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Statistical Analysis of Traffic Injury Severity: The Case Study of Addis Ababa, Ethiopia

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Abstract: **Road traffic accident is the cause of significant loss of human and economic resources all over the world especially in big cities. The main objective of this study was to identify and describe the factors affecting the injury severity in Addis Ababa. This study based on a secondary data which obtained from Addis Ababa Traffic Police Commission Bureau from July 01, 2011(G.C) to June 30, 2012(G.C). The candidate variables for the study were driver's age, driver's sex, driver's education status, driver's experience, driver's defect, vehicle type, vehicle owner, vehicle defect, road topography, road junction, road surface, weather condition, light condition, pedestrian physical fitness, time, day and month. Among the candidate variables, Chi-Square method identified driver's age; driver's sex, driver's education status, driver's experience, driver's defect, vehicle type, vehicle owner, vehicle defect, road topography, road junction, weather condition, pedestrian physical fitness, time, and month were significant variables. In order to make interpretation on factors affecting the injury severity of crashes in Addis Ababa, Multinomial model was used. The results indicated that driver's age, driver's education status, driver's experience, vehicle type and road topography were positively associated with injury severity. The predicted probability of injury severity also showed that the probability of property damage only and severe injury were high. In order to reduce injury severity in Addis Ababa, all concerned bodies should give attention to the factors which were positively associated with injury severity.**

Keywords: **Injury Severity Levels and MNL Model.**

1. INTRODUCTION

1.1 Background:

Road traffic accident is the cause of significant loss of human and economic resources worldwide. The World Health Organization (WHO) estimated that 1.17 million deaths occur each year worldwide due to road traffic accidents which of about 70 of the deaths occur in developing countries. It indicated that 55 percent of the deaths involve pedestrians, out of which 35 are children. Over 10 million are also crippled or injured each year. It has been estimated that at least 6 million will die and 60 million will be injured in developing countries during the next 10 years unless urgent actions are taken (EEsa, 2012). The rate of traffic accidents in Addis Ababa goes up together with the increase of motor vehicles and population size. The rise in automobile ownership together with the poor condition of the roads has resulted in the high level of traffic safety and congestion problems. Moreover the death rate is 136 per 10,000 vehicles and Ethiopia is losing over 400 million birr yearly as a result of road accidents. The share of Addis Ababa city in the total number of accidents was 60 percent in 1989 with annual average traffic accident growth of 31.4 percent. Nowadays, Addis Ababa is experiencing around 700 accidents per month resulting in various levels of injury (Tesema,T.et al, 2005).

1.2 Statement of the Problem:

Road traffic accident (RTA) is defined as an accident that occurred on a way or street open to public traffic; resulted in one or more persons being killed or injured, and at least one moving vehicle was involved. This study was attempted to address the following questions.

- Which variables are significantly affect occurrence of injuries severity?
- How multinomial model can be applied and interpret to crash injury severity data?

1.3 Objectives:

1.3.1 General Objective:

To identify and describe the major factors that affect occurrence of traffic injury severities by using multinomial model in Addis Ababa, Ethiopia.

1.3.2 Specific Objectives:

- To describe and identify the main contributing factors to crash injuries severity.
- To apply multinomial logit model to crash injury severity data.
- To make probabilistic prediction of injury severity.
- To provide useful information for policy makers and researchers based on the results obtained in this study.

2. LITERATURE REVIEW

2.1 Crash Severity Models:

When dependent variable carries a highly discrete value, a multinomial logit or ordered probit is used. The Multinomial Logit (MNL) model is often used to predict the crash severity. Although MNL models do not recognize order in injury levels, they do avoid certain restrictions posed by standard ordered models. They allow variables to have opposing effects regardless of injury order; for example, air bags may cause more injuries but fewer fatalities. Thus, MNL models are still applied in many studies for the crash severity analysis.

Khorashadi et al. (2005) explored the differences of driver injury severities in rural and urban accidents involving large trucks. Using 4- years of California accident data and multinomial logit model approach, they found considerable differences between rural and urban accident injury severities. In particular, they found that the probability of severe/fatal injury increases by 26% in rural areas and by 700% in urban areas when a tractor-trailer combination is involved, as opposed to a single-unit truck being involved. They also found that in accidents where alcohol or drug use is identified, the probability of severe/fatal injury is increased by 250% and 800% in rural and urban areas respectively.

Islam and Mannering (2006) studied driver aging and its effect on male and female single vehicle accident injuries in Indiana. They employed multinomial logit models and found significant differences between different genders and age groups. Specifically, they found an increase in probabilities of fatality for young and middle-aged male drivers when they have passengers, an increase in probabilities of injury for middle-aged female drivers in vehicles 6 years old or older, and an increase in fatality probabilities for males older than 65 years old. Nigatu (2012) had done on spatial analysis of traffic accidents. He used Negative Binomials and Bayesian spatial models in order to investigate the effect of determinant factors on vehicle crashes rather than injury severity.

Therefore, this research work is aimed to study the injury severity levels using multinomial regression model.

3. METHODOLOGY

3.1 Data:

The study has been conducted in Addis Ababa, Ethiopia. Accidents are recorded by the traffic police on daily basis. This study based on a secondary data which obtained from Addis Ababa Traffic Police Commission Bureau from July 01, 2011(G.C) to June 30, 2012(G.C) from all sub-cities.

3.2 Sample Data size Selection:

There are 11,529 records in the 2012 crash injury severity data. Since Multinomial logistic regression needs careful consideration of the sample size in order to get good parameter estimation which is an inferential goal of multinomial, the sample size determination is very important. Thus, Sudman (1976) suggests that 100 elements are needed for each major group in the sample and for each minor group, a sample of 20 to 50 elements is necessary. Therefore, percentage of fatal was 0.032 (which is the smallest among injury severity categorical in the data). Since fatal crash is considered as a major group so that 100 elements are considered to be sufficient in this study. The sample size is calculated as: 100/0.032= 3125. Thus, 3,125 sample size determined is sufficient in this study.

3.3 Variables Considered in the Study:

3.3.1 Dependent Variable:

The main interest of this study is to identify and describe the contributing factors to crash Severity and therefore crash severity is the dependent variable in a crash severity prediction model. Crash severity in the crash dataset was divided into four ordered categories: fatal, severe injury, slight injury and PDO.

3.3.2 Independent Variables:

Driver related Variables, Vehicle related Variables, Road and Environment related Variables, Time related variables and Pedestrian related Variables.

3.4 Multinomial Logit Model:

By far the easiest and most widely used discrete choice model is logit (Kenneth, 2002). Its popularity is due to the fact that the formula for the choice probabilities takes a closed form and is readily interpretable.

Assumptions:

- The response variable is treated as categorical and has no natural ordering.
- Unknown error term is independently and identically distributed on a Gumbel or type I extreme value.
- The relative probability of choosing between any two alternatives is independent of all other alternatives, that is called independence from, irrelevant alternatives (IIA) property.
- No correlation among unobserved factors across alternatives.

A decision maker, labeled n, faces J alternatives. The utility that the decision maker obtains from alternative j is decomposed into,

$$U_{nj} = V_{nj} + \in_{nj} \qquad (1)$$

Where a part labeled V_{nj} that is known by the researcher up to some parameters and the logit model is obtained by assuming that each $\in_{nj}$ is independently, identically distributed on Gumbel or type I extreme value. The closed form of this probability can be derived from equation (1) and is given by

$$P_{ni} = \frac{e_{vi}}{\sum_j v_{nj}} \qquad (2)$$

Which is the logit choice probability (Kenneth, 2002).

3.5 Parameter Estimation of Multinomial Logit Model:

The estimation of the model parameters can be carried out through the method of maximum likelihood. The probability of person n experiencing the severity level i can be expressed as

$$\prod_i (P_{ni}) Y_{ni} \qquad (3)$$

Where Y_{ni} = 1 if person n experienced severity level i and zero otherwise. Since Y_{ni}= 0 for all non-chosen alternatives and P_{ni} raised to the power of zero is 1, this term is simply the probability of the chosen alternative. From equation (3) ,assuming that each decision maker‘s choice is independent of that of other decision makers, the probability of each person in the sample choosing the alternative that he or she was observed to choose is

$$L(\beta) = \prod_{n=1}^{N} \prod_i (P_{ni})^{Y_{ni}} \qquad (4)$$

Where β a vector containing the parameters of the model.

The log likelihood function is then from equation (4) is

$$LL(\beta) = \sum_{n=1}^{N} \sum_i Y_{ni} \ln P_{ni} \qquad (5)$$

And the estimator is the value of β that maximizes this function. At the maximum of the Likelihood function, its derivative with respect to each of the parameters is zero that is from equation (5) ,

$$\frac{dLL(\beta)}{d(\beta)} = 0 \qquad (6)$$

The maximum likelihood estimates are therefore the values of β that satisfy this first order condition.

3.6 Evaluation for Severity Prediction Model:

Goodness of fit tests can be conducted to test how well the model fits the data. The following test can be conducted:

The likelihood ratio index(ρ) is defined as:

$$\rho = 1\text{-}\frac{LL(\beta')}{LL(0)} \qquad (7)$$

Where $LL(\beta')$ is the value of the log-likelihood function at convergence with all parameters estimated. LL (0) is its value when all parameters except the constant are set equal to zero. If the estimated parameters do no better, in terms of the likelihood function, than zero parameters, then $LL(\beta') = LL(0)$ and ρ =0. When ρ =1, the model is achieved because each crash severity in the calibration data set is predicted perfectly.

4. RESULTS

4.1 Variable Selection:

The selection of independent variables included the following considerations: factors identified in the literature as contributing to crash severity, human factors, and factors related to crashes with high severities. There are many attributes within each crash record stored in the annual crash database and they can be divided into three categories: human related, roadway and environmental related, and vehicle related. The analysis started by testing the significance of the association, that each explanatory variable could have with the dependent variables. For these purposes the chi-square test is applied and given in Table-1 below. Even though the dependent variable is count of injuries severity given accident occurrence, during the application of chi-square test, it was assumed as a categorical variable. This was done for making the chi-square test more reliable in its results. Accordingly, the categories for the dependent variable are for injuries severity: property damage only, slight injury, severe injury and fatal. The chi-square test results at appendix table 1 indicate that the variables: Age of Drivers, Driver's Gender, Driver's Education Level, Driver's Experience, Vehicle Type, Vehicle Owner, Vehicle Defect, Road Topography, Type of Road surface, Road Junction, Weather Condition, Time, Pedestrian physical fitness and Month are significantly associated with the dependent variable. While Day, Condition of Light and Type of Road Surface are not significant.

4.2 MNL Model Estimation Results:

The dependent variable, crash injury severity, was coded as fatal, severe injury, slight injury and PDO crash in the original crash dataset. In the process of model estimation in the STATA software, crash severity was described in terms of alternatives 1, 2, 3, and 4, representing crash injury severity ranging from PDO to fatal crash respectively. A MNL model can be described by a situation where the main influences on the choice outcome are the characteristics of the observations (i.e. individual crash). Our data are described only by the characteristics of crashes whose attributes do not vary across outcomes. For example, the time of a crash does not vary across severity level for that individual crash, but it does among observations in the dataset as a whole. The response variable, crash injury severity is going to be treated as categorical under the assumption that the levels of injury status have no natural ordering and are going to allow STATA to choose the reference group, as default. In practice, when estimating the model, coefficients of the reference group are set to zero. Since 4 injury severities exist, only (4-1) distinct sets of parameters can be identified and estimated. Multinomial logistic regression, like binary and ordered logistic regression, uses maximum likelihood estimation, which is an iterative procedure. The first iteration (called iteration 0) is the log likelihood of the null or empty model; that is, a model with no predictors. At the next iteration, the predictor(s) are included in the model. At each of iteration, the log likelihood decreases because the goal is to minimize the log likelihood. When the difference between successive iterations is very small, the model is said to be converged, the iterating stops, and the results are displayed.

4.3 Parameter Estimation and Interpretation of MNL:

In multinomial regression estimation, the three parameters are estimated: slight injury relative to PDO, severe injury relative to PDO and fatal relative to PDO. The coefficients of the estimated model can be interpreted as follows. A positive significant coefficient on a variable indicates that the variable is associated with a higher probability of being in that group choice relative to the reference group. The implication is that the probability of a crash at that level of severity is greater than the probability of placing it in the reference group. The negative sign means that the probability of a crash at that level of severity is smaller than the probability of placing it in the reference group. For example, the coefficient of driver age use is a positive value of 5.47 for the severity level of slight injury, indicating that the probability of a crash to be a slight injury crash is higher than a PDO crash if a level changes in level of diver age. An important feature of the multinomial logit model is that it estimates k-1 models, where k is the number of levels of the dependent variable. In this study, STATA by default set PDO as the reference group. Since the parameter estimates are relative to the reference group, the standard interpretation of the multinomial logit is that for a level change in the predictor variable, the logit of outcome k relative to the reference group is expected to change by its respective parameter estimate given the other variables in the model are held constant. The detailed Multinomial output result is given at appendix.

4.4 MNL Model Goodness of Fit Test:

4.4.1 over all Test of Model Adequacy:

The Likelihood Ratio (LR) Chi-Square tests LR $chi^2(42)$ that for the three equations, slight injury relative to PDO, severe injury relative to PDO and fatal relative to PDO for, at least one of the predictors' regression coefficient is not equal to zero. The number in the parentheses indicates the degrees of freedom of the Chi-Square distribution used to test the LR Chi-Square statistic and is defined by the number of models estimated (3) times the times the number of predictors in the model (14) equal to (42). The LR Chi-Square statistic can be calculated by,

$$-2 \times \left(L(null\ model) - L(fitted\ model)\right)$$
$$= -2 \times ((-2237.66) — 486.79942)$$
$$= 4962.11942$$

Where L(null model) is from the log likelihood with just the response variable in the model (Iteration 0) and L(fitted model) is the log likelihood from the final iteration (assuming the model converged) with all the parameters. The null hypothesis is that all of the regression coefficients across models are simultaneously equal to zero. In other words, this is the probability of obtaining this chi-square statistic (4962.11942) if there is in fact no effect of the predictor variables. The small p-value from the LR test < 0.00001, would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero.

4.4.2 Likelihood Ratio Index:

The likelihood ratio index ρ is calculated as from equation (7),

$$\rho = 1 - \frac{LL(\beta')}{LL(0)}.$$

Where $LL(\beta')$ is the value of the log-likelihood function at convergence and LL (0) is the first iteration. Thus,

$$\rho = 1 - \frac{-486.79942}{-2237.66}$$
$$= 0.7825$$

The goodness fit test for MNL model result is shown in Table-2 below. Since $\rho > 0$, that is 78.25% then the estimated parameters do better, in terms of the likelihood function than zero parameters or null model.

Table 2: Result of MNL Model Goodness of Fit Test

Log likelihood at Zero	-2237.66
Log likelihood at Convergence	-486.79942
Number of Observations	3,125
LR index (ρ)	0.7825

5. DISCUSSION

This study focused on Crash prediction model of the injury severity. Therefore, I have the following discussion. From the driver related variables driver's age, driver's education and driver's experience are positively associated on injury severity. Similar results were found by Abdel-aty et al.(1998), their result suggest that injury severity is positively associate with age; they conclude that middle-age drivers are more likely to be involved in crash injury severity. Among vehicle related variables only vehicle owner is positively associated for all injury severity. Similar result were found by (O'Donnel and Connor, 1996).

6. PREDICTED PROBABILITIES

One of the objectives of the study is to predict the future status of crash injury severity. In order to observe how crash injuries severities are going on for the future, we have predicted the probabilities for each level of injury severity by applying multinomial logit to the data. And the predicted probabilities for Property damage and severe injury are high in most of predicted crash events while low for slight injury, and fatal. The result of predicted probabilities for injury severity is given by Table-3 at Appendix.

7. CONCLUSIONS

This study set out to address the following objectives. First, to identify and describe the main contributing factors to crash injuries severity in Addis Ababa including driver related, vehicle related, driver and vehicle related, road and environment related, time related and pedestrian related factors. Second, to apply multinomial logit model to crash injury severity data and making probability prediction of injury severity. The following conclusions have been drawn based on the analysis conducted in this study. In order to identify and describe the factors contributing to the severity of crashes in Addis Ababa, it was decided to fit alternative discrete choice model to injury severity data in Addis Ababa so that the significance and magnitude of the coefficients estimated in the model would identify and describe the factors affecting crash severity. Multinomial Logit model were used. Results indicate that from the driver related variables driver's age, driver's education, and driver's experience are positively associated with injuries severity. Among vehicle related variables only vehicle owner is positively associate with injury severity. Among Road related variables only road topography is positively associated with injury severity. In order to reduce injury severity in Addis Ababa, all concerned bodies should give attention to the factors which were positively associated with injury severity. As recommendation, further studies are recommended to apply Ordered mixed logit and Bayesian ordered probit because of underreported crash injury severity may exist.

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BIOGRAPHY

The author of this Paper was born in East Wollaga zone of Oromiya Regional State of Ethiopia from his mother Biritu Atomsa and his father Alemayehu Berkessa in September 1989. And he completed his elementary education at Lelistu Oda Elementary and Junior Secondary School, and continued his secondary school education at Biftu Nekemte Senior Secondary School, and followed his preparatory at Nekemte Preparatory School. In 2006/7, he took Ethiopian Higher Education Entrance Qualification Certificate and successfully passed. He joined Applied Mathematics Department of Natural Science Faculty of Jigjiga University, in September 2007 and graduated in July 2010 with Bachelor of Science Degree in Applied Mathematics. Soon after graduation, the author joined SodoUniversity, served as an instructor of Mathematics from September 2010 to August 2011. He joined Mathematical and Statistical Modeling (MASTMO) graduate studies of School of Mathematical and Statistical Sciences at Hawassa University in collaboration with Norwegian University of Science and Technology (NTNU) in 2011. He graduated his MSc in Mathematical and Statistical Modeling specialization in July 2013.

APPENDIX - A

Inferential Statistical Results

Table1: Chi-square Test of Association

Variables	Chi-square	Df	P-value
Driver's Age	29.004	12	0.004*
Driver's Gender	19.836	6	0.003*
Day	8.433	18	0.971
Driver's Educational Level	99.550	15	0.000*
Driver's Experience	48.884	15	0.000*
Driver's Defect	77.793	12	0.000*
Vehicle Type	89.388	21	0.000*
Vehicle Owner	90.237	9	0.000*
Vehicle Owner	94.881	6	0.001*
Road Topography	78.780	9	0.000*
Type of Road Surface	10.694	6	0.098
Condition of Light	17.912	9	0.078

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Road Junction	43.499	12	0.000*
Weather Condition	95.113	9	0.000*
Time	62.623	9	0.001*
Pedestrians Physical Fit	93.402	9	0.000*
Month	63.188	33	0.004*

(* Significant at 5% level of α *value*)

Multinomial Out Put Results

```
1 . use "C:\Users\TOSHIBA\Desktop\injury severity.dta", clear

2 . mlogit Severity DriverAge DriverGender DriverEducation DriverExperience DriverDefect Vehicle
  > me PedesPhy Month

  Iteration 0:   log likelihood =   -2237.66
  Iteration 1:   log likelihood = -1212.4691
  Iteration 2:   log likelihood = -800.93042
  Iteration 3:   log likelihood = -610.57359
  Iteration 4:   log likelihood = -547.20299
  Iteration 5:   log likelihood = -517.95758
  Iteration 6:   log likelihood = -506.91696
  Iteration 7:   log likelihood = -489.61842
  Iteration 8:   log likelihood = -486.96889
  Iteration 9:   log likelihood = -486.80055
  Iteration 10:  log likelihood = -486.79942
  Iteration 11:  log likelihood = -486.79942

  Multinomial logistic regression                   Number of obs   =       3125
                                                    LR chi2(42)     =    3501.72
                                                    Prob > chi2     =     0.0000
  Log likelihood = -486.79942                       Pseudo R2       =     0.7825
```

Severity	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
PDO	(base outcome)					
Slight_inj~y						
DriverAge	5.471312	1.309397	4.18	0.000	2.904941	8.037683
DriverGender	-51.83329	6.85406	-7.56	0.000	-65.267	-38.39958
DriverEduc~n	8.419103	1.73937	4.84	0.000	5.009999	11.82821
DriverExpe~e	2.267215	.9156558	2.48	0.013	.4725628	4.061868
DriverDefect	-13.9591	1.702155	-8.20	0.000	-17.29527	-10.62294
VehicleType	-12.44922	1.920046	-6.48	0.000	-16.21245	-8.686004
VehicleOwner	48.01254	6.821759	7.04	0.000	34.64213	61.38294
VehicleDef~t	5.69636	1.654418	3.44	0.001	2.453762	8.938959
RoadTopo	-1.037355	.7189918	-1.44	0.149	-2.446553	.3718428
RoadJunction	3.949552	.6626049	5.96	0.000	2.65087	5.248233
WeatherCon~n	4.279541	1.183195	3.62	0.000	1.960522	6.598561
Time	-11.75533	3.494152	-3.36	0.001	-18.60374	-4.90692
PedesPhy	-1.094336	.3429114	-3.19	0.001	-1.76643	-.4222423
Month	2.656543	1.172998	2.26	0.024	.357509	4.955576

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_cons	7.71316	3.993112	1.93	0.053	-.1131963	15.53952
Severe_inj~y						
DriverAge	4.103134	1.310788	3.13	0.002	1.534037	6.672231
DriverGender	-52.8526	6.847537	-7.72	0.000	-66.27352	-39.43167
DriverEduc~n	10.39919	1.721577	6.04	0.000	7.024958	13.77342
DriverExpe~e	4.433448	.8845831	5.01	0.000	2.699697	6.167199
DriverDefect	-12.73875	1.699888	-7.49	0.000	-16.07047	-9.407031
VehicleType	-12.27677	1.917135	-6.40	0.000	-16.03429	-8.519258
VehicleOwner	48.62818	6.823981	7.13	0.000	35.25342	62.00294
VehicleDef~t	1.690294	1.596181	1.06	0.290	-1.438164	4.818752
RoadTopo	2.510436	.6550998	3.83	0.000	1.226464	3.794408
RoadJunction	2.835117	.6720923	4.22	0.000	1.51784	4.152393
WeatherCon~n	1.134009	1.169656	0.97	0.332	-1.158474	3.426493
Time	-13.39746	3.468206	-3.86	0.000	-20.19501	-6.599898
PedesPhy	-.9582841	.3094139	-3.10	0.002	-1.564724	-.351844
Month	2.408608	1.171299	2.06	0.040	.1129034	4.704313
_cons	10.28067	3.862072	2.66	0.008	2.71115	17.85019
Fatal						
DriverAge	9.365733	1.518521	6.17	0.000	6.389486	12.34198
DriverGender	-46.12872	7.042778	-6.55	0.000	-59.93231	-32.32513
DriverEduc~n	3.234841	1.7873	1.81	0.070	-.268202	6.737884
DriverExpe~e	6.306546	1.134205	5.56	0.000	4.083546	8.529547
DriverDefect	-13.15841	1.728326	-7.61	0.000	-16.54587	-9.770957
VehicleType	-5.374058	1.880578	-2.86	0.004	-9.059923	-1.688193
VehicleOwner	46.21305	6.829494	6.77	0.000	32.82749	59.59862
VehicleDef~t	-3.565813	1.492298	-2.39	0.017	-6.490664	-.6409623
RoadTopo	2.739837	1.184511	2.31	0.021	.4182389	5.061436
RoadJunction	5.330992	.7006115	7.61	0.000	3.957818	6.704165
WeatherCon~n	-5.518251	1.582701	-3.49	0.000	-8.620288	-2.416215
Time	-11.32254	3.54038	-3.20	0.001	-18.26156	-4.383527
PedesPhy	-.0380161	.6686622	-0.06	0.955	-1.34857	1.272538
Month	-1.282326	1.132377	-1.13	0.257	-3.501744	.9370911
_cons	12.52016	3.367739	3.72	0.000	5.919509	19.1208

Table 3: Predicted probability of injury severity by using multinomial model.Predict p1 p2 p3 p4 (option pr assumed; predicted probabilities).List p1 p2 p3 p4 in 1/15

Levels	P1(PDO)	P2(Slight injury)	P3(Severe injury)	P4(Fatal)
1	0.844	0.023	0.122	0.011
2	0.817	0.020	0.158	0.005
3	0.872	0.046	0.052	0.030
4	0.785	0.085	0.105	0.026
5	0.635	0.059	0.231	0.045
6	0.934	0.022	0.033	0.011
7	0.249	0.301	0.418	0.330
8	0.821	0.034	0.105	0.004
9	0.468	0.051	0.007	0.041
10	0.847	0.082	0.062	0.080
11	0.572	0.088	0.290	0.050
12	0.632	0.124	0.164	0.078
13	0.941	0.020	0.023	0.016
14	0.653	0.121	0.164	0.062
15	0.122	0.357	0.408	0.112