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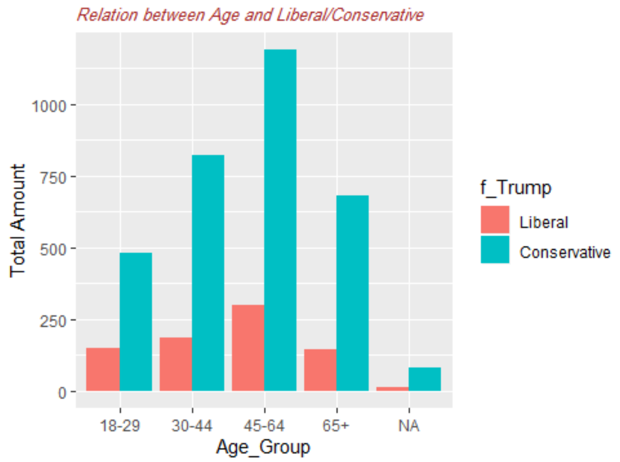
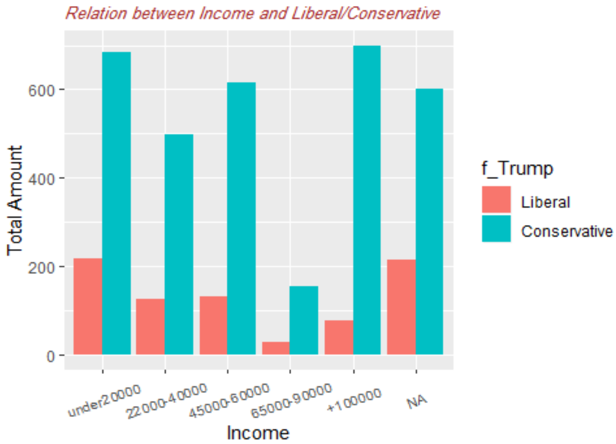
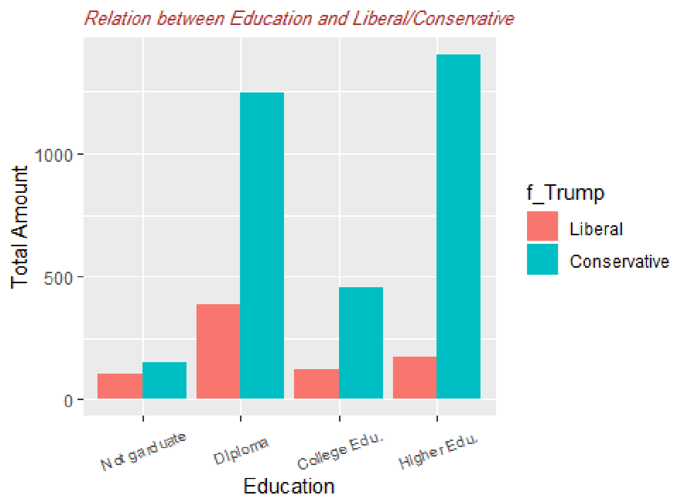
Home Exercise 1

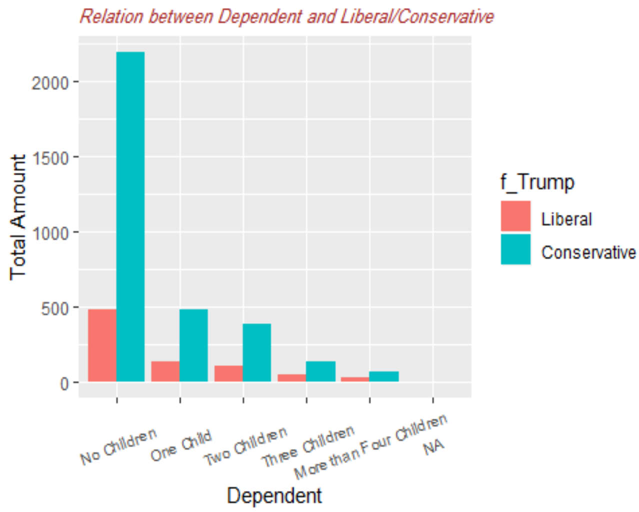
Statistical Learning (AMI22T)

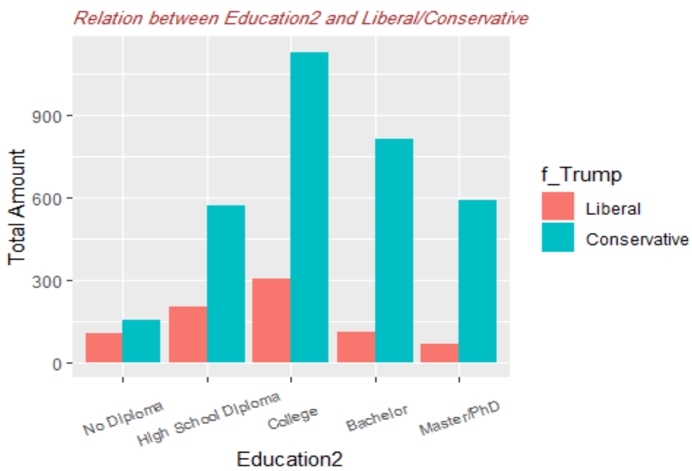
American National Election Studies (ANES), is a complex sample survey that collects responses on political belief and behavior from eligible voters in the U.S. Administered by Stanford University and the University of Michigan, and funded by the National Science Foundation, ANES is designed to generalize to all eligible voters in the U.S., so results give us a statistically sound view of what voters really think. The ANES2016 data set is an excerpt from that survey. At the part1 of this Lab we want to explore the relationship between a number of independent variables and a dependent variable(considering Donald Trump as Liberal (or conservative)). At first , by considering the structure of the dataset, after recoding all the variables and cleaning the dataset, we will demonstrate by the different graphs , the relation between all personal characteristics and considering Trump as Liberal or Conservative.

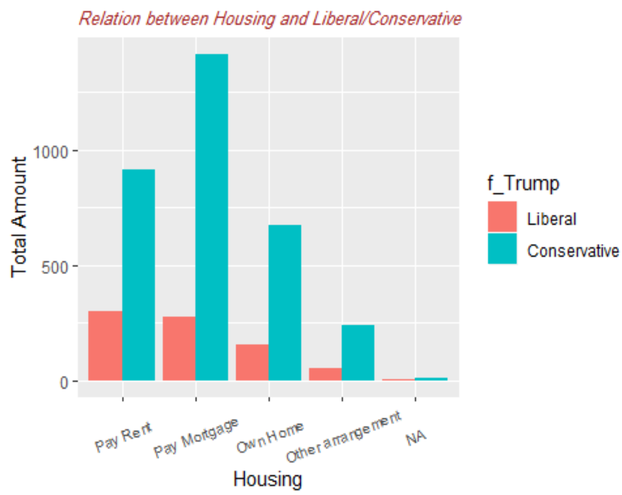


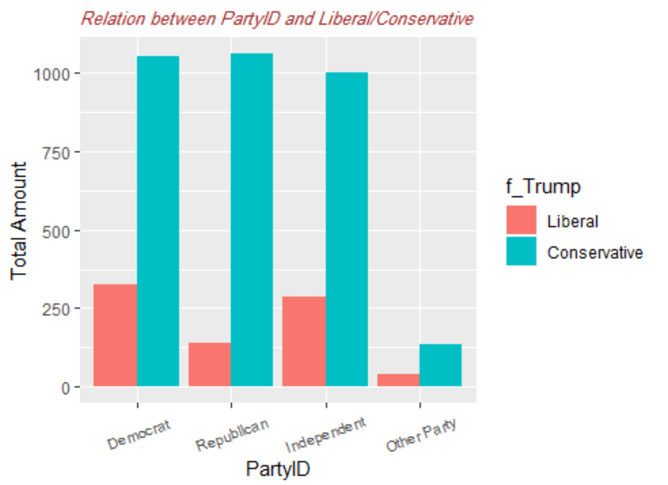


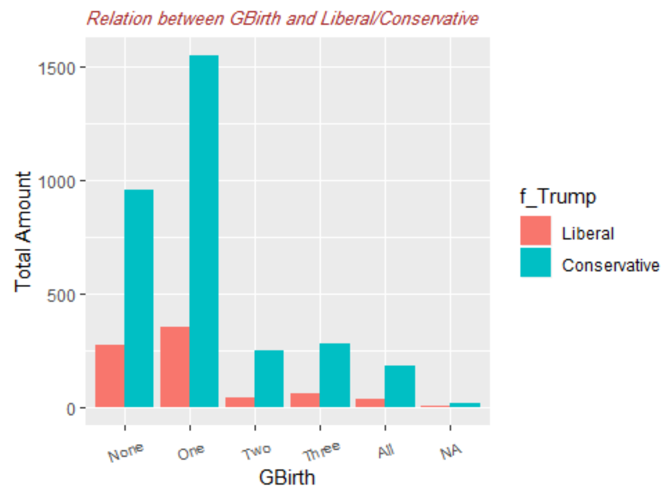


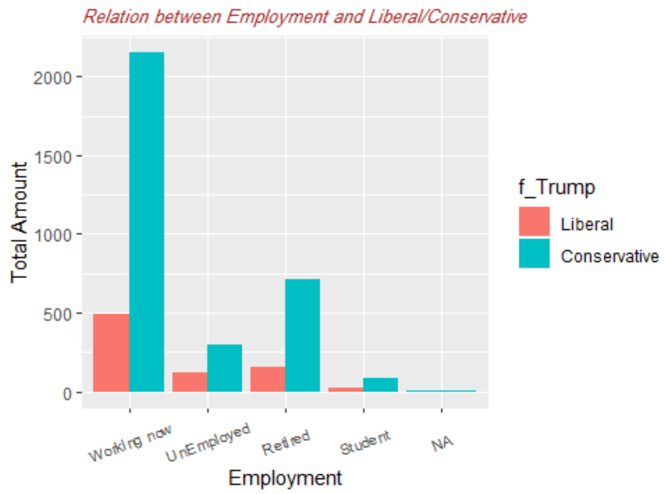


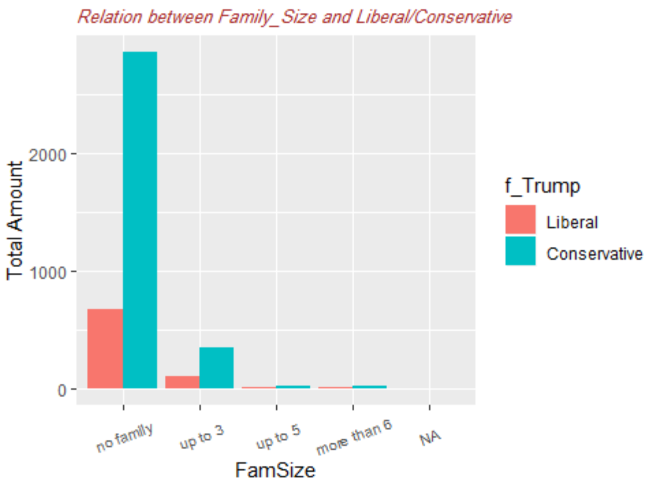


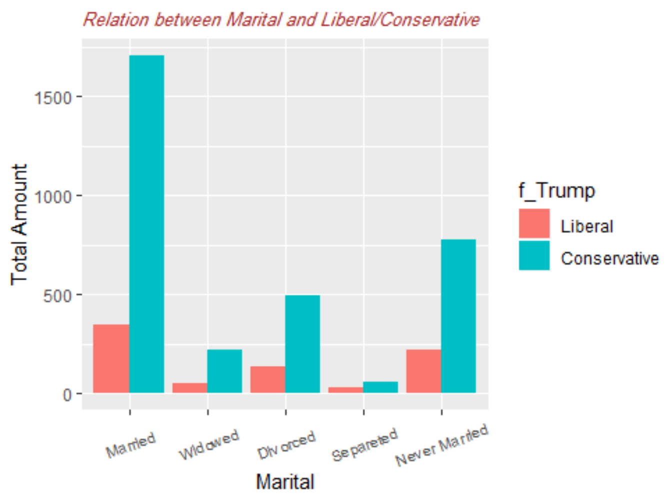


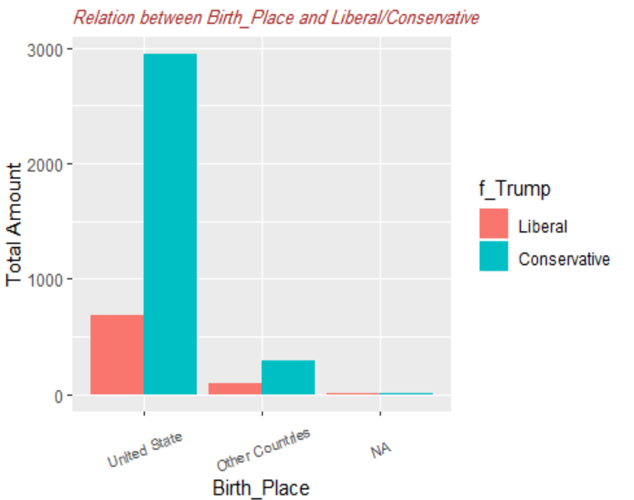












After visualization and identifying the role of personal and family characteristics, we will demonstrate the validity of our results by Logistic Regression Method that is more appropriate in this case. That is because of the binary DV (considering Trump as Liberal or not) that does not follow the normal distribution. After that we construct a logit regression model that explores how certain IVs predict a scale for Trump as Liberal or Conservative.

Construct a logit Regression Model:

1-Recode and factor the Trump variable to make it binary and exclude candidates other than Trump, where slightly liberal to extremely liberal as “Liberal” and equal to "0", and moderate to Extremely conservative as “Conservative” and equal to "1".

The number of candidate who consider Trump as Liberal or Conservative:

Liberal	Conservative
805	3299

2- select a subset of the data as independent variables and Trump as dependent variable and remove missing observations by dplyr: package and select function:

"Trump", "Age", "Education", "Income", "Employment", "Dependent", "PartyID"

3-Build the generalized linear model and by summary of the model we will see the coefficients like table 1, there really is not much we can get from looking at them alone; however, from looking at the coefficients alone, we can tell that education, Income and dependent, affect the probability of considering Trump as Conservative.

	Estimate	Std. Error	Z Value	Pr(>|z|)
(Intercept)	0.6033637	0.2144858	2.813	0.004907 **
Age	-0.0006297	0.0021781	-0.289	0.772507
Education	0.0498788	0.0142814	3.493	0.000478 ***
Income	0.0298353	0.0044425	6.716	1.87e-11 ***
Employment	-0.0248793	0.0176668	-1.408	0.159057
Dependent	-0.1735515	0.0355132	-4.887	1.02e-06 ***
PartyID	0.0306324	0.0438018	0.699	0.484338

table1- the output of summary(logit)

By using exp() function we convert logged odd to odd to analyze the effect of variables on probability of considering Trump as conservative:

(Intercept)	Age	Education	Income	Employment	Dependent	PartyID
1.8282582	0.9993705	1.0511436	1.0302848	0.9754277	0.8406738	1.0311064

Odds are difficult to interpret intuitively, but we can say that odds greater than 1 indicate increased probability, and odds less than one indicate a decrease in probability. The statistically significant coefficients from the model are Dependent, Education and Income. Based on the odds of each 6 variables, we can tell that an increase in Education and Income, improves the probability of Conservative, and an increase in Dependent reduces the probability of it. To get a more intuitive understanding, we can convert these to percentages. To do this we subtract the odds from 1and we do this for Dependent, Education and Income.

Education	Income	Dependent
-0.05114364	-0.03028482	0.1593269

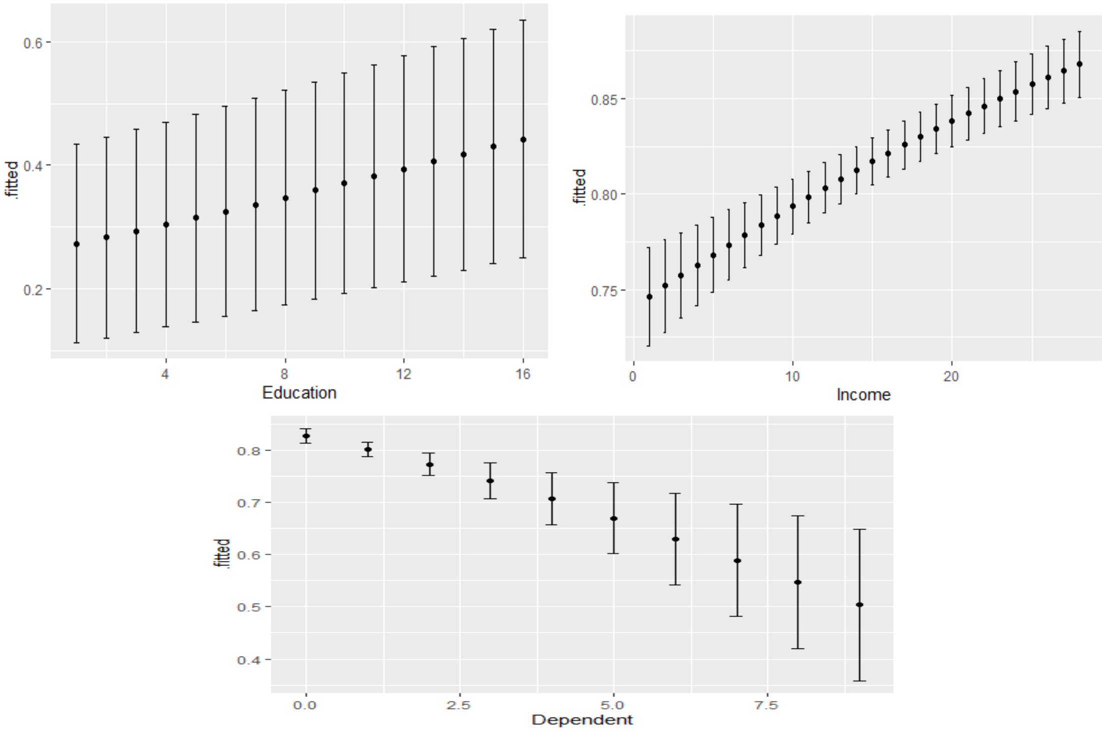
This may seem counter-intuitive, but since we subtracted 1 from the odds, a negative percentage is actually an increase in probability. Perhaps the best reason to use a logit model is that it allows us to generate predicted probabilities of some outcome. logit regression allows us to obtain a predicted probability that a particular outcome occurs, given a certain set of parameters. In our case, we can generate predicted probabilities of being Conservative for Trump. Let’s find the predicted probabilities of being Conservative for Trump as Income increases and all other IVs are held constant at their means. We first need to generate some simulated data that sequences Income from 1 to 28 and holds all other values at their means, then we use the augment() function to calculate predicted probabilities of being conservative for Trump at the various Income levels. To do so, include type.predict="response" This tells augment() to generate predicted probabilities:

A tibble: 28 x 8

Age	Employment	Education	Dependent	PartyID	Income	.fitted	.se.fit
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>

1	47.9	2.70	11.7	0.590	2.07	1	1.08	0.0694
2	47.9	2.70	11.7	0.590	2.07	2	1.11	0.0659
3	47.9	2.70	11.7	0.590	2.07	3	1.14	0.0625
4	47.9	2.70	11.7	0.590	2.07	4	1.17	0.0593
5	47.9	2.70	11.7	0.590	2.07	5	1.20	0.0562
6	47.9	2.70	11.7	0.590	2.07	6	1.23	0.0534
7	47.9	2.70	11.7	0.590	2.07	7	1.26	0.0507
8	47.9	2.70	11.7	0.590	2.07	8	1.29	0.0483
9	47.9	2.70	11.7	0.590	2.07	9	1.32	0.0463
10	47.9	2.70	11.7	0.590	2.07	10	1.35	0.0445

As we would likely expect, increasing Income increases the probability of being Conservative for Trump. At an Income level of 28, there is almost a guarantee of being Conservative for Trump. To get a sense of what this would look like, we can visualize these predicted probabilities rather easily. We need to calculate lower and upper bounds of the confidence interval first, which is done just like with other models. Assign the data frame to an object and then Visualizing the predicted probabilities is similar to how we have visualized in the past. Use geom_point and geom_errorbar().
Now we visualize other variables like Dependant and Education.



As we see by increasing the Education and Income, being Trump as Conservative will increase , and by increasing the Dependent, it will decrease.
Now we add other variables as Independent Variables and analysis the role of other variables on considering Trump as Liberal or Conservative. we should follow the above structure with15 IV.

Coefficients:

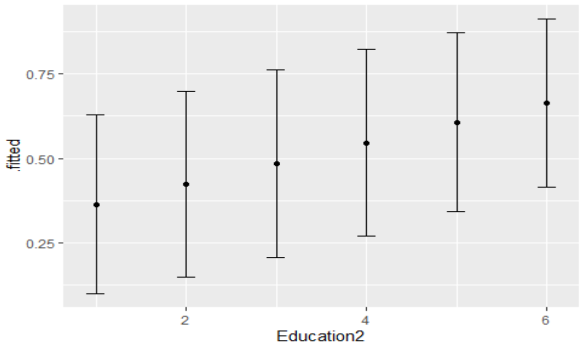
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.169046	0.309398	0.546	0.58481	
Age	-0.004037	0.002812	-1.436	0.15112	
Media	0.039440	0.020953	1.882	0.05979	.
FamSize	-0.038121	0.037549	-1.015	0.30999	
Partner	0.051025	0.058120	0.878	0.37999	
SpouseEdu	0.022486	0.010000	2.249	0.02454	*
GBirth	0.050650	0.029134	1.738	0.08213	.
Housing	0.080601	0.033580	2.400	0.01638	*
Education2	0.247337	0.037714	6.558	5.44e-11	***
Marital	-0.057592	0.045928	-1.254	0.20986	
Education	0.011509	0.016649	0.691	0.48938	

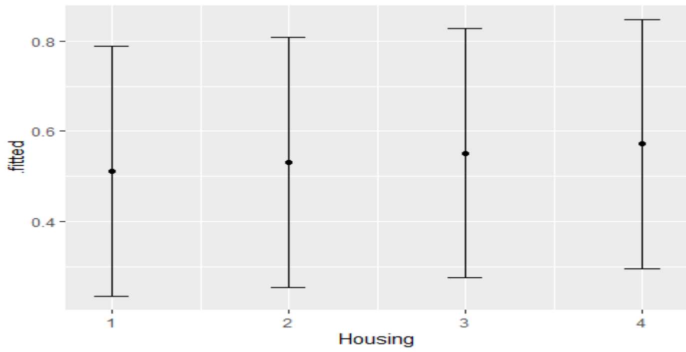
Income	0.015670	0.005040	3.109	0.00188	**
Employment	-0.003942	0.018922	-0.208	0.83498	
Dependent	-0.125961	0.051302	-2.455	0.01408	*
PartyID	0.040296	0.044824	0.899	0.36867	
Birthplace	-0.102528	0.035423	-2.894	0.00380	**

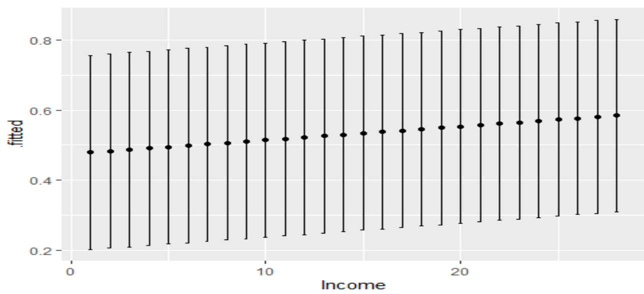
By generalized linear model and summarize the model we will see above coefficients. By looking at the coefficients we can indicate that Housing, Education2, Income, Dependent and BirthPlace affect the probability of being Trump as Liberal or Conservative.

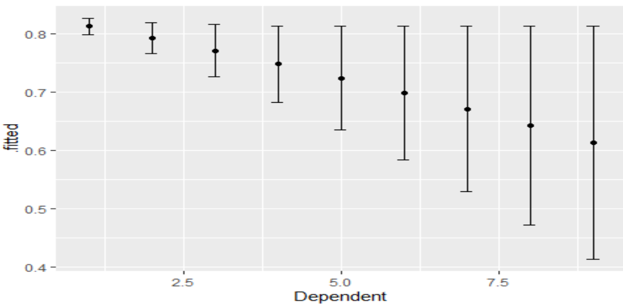
(Intercept)	Age	Media	FamSize	Partner	SpouseEdu	GBirth	Housing
1.1841746	0.9959707	1.0402283	0.9625964	1.0523493	1.0227403	1.0519541	1.0839380
Education2	Marital	Education	Income	Employment	Dependent	PartyID	Birthplace
1.2806103	0.9440352	1.0115757	1.0157934	0.9960661	0.8816493	1.0411184	0.9025529

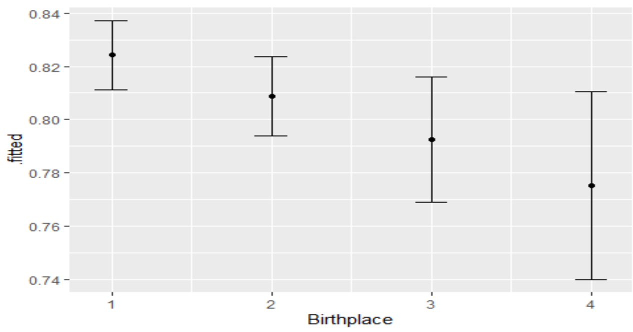
By using exp() function we indicate that increasing the Dependent, will decrease the probability and increasing Education2 will increase the probability of being Trump as Liberal or Conservative. Now we visualize the most important predicted probabilities and it is clear that by increasing the Education , housing and income people believe that Trump will be conservative and by decreasing the dependent and birthplace, people believe on it too.











2. Build a suitable prediction model to predict an individual's party identification using the respective individual's other personal, and family characteristics. Experiment with different methods, and model specifications, and motivate your choice.

For this part of problem, as the response variable is party Identification that has 3 different values like Democrat, Republican and Independent , and these values are not ordered, hence we use Multinomial Logistic Regression. Multinomial Logistic Regression is a classification method that generalizes logistic regression to multiclass problems, i.e. with more than two possible discrete outcomes. In multinomial logistic regression the objective is to model the probability πj to belong to a specific group j=1,2,…,g using covariates x. Multinomial Logistic Regression is used to model categorical dependent variable and is used when there are more than one categories for the dependent variable and the categories cannot be ordered.
we want to make a model which by different personal and family characteristics, predict the probability of individual's party Identification. All the variables are predictive variables.
After importing and reading the dataset , by looking at the str of dataset, we notice we have 18 variables, 17 variables are features and one is categorical variable, and we see the PartyID is as int, we should change the type by factor or as.factor and convert it to factor, then we should identify the level. By default the first category is the refrence. Hence we select the reference and we select"2" that it means "Republican". Now we should develop Multinomial Logistic regression Model. Here we use nnet package for developing this Model. After we run the model, nnet reports the summary iterations and declaration about model convergence. In our case, the model converged quite quickly.

weights: 64 (45 variable)
initial value 5812.732256
iter 10 value 5146.829898
iter 20 value 5129.334110
iter 30 value 5109.151730
iter 40 value 5084.290807
iter 50 value 5047.650905
final value 5047.597587
converged

The results show that it started with very high error and after 10 iterations it reduced to 5146 from 5812 and so on and finally it converges to a lower value 5047.

Let's take a look at the output of the model.

Coefficients:

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent	Marital
1	-0.7126353	0.04770003	0.15606106	-0.014391491	0.0003325885	0.009120503	0.03492679	0.2080866
3	0.5310714	-0.02728582	0.04948956	-0.008332065	-0.0073928609	0.003121725	0.04547733	0.1703337
4	-1.3426310	-0.03957702	0.12633370	-0.018898351	-0.0069983144	-0.001217992	0.11251063	0.1644603

	Media	FamSize	Partner	Education	SpouseEdu	GBirth	Housing
1	0.05827060	0.03078922	0.050445172	-0.0009597554	0.007032988	0.052504763	-0.1563744
3	-0.02621910	-0.01151803	-0.009383466	-0.0049093771	-0.004451121	0.051452772	-0.0661498
4	-0.01258146	-0.02108910	0.024685249	0.0151664080	0.001917192	0.006363799	-0.2336829

From the above table we can see the coefficients. These are the logit coefficients relative to the reference Republican. For example under "Education2", the 0.0477 suggests that for one unit increase in "Education2", the logit coefficient for "Democrat" relative to "Republican" will go up by that amount,0.0477. In other words, if Education2 increases one unit, your chances of being Republican category, are lower compared to being in high Democrat category. The multinom() function does not provide p-values, we can get significance of the coefficients using the stargazer() function from the package –stargazer.

```
==================================================
                       Dependent variable:
                  --------------------------------
                      1          3          4
                     (1)        (2)        (3)
--------------------------------------------------
Education2          0.048     -0.027     -0.040
                   (0.035)    (0.036)    (0.060)

Birthplace         0.156***    0.049      0.126*
                   (0.036)    (0.035)    (0.066)

Income            -0.014***   -0.008*    -0.019**
                   (0.005)    (0.005)    (0.009)

Age                 0.0003   -0.007***   -0.007
                   (0.003)    (0.003)    (0.005)

Employment          0.009      0.003     -0.001
                   (0.019)    (0.019)    (0.037)

Dependent           0.035      0.045      0.113
                   (0.053)    (0.052)    (0.093)

Marital            0.208***   0.170***    0.164*
                   (0.049)    (0.049)    (0.087)

Media              0.058***   -0.026     -0.013
                   (0.022)    (0.021)    (0.040)

FamSize             0.031     -0.012     -0.021
                   (0.039)    (0.039)    (0.073)

Partner             0.050     -0.009      0.025
                   (0.058)    (0.058)    (0.105)

Education          -0.001     -0.005      0.015
                   (0.015)    (0.016)    (0.018)

SpouseEdu           0.007     -0.004      0.002
                   (0.007)    (0.008)    (0.013)

GBirth              0.053*     0.051*     0.006
                   (0.028)    (0.029)    (0.053)

Housing           -0.156***   -0.066    -0.234***
                   (0.039)    (0.041)    (0.057)

Constant          -0.713**     0.531*   -1.343***
                   (0.284)    (0.281)    (0.505)

--------------------------------------------------
Akaike Inf. Crit. 10,185.190 10,185.190 10,185.190
==================================================
Note:                  *p<0.1; **p<0.05; ***p<0.01
```

Further, usually we get one set of estimates from the model but here we clearly see three sets in three rows. In logistic regression, one level of the dependent variable is taken as reference and separate model coefficients are estimated on the remaining levels. In our case PartyID has 4 levels (1st, 2nd,3nd, and 4rd level). By default the lowest level (PartyID = 1) is taken as a reference. But here we select reference 2 . Therefore, for the remaining three levels 1 , 3 and 4 we get model coefficients. That's why in the output above we see the rows for Coefficients are marked 1,3. and 4. From the above table we see that Income, Housing and housing have negative impact and other features have positive impacts .

Let's write one of these equations so we will understand what's going on.

ln(p(PartyId=1)/p(PartyID =2)) =- 0.7126353+ 0.04770003*Education2 +0.15606106*Birthplace-0.014391491*Income-0.0003325885*Age+0.009120503*Employment+0.03492679*Dependent+0.2080866*Marital+0.05827060*Media+0.03078922*FamSize+0.050445172*Partner-0.0009597554*Education+0.007032988*SpouseEdu+0.05250476*GBirth-0.1563744*Housing

ln(p(PartyID=3)/p(PartyID=2))

ln(p(PartyID=4)/p(PartyID=2))

Relative risk ratios allow an easier interpretation of the logit coefficients. They are the exponentiated value of the logit coefficients.

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent	Marital	Media
1	0.4903503	1.0488560	1.168898	0.9857116	1.0003326	1.0091622	1.035544	1.231320	1.0600018
3	1.7007535	0.9730831	1.050735	0.9917025	0.9926344	1.0031266	1.046527	1.185700	0.9741216
4	0.2611577	0.9611959	1.134661	0.9812791	0.9930261	0.9987827	1.119084	1.178757	0.9874974

	FamSize	Partner	Education	SpouseEdu	GBirth	Housing
1	1.0312681	1.0517392	0.9990407	1.0070578	1.053908	0.8552389
3	0.9885480	0.9906604	0.9951027	0.9955588	1.052799	0.9359906
4	0.9791317	1.0249925	1.0152820	1.0019190	1.006384	0.7916128

```
Dependent variable:
                   -------------------------------
                       1          3          4
                      (1)        (2)        (3)
-----------------------------------------------
Education2           1.049      0.973      0.961
                    (0.035)    (0.036)    (0.060)

Birthplace          1.169***    1.051      1.135*
                    (0.036)    (0.035)    (0.066)

Income              0.986***    0.992*    0.981**
                    (0.005)    (0.005)    (0.009)

Age                  1.000     0.993***    0.993
                    (0.003)    (0.003)    (0.005)

Employment           1.009      1.003      0.999
                    (0.019)    (0.019)    (0.037)

Dependent            1.036      1.047      1.119
                    (0.053)    (0.052)    (0.093)

Marital             1.231***   1.186***    1.179*
                    (0.049)    (0.049)    (0.087)

Media               1.060***    0.974      0.987
                    (0.022)    (0.021)    (0.040)

FamSize              1.031      0.989      0.979
                    (0.039)    (0.039)    (0.073)

Partner              1.052      0.991      1.025
                    (0.058)    (0.058)    (0.105)

Education            0.999      0.995      1.015
                    (0.015)    (0.016)    (0.018)

SpouseEdu            1.007      0.996      1.002
                    (0.007)    (0.008)    (0.013)

GBirth               1.054*     1.053*     1.006
                    (0.028)    (0.029)    (0.053)

Housing             0.855***    0.936     0.792***
                    (0.039)    (0.041)    (0.057)

Constant            0.490**     1.701*    0.261***
                    (0.284)    (0.281)    (0.505)

-----------------------------------------------
Akaike Inf. Crit. 10,185.190 10,185.190 10,185.190
===============================================
Note:                 *p<0.1; **p<0.05; ***p<0.01
```

Keeping all other variables constant, if Ecucation2 increases one unit, individual 1.049 times more likely to stay in the Democrat category as compared to the Republican category (the risk or odds is 4% higher). The coefficient, however, is not significant.

Keeping all other variables constant, if Education2 increases one unit, individual is 0.97 times more likely to stay in the Independent category as compared to the Republican category (the risk or odds is 4% lower). The coefficient, however, is not significant.

Getting the Z-stats and p-values

We have noticed that multinom doesn't output Z statistics and p-values. It's however quite easy to get them. Z statistics are simply ratios of model coefficients and standard errors. Once we get them, we can get the p-values using the standard normal distribution.

Let's get a table of coefficients, standard errors, z stats, and p values for PartyID = 2

```
> PartyID2
```

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent
Coefficient	0.71259708	-0.04768474	-1.560584e-01	0.014392503	-0.0003322532	-0.00911694	-0.03491878
Std. Errors	0.28405217	0.03457319	3.624258e-02	0.004893056	0.0027422389	0.01923411	0.05273964
z stat	2.50868379	-1.37924035	-4.305942e+00	2.941414145	-0.1211612739	-0.47399860	-0.66209733
p value	0.01211819	0.16782066	1.662767e-05	0.003267174	0.9035632970	0.63550090	0.50790884

	Marital	Media	FamSize	Partner	Education	SpouseEdu
Coefficient	-2.080847e-01	-0.058264844	-0.03079055	-0.05044667	0.0009516589	-0.007033927
Std. Errors	4.891457e-02	0.022014176	0.03947399	0.05782005	0.0146124210	0.006773064
z stat	-4.254044e+00	-2.646696553	-0.78002124	-0.87247717	0.0651267078	-1.038514829
p value	2.099438e-05	0.008128225	0.43537837	0.38294812	0.9480731158	0.299030435

	GBirth	Housing
Coefficient	-0.05250603	1.563715e-01
Std. Errors	0.02838224	3.948787e-02
z stat	-1.84996051	3.959987e+00
p value	0.06431924	7.495388e-05

Let's also get a table of coefficients, standard errors, z stats, and p values for PartyId = 3

```
> PartyID3
```

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent
Coefficient	1.243642e+00	-0.07498222	-0.106568065	0.006059667	-0.007725253	-0.005996223	0.01055074
Std. Errors	2.684625e-01	0.03447073	0.034501006	0.004679555	0.002558300	0.018060576	0.04925598
z stat	4.632459e+00	-2.17524285	-3.088839312	1.294923916	-3.019682591	-0.332006185	0.21420218
p value	3.613485e-06	0.02961192	0.002009401	0.195346477	0.002530397	0.739884589	0.83038940

	Marital	Media	FamSize	Partner	Education	SpouseEdu	GBirth
Coefficient	-0.0377489	-8.448529e-02	-0.04230690	-0.05983516	-0.003948923	-0.011484762	-0.001053745
Std. Errors	0.0433623	2.038276e-02	0.03691157	0.05430209	0.015217870	0.007039644	0.027907522
z stat	-0.8705465	-4.144938e+00	-1.14616895	-1.10189414	-0.259492516	-1.631440613	-0.037758445
p value	0.3840018	3.399052e-05	0.25172525	0.27050770	0.795255256	0.102797381	0.969880276

	Housing
Coefficient	0.090221860
Std. Errors	0.034216995
z stat	2.636755805
p value	0.008370306

Here we analysis the p-value of each predictor:

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent
2	0.012118190833	0.16782066	0.00001662767	0.003267174	0.903563297	0.6355009	0.5079088
3	0.000003613485	0.02961192	0.00200940089	0.195346477	0.002530397	0.7398846	0.8303894
4	0.201266998325	0.13490400	0.64389622544	0.626749093	0.142119845	0.7752527	0.3927680

	Marital	Media	FamSize	Partner	Education	SpouseEdu	GBirth	Housing
2	0.00002099438	0.00812822536	0.4353784	0.3829481	0.9480731	0.2990304	0.06431924	0.00007495388
3	0.38400182993	0.00003399052	0.2517253	0.2705077	0.7952553	0.1027974	0.96988028	0.00837030632
4	0.60357147346	0.07116149028	0.4649604	0.8000504	0.3347416	0.6804514	0.37458533	0.12234244431

Now we should make prediction by predict function :

	1	2	3	4
1	0.1814663	0.3668001	0.4100135	0.04172002
2	0.3638985	0.2389003	0.3620599	0.03514140
3	0.2928088	0.2116161	0.3909280	0.10464715
4	0.2545575	0.4241614	0.2894475	0.03183362
5	0.3608641	0.1957758	0.3682398	0.07512031
6	0.3957992	0.3210145	0.2406460	0.04254031

Misclassification Error: we can compare the predictions of model with actual data and see misclassification. By running the command we see the below table:

pred	1	2	3	4
1	711	405	514	85
2	434	565	423	55
3	292	248	409	52
4	0	0	0	0

Numbers from 1 to 4 in the header are, actual data, it means:
1= Democrat
2= Republican
3= Independent
4= Other party
And vertical numbers are predictions from model. The model tell us that 711 individuals are democrat, 434 individuals should be democrat, but these are predicted to belong to Republican category, 292 individuals are predicted to belong Independent category, and so on. We can calculate missclassification by : 1-sum(diag(tab))/sum(tab)= 0.59. Through z test , we can find confidence by below table. Confidence number= 1- p value.

	(Intercept)	Education2	Birthplace	Income	Age	Employment	Dependent	Marital
1	0.012112409	0.1676607	0.0000166225	0.003269308	0.903466337	0.6353687	0.5078116	2.099006e-05
3	0.059132796	0.4489145	0.1597241736	0.095387882	0.006235984	0.8713240	0.3807080	4.501441e-04
4	0.007790039	0.5083847	0.0549464020	0.045900957	0.169485887	0.9736977	0.2274907	5.969433e-02

	Media	FamSize	Partner	Education	SpouseEdu	GBirth	Housing
1	0.008121979	0.4353981	0.3829606	0.9476243	0.2990915	0.06432541	7.493125e-05
3	0.212327448	0.7693130	0.8710129	0.7567338	0.5658013	0.07394950	1.041088e-01
4	0.751643515	0.7714593	0.8136930	0.3939049	0.8828078	0.90373157	4.017109e-05

The table show us that Birthplace, Income, Marital, Media and Housing have significant role for Democrat when reference is Republican , and Age, Marital ,Housing have significant role for Independent when reference is Democrat.
In the next step, we drop all variable that have confidence number below 0.95, and create the new model again.

```
Coefficients:
```

	(Intercept)	Birthplace	Income	Age	Marital	Media	Housing
1	-0.3692217	0.16515963	-0.01079582	-0.0007475762	0.2165208	0.05942147	-0.15484197
3	0.4167994	0.06222009	-0.01002918	-0.0071159945	0.1784672	-0.03130664	-0.06552722
4	-1.1812085	0.12962309	-0.02046568	-0.0080422502	0.1690538	-0.01242739	-0.23963416

Std. Errors:

	(Intercept)	Birthplace	Income	Age	Marital	Media	Housing
1	0.2048712	0.03582994	0.004468139	0.002309574	0.02718863	0.02174411	0.03921550
3	0.1978547	0.03466250	0.004507226	0.002294912	0.02717421	0.02069405	0.04028900
4	0.3592999	0.06413591	0.008507534	0.004299160	0.05003186	0.03906115	0.05434993

Residual Deviance: 10193.18

AIC: 10235.18

Now we should interpret our model by running z test and calculate p value:

	(Intercept)	Birthplace	Income	Age	Marital	Media	Housing
1	0.071511738	4.035553e-06	0.01568438	0.746175911	1.776357e-15	0.006280568	7.864609e-05
3	0.035152841	7.264959e-02	0.02607226	0.001930185	5.115974e-11	0.130321960	1.038583e-01
4	0.001010712	4.327264e-02	0.01614616	0.061392758	7.277009e-04	0.750369532	1.038022e-05

Equation:

ln[P(PartyID=1)/P(PartyID=2)]=0.071511738+(4.035553e-06*Birthplace)+(0.01568438*Income)
+(0.746175911*Age)+(0.006280568*Media)+(1.0776357e-15*Marital)+(7.864609e-05*Housing)

ln[P(PartyID=3)/P(PartyID=2)]=0.035152841+(7.264959e-02*Birthplace)+(0.02607226*Income)
+(0.001930185*Age)+(0.130321960*Media)+(5.115974e-11*Marital)+(1.038583e-01*Housing)