

# DATA 621: BUSINESS ANALYTICS AND DATA MINING

## HOMEWORK#4: LOGISTIC REGRESSION

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## 1 Overview

In this homework assignment, you will explore, analyze and model a data set containing approximately 8000 records representing a customer at an auto insurance company. Each record has two response variables. The first response variable, `TARGET_FLAG`, is a 1 or a 0. A “1” means that the person was in a car crash. A zero means that the person was not in a car crash. The second response variable is `TARGET_AMT`. This value is zero if the person did not crash their car. But if they did crash their car, this number will be a value greater than zero.

Your objective is to build multiple linear regression and binary logistic regression models on the training data to predict the probability that a person will crash their car and also the amount of money it will cost if the person does crash their car. You can only use the variables given to you (or variables that you derive from the variables provided). Below is a short description of the variables of interest in the data set:

Variable Names	Definition	Theoretical Effect
INDEX	Identification Variable (do not use)	None
TARGET_FLAG	Was Car in a crash? 1=YES 0=NO	None
TARGET_AMT	If car was in a crash, what was the cost	None
AGE	Age of Driver	Very young people tend to be risky. Maybe very old people also.
BLUEBOOK	Value of Vehicle	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_AGE	Vehicle Age	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_TYPE	Type of Car	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_USE	Vehicle Use	Commercial vehicles are driven more, so might increase probability of collision
CLM_FREQ #	Claims (Past 5 Years)	The more claims you filed in the past, the more you are likely to file in the future
EDUCATION	Max Education Level	Unknown effect, but in theory more educated people tend to drive more safely
HOMEKIDS #	Children at Home	Unknown effect
HOME_VAL	Home Value	In theory, home owners tend to drive more responsibly
INCOME	Income	In theory, rich people tend to get into fewer crashes
JOB	Category	In theory, white collar jobs tend to be safer
KIDSDRIV #	Driving Children	When teenagers drive your car, you are more likely to get into crashes
MSTATUS	Marital Status	In theory, married people drive more safely
MVR_PTS	Motor Vehicle Record Points	If you get lots of traffic tickets, you tend to get into more crashes
OLDCLAIM	Total Claims (Past 5 Years)	If your total payout over the past five years was high, this suggests future payouts will be high
PARENT1	Single Parent	Unknown effect
RED_CAR	A Red Car	Urban legend says that red cars (especially red sports cars) are more risky. Is that true?
REVOKED	License Revoked (Past 7 Years)	If your license was revoked in the past 7 years, you probably are a more risky driver.
SEX Gender	Gender	Urban legend says that women have less crashes then men. Is that true?
TIF	Time in Force	People who have been customers for a long time are usually more safe.
TRAVTIME	Distance to Work	Long drives to work usually suggest greater risk
URBANICITY	Home/Work Area	Unknown
YOJ	Years on Job	People who stay at a job for a long time are usually more safe

## 1.1 Deliverables

- A write-up submitted in PDF format. Your write-up should have four sections. Each one is described below. You may assume you are addressing me as a fellow data scientist, so do not need to shy away from technical details.
- Assigned predictions (probabilities, classifications, cost) for the evaluation data set. Use 0.5 threshold.
- Include your R statistical programming code in an Appendix.

## 1.2 Write Up:

### 1.2.1 1. DATA EXPLORATION (25 Points)

Describe the size and the variables in the insurance training data set. Consider that too much detail will cause a manager to lose interest while too little detail will make the manager consider that you aren't doing your job. Some suggestions are given below. Please do NOT treat this as a check list of things to do to complete the assignment. You should have your own thoughts on what to tell the boss. These are just ideas.

- a. Mean / Standard Deviation / Median
- b. Bar Chart or Box Plot of the data
- c. Is the data correlated to the target variable (or to other variables?)
- d. Are any of the variables missing and need to be imputed "fixed"?

### 1.2.2 2. DATA PREPARATION (25 Points)

Describe how you have transformed the data by changing the original variables or creating new variables. If you did transform the data or create new variables, discuss why you did this. Here are some possible transformations.

- Fix missing values (maybe with a Mean or Median value)
- Create flags to suggest if a variable was missing
- Transform data by putting it into buckets
- Mathematical transforms such as log or square root (or use Box-Cox)
- Combine variables (such as ratios or adding or multiplying) to create new variables

### 1.2.3 3. BUILD MODELS (25 Points)

Using the training data set, build at least two different multiple linear regression models and three different binary logistic regression models, using different variables (or the same variables with different transformations). You may select the variables manually, use an approach such as Forward or Stepwise, use a different approach such as trees, or use a combination of techniques. Describe the techniques you used. If you manually selected a variable for inclusion into the model or exclusion into the model, indicate why this was done.

Discuss the coefficients in the models, do they make sense? For example, if a person has a lot of traffic tickets, you would reasonably expect that person to have more car crashes. If the coefficient is negative (suggesting that the person is a safer driver), then that needs to be discussed. Are you keeping the model even though it is counter intuitive? Why? The boss needs to know.

### 1.2.4 4. SELECT MODELS (25 Points)

Decide on the criteria for selecting the best multiple linear regression model and the best binary logistic regression model. Will you select models with slightly worse performance if it makes more sense or is more parsimonious? Discuss why you selected your models.

For the multiple linear regression model, will you use a metric such as Adjusted R<sup>2</sup>, RMSE, etc.? Be sure to explain how you can make inferences from the model, discuss multi-collinearity issues (if any), and discuss other relevant model output. Using the training data set, evaluate the multiple linear regression model based on (a) mean squared error, (b) R<sup>2</sup>, (c) F-statistic, and (d) residual plots. For the binary logistic regression model, will you use a metric such as log likelihood, AIC, ROC curve, etc.? Using the training data set, evaluate the binary logistic regression model based on (a) accuracy, (b) classification error rate, (c) precision, (d) sensitivity, (e) specificity, (f) F1 score, (g) AUC, and (h) confusion matrix. Make predictions using the evaluation data set.

## 2 Import Data

```
df_insur_eval <-
  read.csv(paste0(url_git,"insurance-evaluation-data.csv"))

head(df_insur_eval,n=10)
```

##	INDEX	TARGET_FLAG	TARGET_AMT	KIDSDRIV	AGE	HOMEKIDS	YOJ	INCOME	PARENT1
## 1	3	NA	NA	0	48	0	11	\$52,881	No
## 2	9	NA	NA	1	40	1	11	\$50,815	Yes
## 3	10	NA	NA	0	44	2	12	\$43,486	Yes
## 4	18	NA	NA	0	35	2	NA	\$21,204	Yes
## 5	21	NA	NA	0	59	0	12	\$87,460	No
## 6	30	NA	NA	0	46	0	14		No
## 7	31	NA	NA	0	60	0	12	\$37,940	No
## 8	37	NA	NA	0	54	0	12	\$33,212	No

## 9	39	NA	NA	2	36	2	12	\$130,540	Yes
## 10	47	NA	NA	0	50	0	8	\$167,469	No
##	HOME_VAL	MSTATUS	SEX	EDUCATION	JOB	TRAVTIME	CAR_USE		
## 1	\$0	z_No	M	Bachelors	Manager	26	Private		
## 2	\$0	z_No	M	z_High School	Manager	21	Private		
## 3	\$0	z_No	z_F	z_High School	z_Blue Collar	30	Commercial		
## 4	\$0	z_No	M	z_High School	Clerical	74	Private		
## 5	\$0	z_No	M	z_High School	Manager	45	Private		
## 6	\$207,519	Yes	M	Bachelors	Professional	7	Commercial		
## 7	\$182,739	Yes	z_F	z_High School	z_Blue Collar	16	Commercial		
## 8	\$158,432	Yes	M	<High School	z_Blue Collar	27	Commercial		
## 9	\$344,195	z_No	z_F	Bachelors	z_Blue Collar	5	Commercial		
## 10	\$0	z_No	z_F	PhD	Doctor	22	Private		
##	BLUEBOOK	TIF	CAR_TYPE	RED_CAR	OLDCLAIM	CLM_FREQ	REVOKED	MVR_PTS	CAR_AGE
## 1	\$21,970	1	Van	yes	\$0	0	No	2	10
## 2	\$18,930	6	Minivan	no	\$3,295	1	No	2	1
## 3	\$5,900	10	z_SUV	no	\$0	0	No	0	10
## 4	\$9,230	6	Pickup	no	\$0	0	Yes	0	4
## 5	\$15,420	1	Minivan	yes	\$44,857	2	No	4	1
## 6	\$25,660	1	Panel Truck	no	\$2,119	1	No	2	12
## 7	\$11,290	1	Sports Car	no	\$0	0	No	0	1
## 8	\$24,000	4	Panel Truck	no	\$0	0	No	5	NA
## 9	\$27,200	4	Minivan	no	\$0	0	No	0	9
## 10	\$34,150	4	Sports Car	no	\$0	0	No	3	1
##	URBANICITY								
## 1	Highly Urban/	Urban							
## 2	Highly Urban/	Urban							
## 3	z_Highly Rural/	Rural							
## 4	z_Highly Rural/	Rural							
## 5	Highly Urban/	Urban							
## 6	Highly Urban/	Urban							
## 7	Highly Urban/	Urban							
## 8	Highly Urban/	Urban							
## 9	z_Highly Rural/	Rural							
## 10	Highly Urban/	Urban							

```
df_insur_train <-
  read.csv(paste0(url_git,"insurance_training_data.csv"))

head(df_insur_train,n=10)
```

##	INDEX	TARGET_FLAG	TARGET_AMT	KIDSDRIV	AGE	HOMEKIDS	YOJ	INCOME	PARENT1
## 1	1	0	0	0	60	0	11	\$67,349	No
## 2	2	0	0	0	43	0	11	\$91,449	No
## 3	4	0	0	0	35	1	10	\$16,039	No
## 4	5	0	0	0	51	0	14		No
## 5	6	0	0	0	50	0	NA	\$114,986	No
## 6	7	1	2946	0	34	1	12	\$125,301	Yes
## 7	8	0	0	0	54	0	NA	\$18,755	No
## 8	11	1	4021	1	37	2	NA	\$107,961	No
## 9	12	1	2501	0	34	0	10	\$62,978	No
## 10	13	0	0	0	50	0	7	\$106,952	No
##	HOME_VAL	MSTATUS	SEX	EDUCATION	JOB	TRAVTIME	CAR_USE		
## 1	\$0	z_No	M	PhD	Professional	14	Private		

## 2	\$257,252	z_No	M	z_High School	z_Blue Collar	22	Commercial		
## 3	\$124,191	Yes	z_F	z_High School	Clerical	5	Private		
## 4	\$306,251	Yes	M	<High School	z_Blue Collar	32	Private		
## 5	\$243,925	Yes	z_F	PhD	Doctor	36	Private		
## 6	\$0	z_No	z_F	Bachelors	z_Blue Collar	46	Commercial		
## 7		Yes	z_F	<High School	z_Blue Collar	33	Private		
## 8	\$333,680	Yes	M	Bachelors	z_Blue Collar	44	Commercial		
## 9	\$0	z_No	z_F	Bachelors	Clerical	34	Private		
## 10	\$0	z_No	M	Bachelors	Professional	48	Commercial		
##	BLUEBOOK TIF	CAR_TYPE	RED_CAR	OLDCLAIM	CLM_FREQ	REVOKED	MVR_PTS	CAR_AGE	
## 1	\$14,230	11	Minivan	yes	\$4,461	2	No	3	18
## 2	\$14,940	1	Minivan	yes	\$0	0	No	0	1
## 3	\$4,010	4	z_SUV	no	\$38,690	2	No	3	10
## 4	\$15,440	7	Minivan	yes	\$0	0	No	0	6
## 5	\$18,000	1	z_SUV	no	\$19,217	2	Yes	3	17
## 6	\$17,430	1	Sports Car	no	\$0	0	No	0	7
## 7	\$8,780	1	z_SUV	no	\$0	0	No	0	1
## 8	\$16,970	1	Van	yes	\$2,374	1	Yes	10	7
## 9	\$11,200	1	z_SUV	no	\$0	0	No	0	1
## 10	\$18,510	7	Van	no	\$0	0	No	1	17
##	URBANICITY								
## 1	Highly	Urban/	Urban						
## 2	Highly	Urban/	Urban						
## 3	Highly	Urban/	Urban						
## 4	Highly	Urban/	Urban						
## 5	Highly	Urban/	Urban						
## 6	Highly	Urban/	Urban						
## 7	Highly	Urban/	Urban						
## 8	Highly	Urban/	Urban						
## 9	Highly	Urban/	Urban						
## 10	z_Highly	Rural/	Rural						