis, provided that an adequate tree-pruning mechanism is incorporated.

(2) The sheep-versus-goats approach to constructing a training set for a tree-growing program is more revealing than unselective scanning of a database, but is open to objections if the selection criteria are inadequate.

4.3.2 Practical matters

A study of this kind, taken on its own, does not provide an adequate basis for recommending countermeasures. However, the following findings in particular may be worth considering with the other evidence available when countermeasures are being designed in relation to the types of accident we have studied here.

Firstly, our results suggest that older drivers (who are generally safer than the average even up to the age of 65) have specific problems with right turns at junctions of fast busy roads. The type of turn determines the nature of the problem. Turning Onto a larger road, older drivers tend not to wait long enough (or at all) - a fault they share with young drivers. Turning Off a major road, however, they tend to stop and wait too long. Here the problem would seem to be hesitancy.

Comparison of real with hypothetical accidents suggests that drivers turning Off a fast road need to be more attentive to vehicles approaching from ahead and behind than they are at present.

Like other researchers in this field, we find an excessive accident involvement of younger drivers.

Finally, our results emphasize once again the vulnerability of bicycles, motorbikes and pedestrians. Failure of drivers in larger vehicles to notice such road users is the most important single causal factor precipitating injuries in our database. Not only do motorists fail to notice 2-wheelers on the road, they also give little thought to them off the road:
whereas 23\% of the real accidents in our sample involved a Collider on two wheels or on foot, only 9\% of the hypothetical accidents described by our informants did so ($t = 2.93$; $p < 0.005$); and none of the informants described an accident involving a 2-wheeled Turner.

4.4 FUTURE DIRECTIONS

We believe that this project has opened up a mode of road-accident research which represents a viable compromise between traditional in-depth studies and nomothetic research. It has the potential of being

(a) cheaper than traditional in-depth studies, but at the same time,
(b) more informative than analyses of large aggregated data sets.

In order to fulfil this potential, however, improvements need to be made in four key areas.

Firstly, we need to make further progress in coding, drawing on the lessons learned in the development of TRAAL, as outlined in section 4.2.3.

Secondly, more work remains to be done on tailoring inductive software to the requirements of this kind of research. The rule-finding approach using PC/BEAGLE and the decision-tree program was certainly interesting enough to warrant further attention. We believe that its efficacy could be greatly improved by further development of special-purpose inductive programs, more fully tailored to suit the needs of road-accident analysis.

Thirdly, it is now apparent that research of this kind needs to be done in the context of planned follow-up studies. Rule-finding tends to generate a need for fresh observational data for validation purposes. For example, our finding that poor weather has a more adverse effect on right turns onto than off a larger road could be tested by a simple conflict study.

Fourthly, it is important to focus on coherent sub-classes of road accidents. Natural categorizations cannot always be foreseen at the outset so it is an essential part of such an approach to allow for the identification of ‘syndromes’ (a process in which inductive software can be very helpful) at an early stage.

Finally, more work is required on the problems of case aggregation. This is an issue that has bedeviled detailed case-based research in many fields, including work on road accidents. At worst, it is sometimes said that case studies show little about the processes of interest until they reach a considerable level of detail, at which point each case appears unique and no synthesis or predictive generalization is possible.

We do not accept this pessimistic assessment. On the contrary, we regard aggregation over cases as an important and tractable problem, on which further research would pay dividends. Combining the results of a number of case studies is of course a quite different matter, serving different purposes and requiring different methods, from the aggregation of data to provide an adequate pool prior to conventional analysis. If done appropriately it permits a number of ‘natural categories’ to be identified, rather like medical syndromes, each with consistent and reliably generalizable characteristics, and a set of diagnostic features by which future instances can be recognized. These can then form the basis of appropriate future practice, grouping like cases with like on firmer grounds than just a
superficial similarity of 'symptoms'. We believe that a well-founded typology of causal patterns will prove to be just as important in understanding road accidents as it has been in medicine, and that projects such as this have a significant role to play in arriving at such a typology.

ACKNOWLEDGEMENTS

We are most grateful to Nottinghamshire Constabulary for their patient assistance in locating suitable cases for analysis; to our driver-informants for their descriptions of hypothetical accidents and safe turns; to other members of the Accident Research Unit for their helpful comments and suggestions; to Mr Chris Ashton of the Nottinghamshire County Council Accident Investigation Unit for assistance with the selection of the sample; and to Dr Graham Grayson and Mr Geoff Maycock of TRRL for their helpful guidance and advice.

REFERENCES


APPENDIX A

Summary of Rules

This appendix contains, for ease of reference, translations into structured English of the induced rules quoted in section 3 of the main report. They are collected under four headings; and each rule is keyed to a section in the report where a fuller discussion may be found.

(1) severity;
(2) real versus hypothetical accidents;
(3) type of right turn;
(4) age group of Turner.

1. Severity

All rules in this section are for discriminating injury from Non-injury accidents.

Rule 1.1 (section 3.1.1)

An injury is more likely

IF
   the Turner changes lane from left to right prior to the turning manoeuvre
   OR
   the colliding vehicle has less than four wheels.
   [N.B. The latter condition includes pedestrians.]

Rule 1.2 (section 3.1.1)

An injury is more likely
IF
   the Turner fails to notice a vehicle or pedestrian
   AND
   the Turner is turning Off a larger road
   OR
   the Turner is turning Onto a larger road in poor weather.

Rule 1.3 (section 3.1.1)

An injury is more likely
IF
   the Collider is a 2-wheeler or Pedestrian
   OR
   the Turner continues through a green light and then fails to notice another vehicle
   OR
   the Turner slows down then fails to notice another vehicle.
Rule 1.4 (section 3.1.1)
An injury is more likely
In Winter (Dec, Jan, Feb):
IF
   The Turner is 60 or over
   OR
   The Turner is under 60 but does not slow down then stop
In Other Seasons (March to November):
IF
   The Turner is 60 or more but does not slow down then stop.

Rule 1.5 (section 3.1.1)
An injury is more likely
IF
   the Turner passes the breath-test
   AND
      EITHER
         it is not fine weather
         OR ELSE
         it is fine and the turn-type is Off and the Turner fails to notice another vehicle.

[N.B. This does not of course mean that being sober is dangerous, but rather that being breathalyzed is far more likely after an injury accident than a damage-only accident. Hence this is a descriptive rather than a predictive rule.]

Rule 1.6 (section 3.1.1)
An injury is more likely
IF
   The Turner fails to notice another road user
   OR
   the Turner does not slow down prior to the junction.

Rule 1.7 (section 3.1.1)
When turning Off an A or B road:
An injury is more likely
IF
   either the Turner or Collider is driving a 2-wheeler (or the Collider is a pedestrian),
   AND
   it is summer (Jun, Jul, Aug) and the Turner does not slow just prior to stopping at the junction.

[N.B. The last condition only excludes the pair of successive acts SLOWS + STOPS; the Turner may still slow down.]
Rule 1.8  (section 3.2.4)

In Onto accidents:

an injury is more likely
IF

the season is winter (Dec, Jan, Feb)
OR ELSE
the collider is on 2 wheels or on foot
OR ELSE
the turner fails to slow prior to turning.

Rule 1.9  (section 3.2.4)

In Off accidents:

an injury is more likely
IF

Turner is on 2 wheels
OR ELSE
Collider approaching from Ahead
[Direction of danger = Ahead.]

2. Real versus Hypothetical Accidents

The rules in this section are for discriminating real serious-injury accidents from hypothetical serious-injury (or fatal) accidents.

Rule 2.1  (section 3.1.2)

A record is more likely to come from a real accident
IF

it is fine weather
AND
the Collider either passes the breath-test or does not provide a breath-test.

Rule 2.2  (Section 3.1.2)

A record is more likely to be from a real accident
IF

the Turner fails to slow down
OR
the Turner is at a simple junction (with less than four arms) on a minor road.

[N.B. These rules do not of course imply that fine weather is a risk factor or that simple junctions are more dangerous than complex ones, still less that the sobriety of other road users presents a hazard to right-turners. Instead they reflect the tendency of our informants to produce relatively dramatic descriptions in which the risks posed by poor weather, complex intersections and intoxicated drivers were especially exaggerated.)
Rule 2.3  (section 3.3.1)

The rule-tree that discriminated hypothetical from real accident sequences based on testing for the presence of particular action couplets is also summarized below.

IF    APPROACHES JUNCTION + INDICATES
THEN  Type = Hypothetical
ELSE IF APPROACHES JUNCTION + SEES TURN-OFF SIGN LATE
THEN  Type = Hypothetical
ELSE IF VIEW OBSTRUCTED + STARTS RIGHT TURN
THEN  Type = Hypothetical
ELSE IF FAILS TO NOTICE VEHICLE + EDGES FORWARD
THEN  Type = Hypothetical
ELSE  Type = Real.

3. Type of Right Turn

The rules in this section discriminate between accidents during right-turns Onto and Off a larger road (i.e. the road with right of way).

Rule 3.1  (section 3.1.3)

A right-turn is more likely to be Onto a larger road IF the Turner does not continue through a green light and there is no danger from behind (but usually from another direction).

Rule 3.2  (section 3.1.3)

A right-turn is more likely to be Onto a larger road IF the Turner slows then stops at the junction OR the direction of danger is from the right.

4. Age of Right Turner

Rule 4.1  (Section 3.1.4)

Young drivers (under 25 years of age) tend to be overrepresented as Turners in accidents:

on B, C or Unclassified roads in any lighting conditions or on A roads after dark; OR
driving two-wheelers on a dry surface; OR
where the Turner is female or driving during the first 9 months of the year (i.e. not a male driving during October, November or December).
Rule 4.2 (section 3.1.4)

Accidents involving elderly drivers (60 years old or more) tend to be characterized by the following conditions:

- there is a high speed limit and the Turner waits for a gap in traffic (i.e., busy main roads);
- OR
- the Collider is also old and the time is before 3 p.m.

Rule 4.3 (section 3.2.5)

In Onto accidents:
Turner is more likely to be a Young male
IF
- Junction has only 3 arms
- Turner does not wait
- Turner does not slow down prior to turn.

Rule 4.4 (section 3.2.5)

In Off accidents:
Turner is more likely to be a Young male:
IF
- Turner does not fail to notice other road user
- Turner is on 2 wheels.
APPENDIX B

Basic statistics

The following tables give details of the main static features of the Nottingham University Right-Turning Database.

<table>
<thead>
<tr>
<th>Type</th>
<th>Freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turning Onto</td>
<td>90</td>
</tr>
<tr>
<td>Turning Off</td>
<td>94</td>
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<table>
<thead>
<tr>
<th></th>
<th>Onto</th>
<th>Off</th>
<th>Total</th>
</tr>
</thead>
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<td>Urbanity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
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<td>163</td>
</tr>
<tr>
<td>Rural</td>
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<td>10</td>
<td>21</td>
</tr>
<tr>
<td>Day</td>
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<td></td>
</tr>
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<td>Weekday (Mon-Fri)</td>
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<tr>
<td>Season</td>
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<td>Winter (Dec/Jan/Feb)</td>
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<td>17</td>
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<tr>
<td>Spring (Mar/Apr/May)</td>
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<td>44</td>
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<tr>
<td>Summer (Jun/Jul/Aug)</td>
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<td>44</td>
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<tr>
<td>Autumn (Sep/Oct/Nov)</td>
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<td>27</td>
<td>53</td>
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<tr>
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<td>P.M. (1200-1759)</td>
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<th>Female</th>
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<th>Turner's Vehicle</th>
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<th>Moped/Motorcycle</th>
<th>Car</th>
<th>Larger vehicles</th>
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<td>9</td>
<td>161</td>
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<thead>
<tr>
<th>Collider's vehicle</th>
<th>Cycle</th>
<th>Moped/motorcycle</th>
<th>Car</th>
<th>Larger vehicles</th>
<th>Other (Static object/Pedestrian)</th>
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<table>
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<th>Ages:</th>
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<tr>
<td>Turners</td>
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<tr>
<td>Off</td>
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| Colliders          |
| All                | Mean = 33.9 s.d. = 15.6 |