# Predicting Family Income for Marketing

Training and comparing Naive Bayes, Logistic regression and CART models to predict if family income is above 50K/Y



# **Executive Summary**



Random Forest classification is the best method to predict household income greater than \$50K since it had the highest accuracy rate predicting family income (83.4%)



# \$25 Million Direct Marketing Campaign Target Group:

- Married couples particularly the husband
- Bachelors & Masters level education

# Agenda

- Understanding raw data Variables, data types
- Cleaning the data Sanitize Missing values, outliers
- Preprocessing Encode variables
- Model Exploration Build and evaluate models
- Model Comparison Find the best predicting model

# Understanding Raw Data

#### **Explore, Check and Convert Data Types**



age	int64		age	int64
workclass	object		workclass	category
fnlwgt	int64		fnlwgt	int64
education	- object		education	category
education num	int64	Ĭ	education_num	category
marital status	object		marital_status	category
<del>-</del>	object		occupation	category
occupation			relationship	category
relationship	object		race	category
race	object		sex	category
sex	object		capital_gain	int64
capital_gain	int64		capital_loss	int64
capital_loss	int64		hours_per_week	int64
hours per week	int64		native_country	category
native country	object		income	category
income	object		dtype: object	

- There are 32561 observations and 15 variables in the raw data
- Employee\_num should be treated as 'category'

# Cleaning the Data

age	143
workclass	0
fnlwgt	992
education	0
education-num	0
marital-status	0
occupation	0
relationship	0
race	0
sex	0
capital-gain	2712
capital-loss	1519
hours-per-week	9008
native-country	0
class	0
dtype: int64	

age	fr	nlwgt	capital-gain	capital-lo	oss hou	rs-per-week
mean	38.581647	1.897784	e+05 1077	.648844 8	7.303830	40.437456

- Before imputing corrections, we needed to identify outliers in the numeric variables
- Replaced all numeric columns null values to their respective mean values
- liminated unusual unknown values such as '?' and replacing the values with the **mode**

# Preprocesing: Improve Model Efficiency

#### Dummy Variables

	workclass_ Local-gov	workclass_ Never- worked	workclass_ Private	١
0	0	0	0	
1	0	0	0	
2	0	0	1	
3	0	0	1	
4	0	0	1	
32556	0	0	1	
32557	0	0	1	
32558	0	0	1	
32559	0	0	1	
32560	0	0	0	
32561 r	rows × 51 co	lumns		

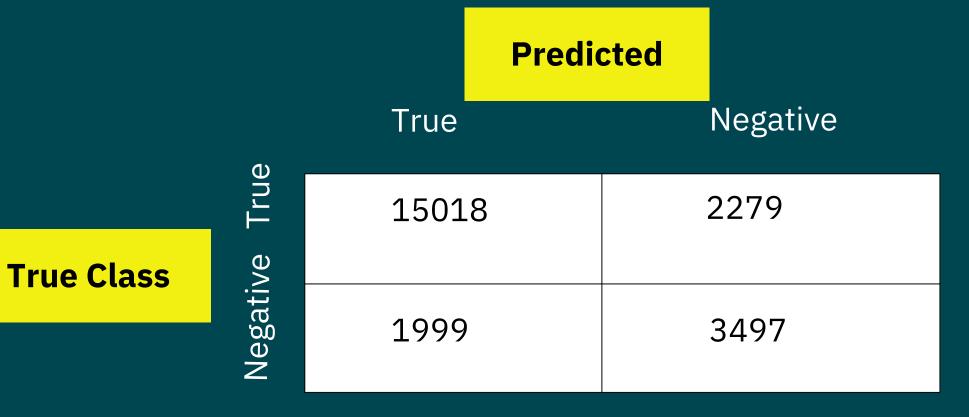
 Using binary dummy - allowing the computer to calculate them with the numeric variables

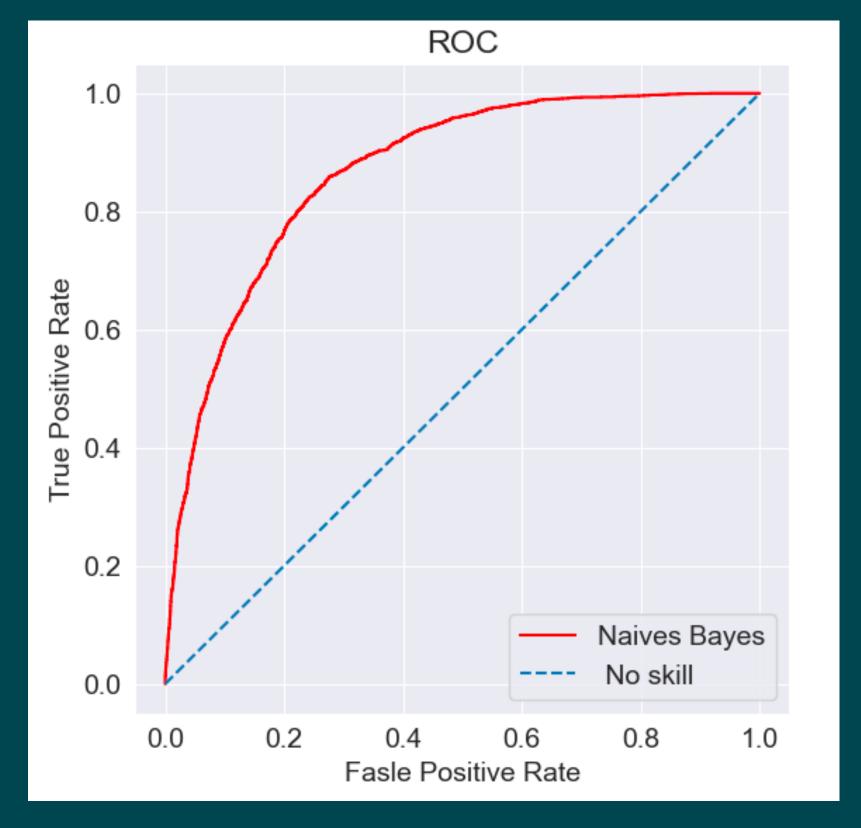
	age	fnlwgt	capital-gain	capital-loss	hours-per-week
count	32561.000000	32561.000000	32561.0	32561.0	32561.000000
mean	38.381609	179631.339130	0.0	0.0	41.565533
std	13.300577	86028.457849	0.0	0.0	3.415436
min	17.000000	12285.000000	0.0	0.0	33.000000
25%	28.000000	117827.000000	0.0	0.0	40.000000
50%	37.000000	178356.000000	0.0	0.0	40.000000
75%	47.000000	226196.000000	0.0	0.0	41.565533
max	78.000000	415847.000000	0.0	0.0	52.000000

 Normalization the numbers (scale the variables to similar sizes) makes the graphing of the values more efficient for the ML methods

# Naive Bayes

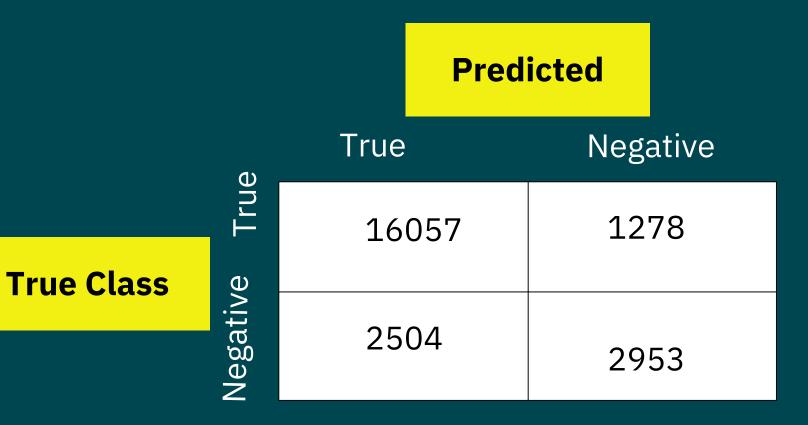
Accuracy	Misclassification	True Positive	False Positive
0.816	0.171	0.926	0.458
Specificity	Precision	Prevalence	ROC
0.541	0.61	0.83	0.868

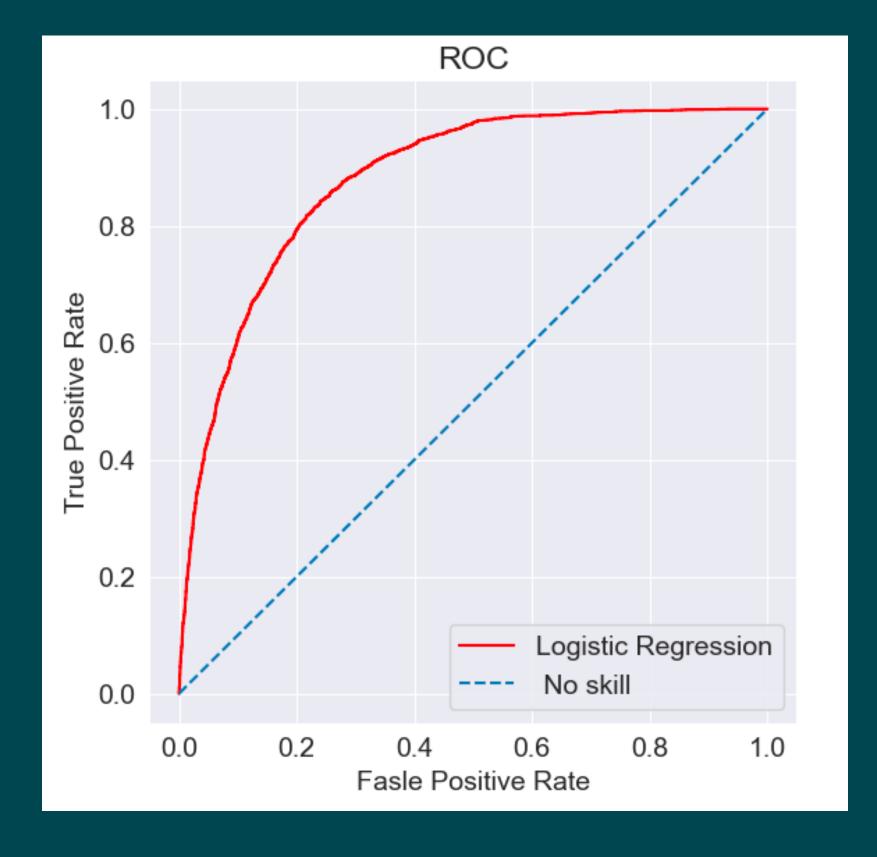




# Logistic Regression

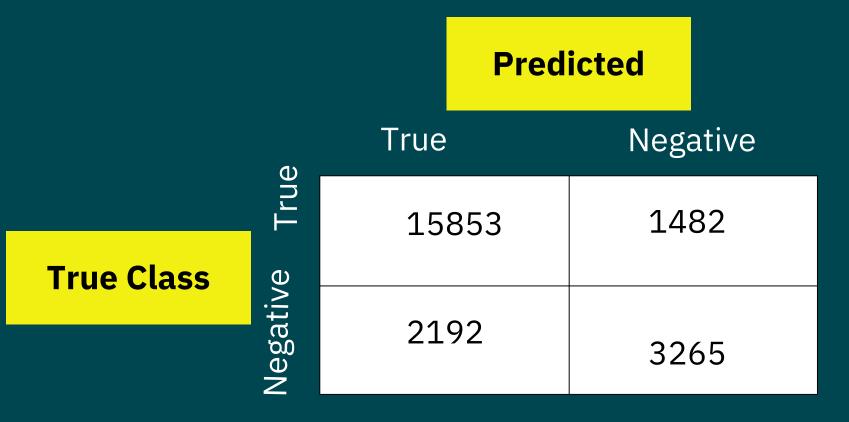
Accuracy	Misclassification	True Positive	False Positive
0.829	0.171	0.826	0.459
Specificity	Precision	Prevalence	ROC
0.541	0.69	0.834	0.88

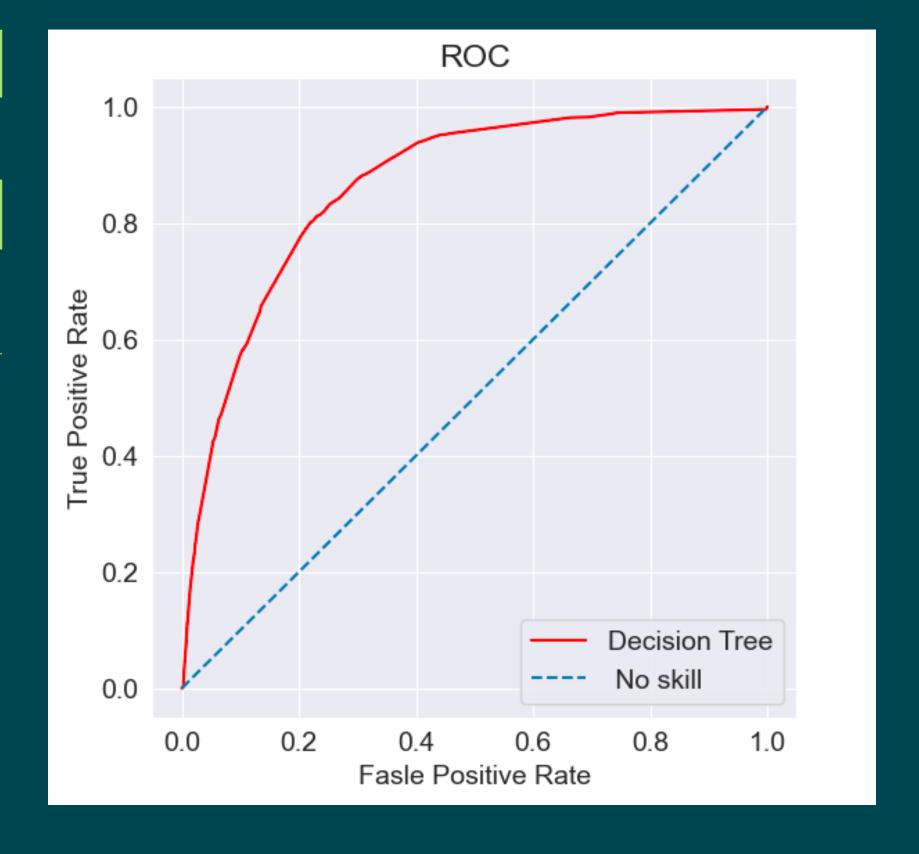




#### **Decision Tree**

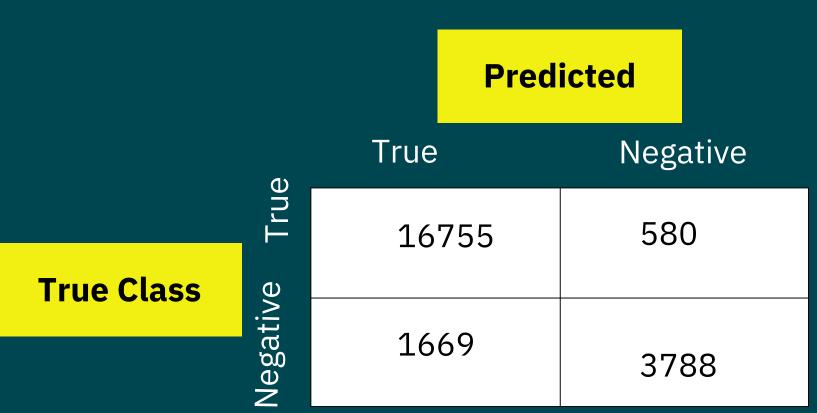
Accuracy	Misclassification	True Positive	False Positive
0.82	0.171	0.915	0.402
Specificity	Precision	Prevalence	ROC
0.598	0.65	0.839	0.865

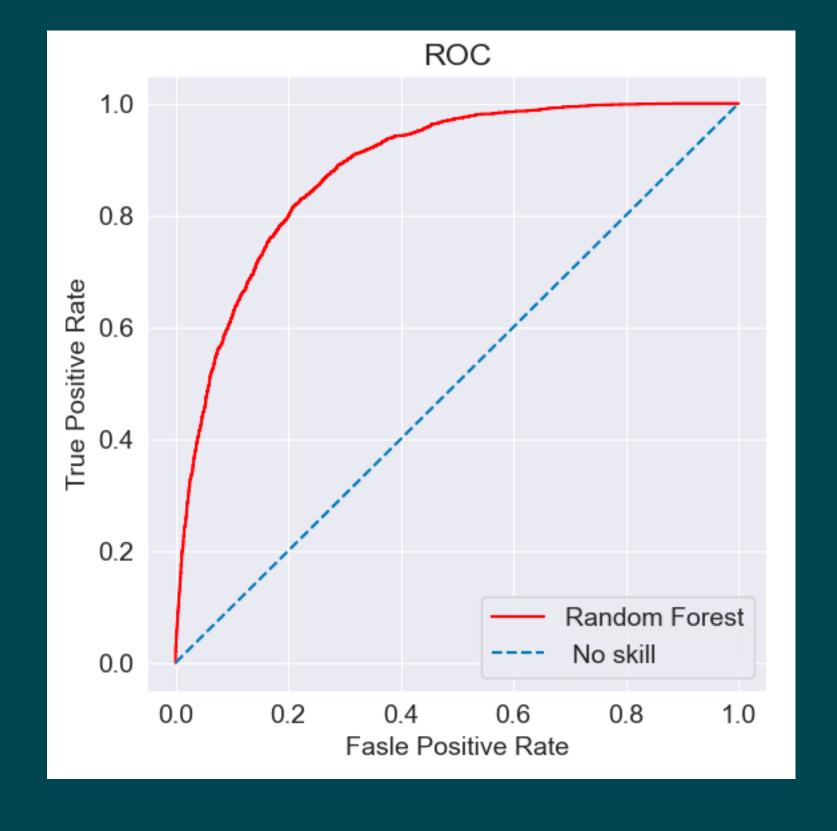




#### Random Forest: Most Accurate Model

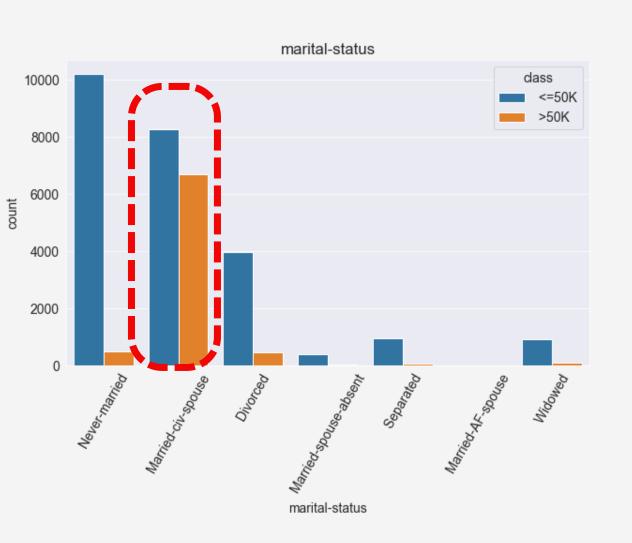
Accuracy	curacy Misclassification True Positive		False Positive		
0.834	0.171	0.967	0.306		
Specificity	Precision	Prevalence	ROC		
0.694	0.72	0.901	0.883		



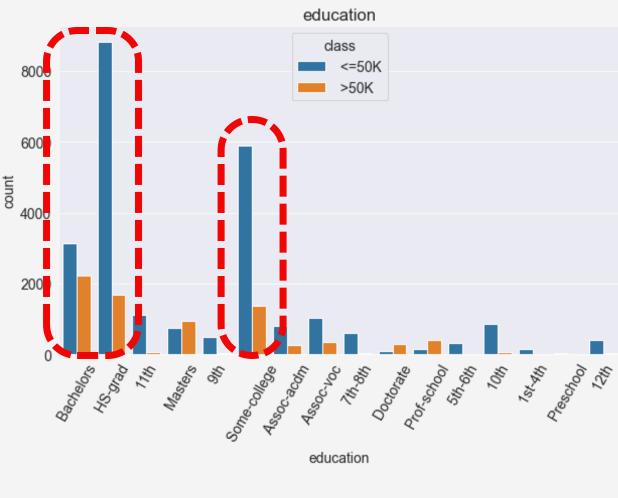


#### Recommendations









- Most accurate model
  - Random Forest Model 83.4%

- Target
  - Married couples particularly the husband
  - Higher educated individuals particularly
     Bachelors and Master Graduates.

# Appendix (1)

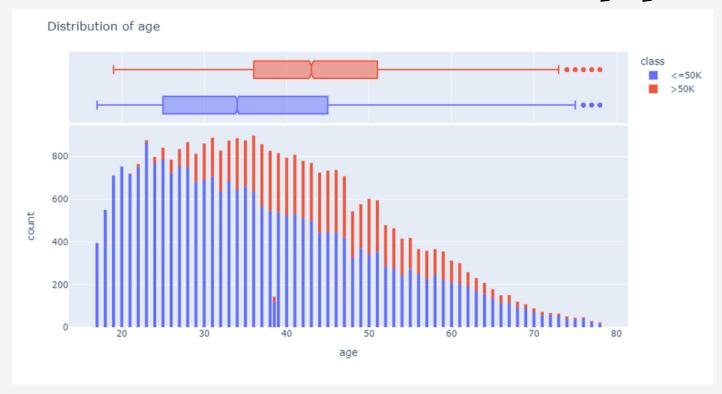
age	int64
workclass	object
	_
education	object
education_num	int64
marital_status	object
occupation	object
relationship	object
race	object
sex	object
capital_gain	int64
capital_loss	int64
hours_per_week	int64
native_country	object
income	object
dtype: object	

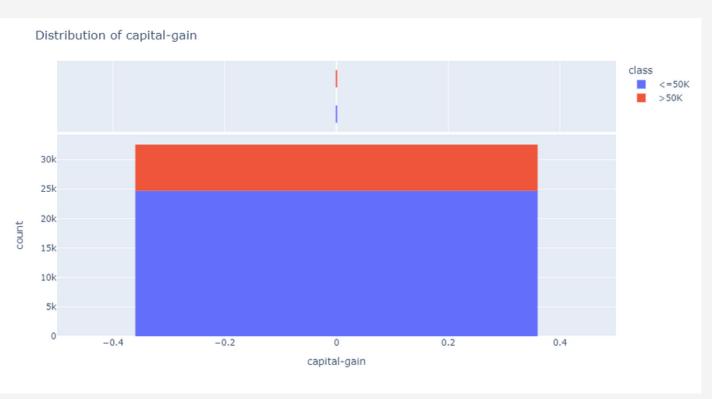
	age	capital_gain	capital_loss	hours_per_week
min	17.000000	0.000000	0.000000	1.000000
max	90.000000	99999.000000	4356.000000	99.000000
median	37.000000	0.000000	0.000000	40.000000
mean	38.581647	1077.648844	87.303830	40.437456
std	13.640433	7385.292085	402.960219	12.347429
skew	0.558743	11.953848	4.594629	0.227643
kurt	-0.166127	154.799438	20.376802	2.916687

Raw Data Variable Types (Q2)

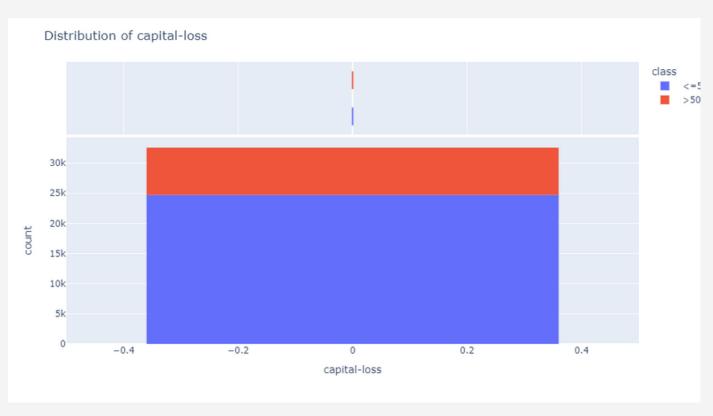
**Statistics of Numeric Values (Q4)** 

#### Appendix (2)



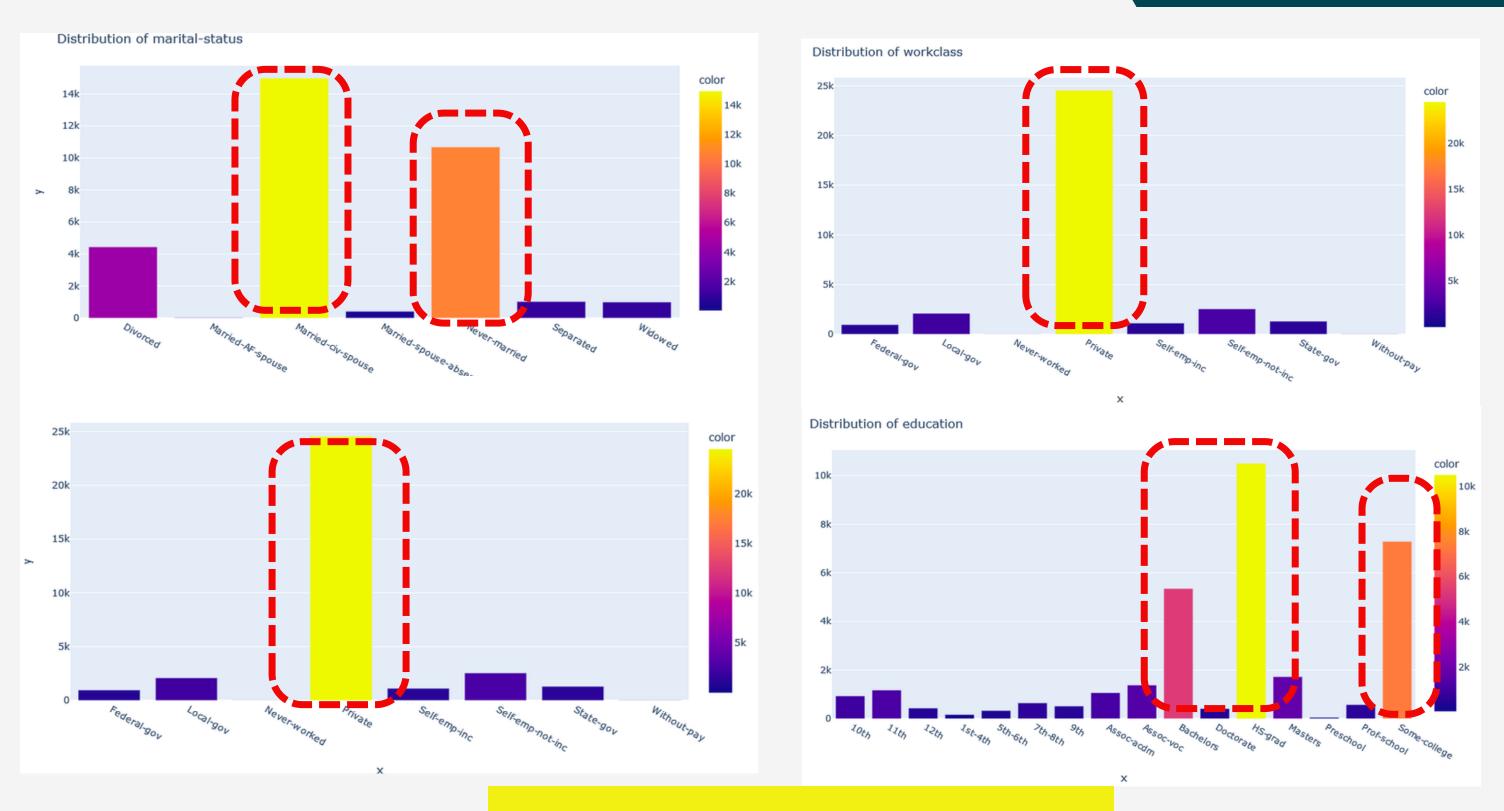






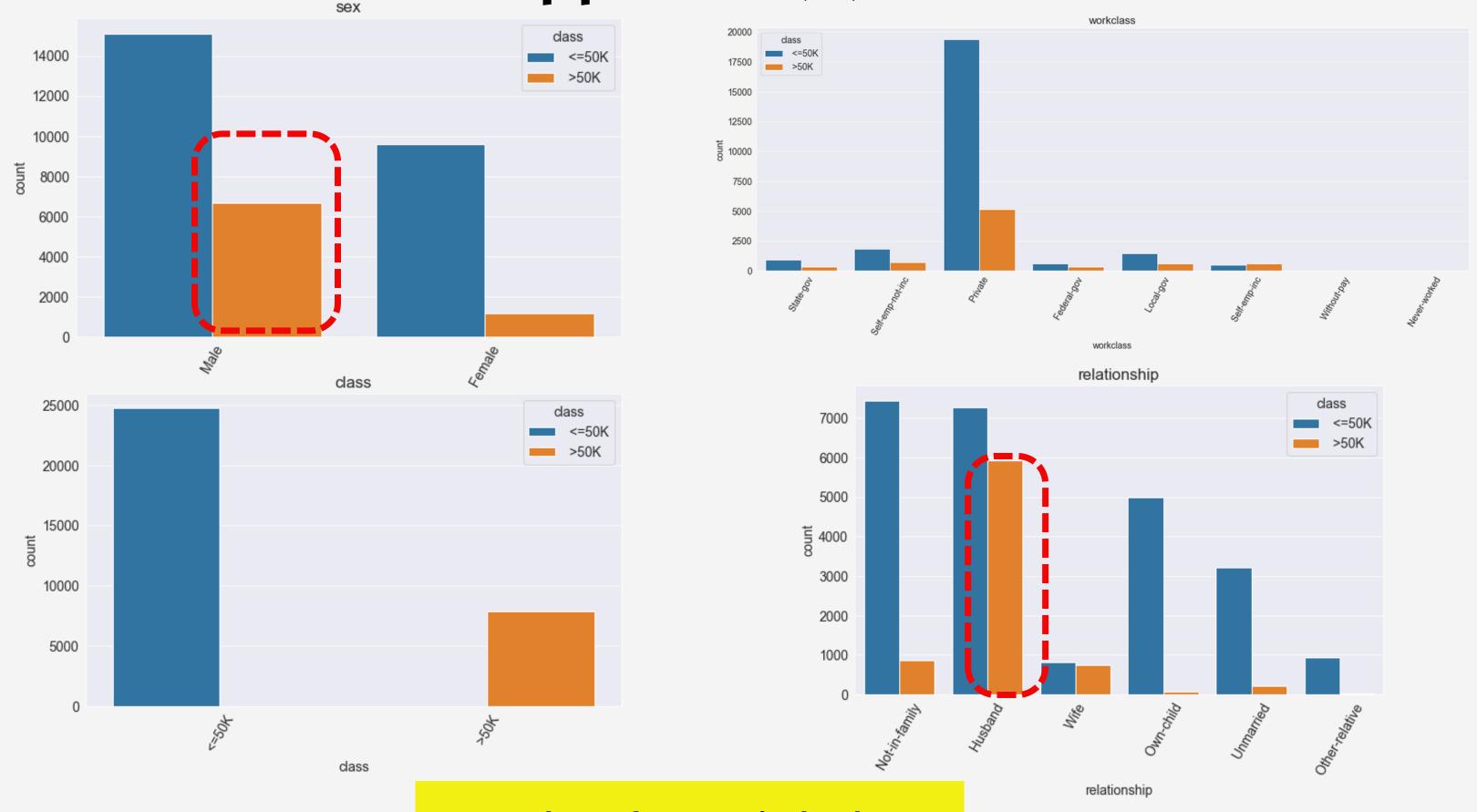
**Bar Chart and Histgram of Numeric Values (Q8)** 

# Appendix (3)



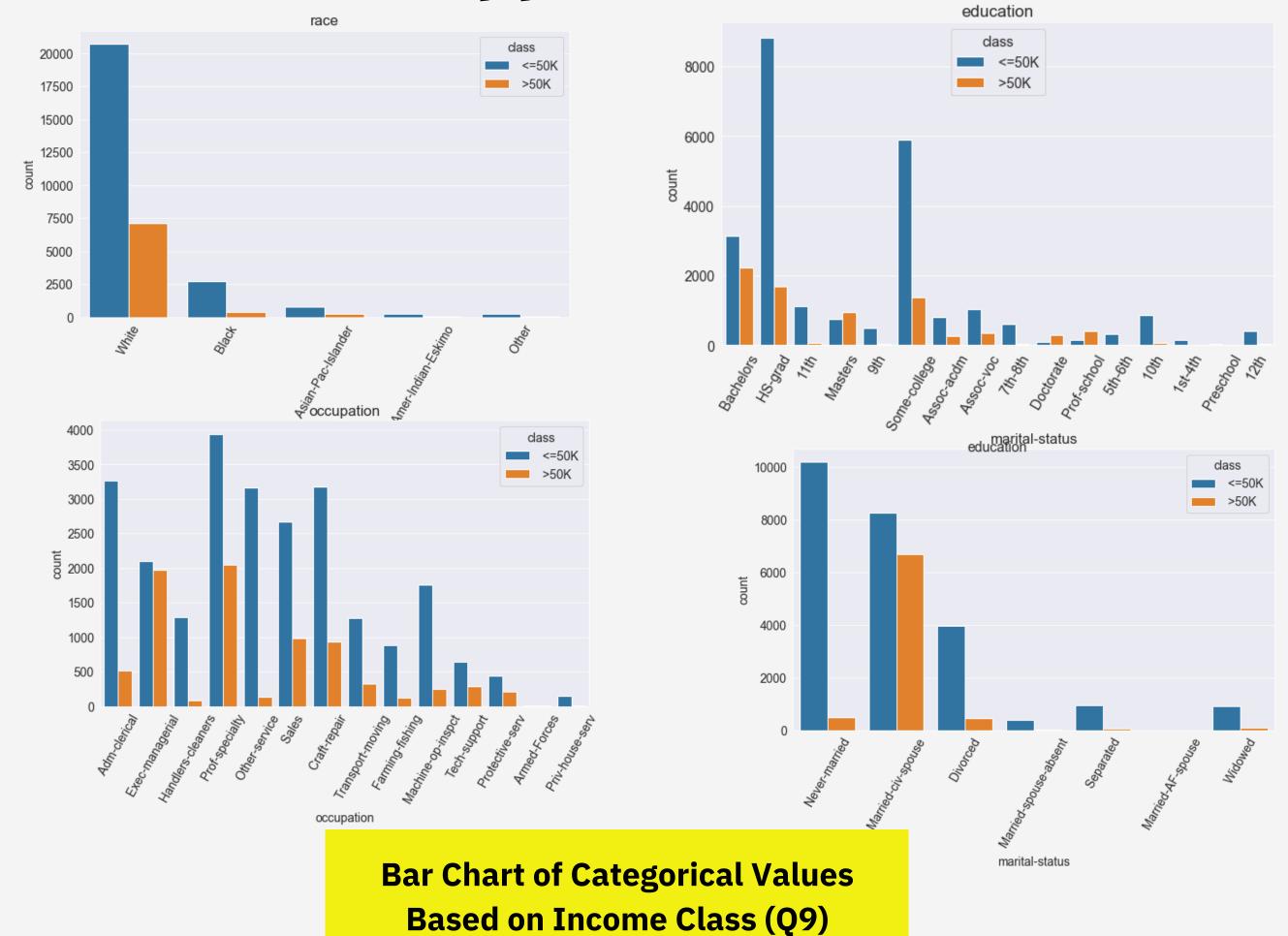
**Bar Chart of Categorical Values (Q9)** 

Appendix (4)

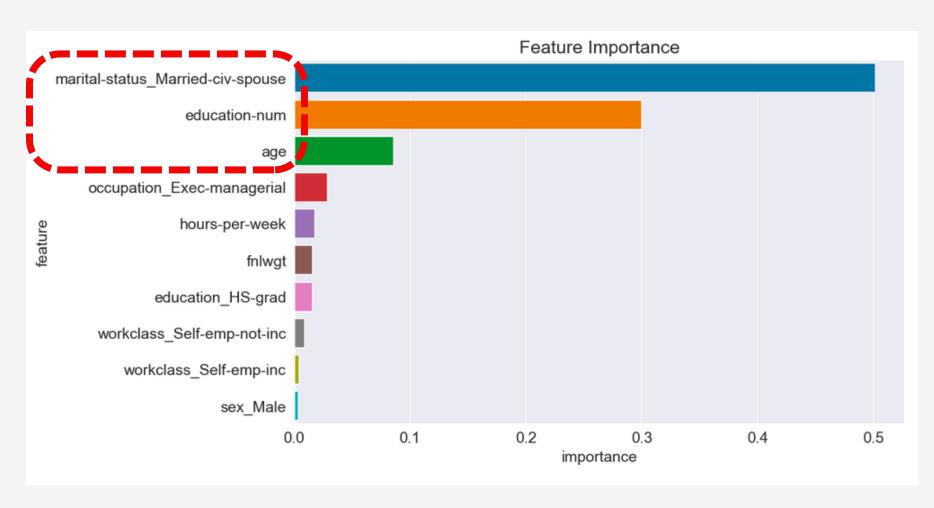


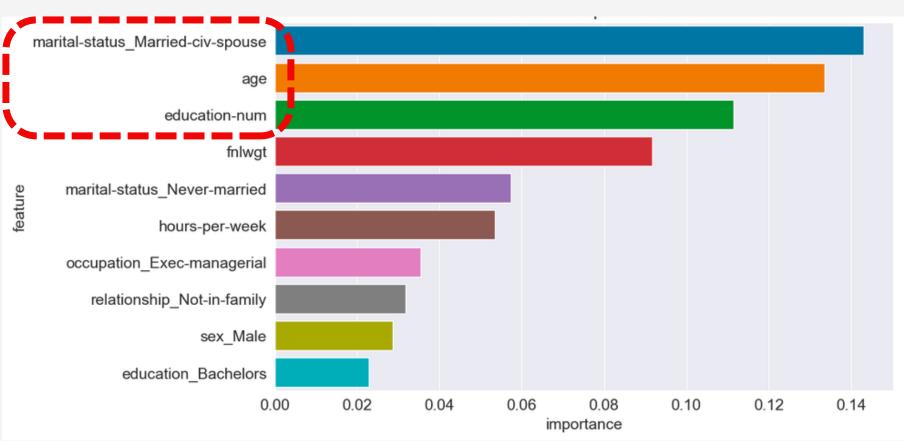
**Bar Chart of Categorical Values Based on Income Class (Q9)** 

#### Appendix (5)



#### Appendix (6)

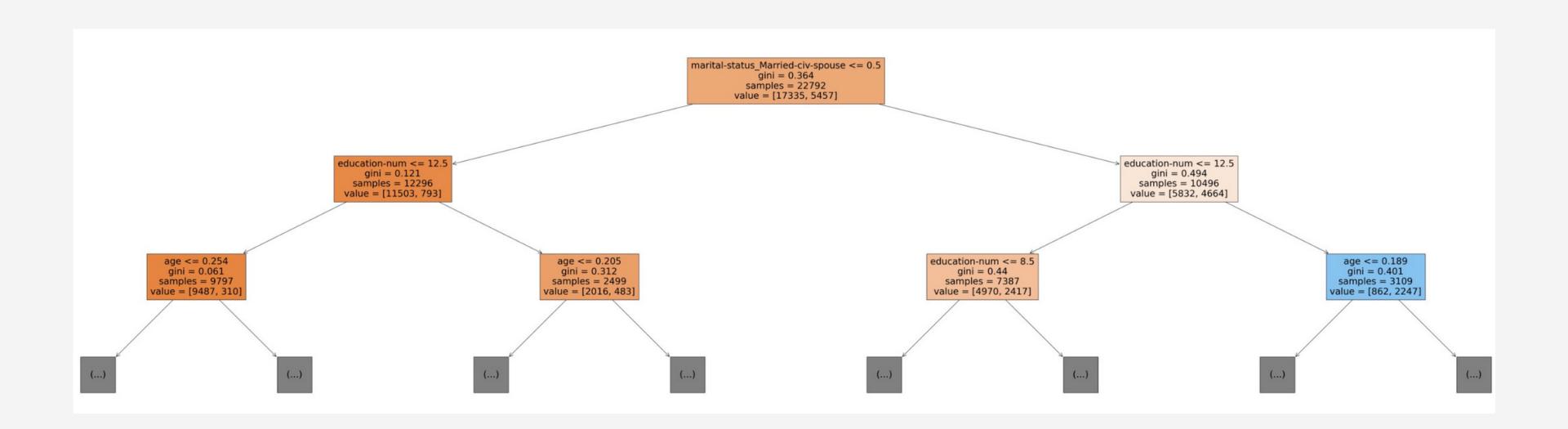




Decison Tree
Most Importand Features (Q12.2)

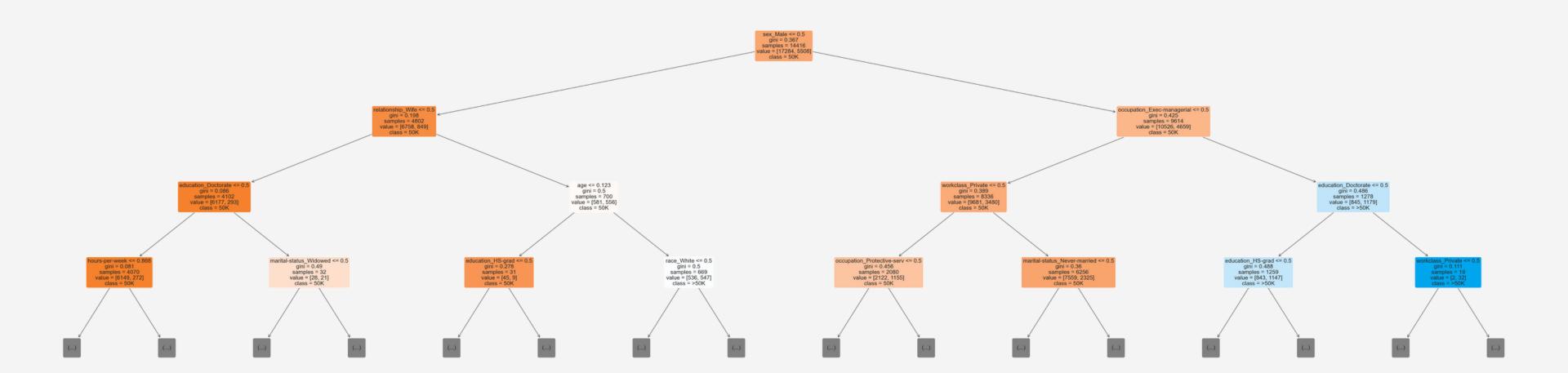
Random Forest
Most Important Features (Q12.2)

### Appendix (7)



**Decison Tree Structure Plot (Q12.3)** 

# Appendix (8)



Random Forest Structure Plot (Q12.3)

# Appendix (9)

	models_name	acc_train	acc_test	misclassification_rate	True Positive rate	False Positive rate	Specificity	Precision	Prevalence	ROC
0	Naive Bayes	81.580000	81.380000	17.100000	92.600000	45.800000	54.100000	61	83.000000	86.000000
1	Logistic Regression	83.400000	82.870000	17.100000	82.600000	45.900000	54.100000	69	83.400000	88.800000
2	Decision Tree	83.880000	82.050000	17.100000	91.500000	40.200000	59.800000	65	83.900000	86.500000
3	Rnadom Forest	90.130000	83.400000	17.100000	96.700000	30.600000	69.400000	72	86.500000	88.300000

**Model Metrics Comparisom (Q13)** 

# Appendix (10)

OLS Regression Results							
=							
Dep. Var	iable:	clas	R-squared:				
0.344 Model:		OL	Adj. R-squared:				
0.341			100000000000000000000000000000000000000				
Method: 126.5		Least Square	F-statistic:				
Date:		Thu, 10 Nov 202	Prob (F-statistic):				
0.00 Time:		15:54:3	B Log-Likelihood: -				
	rvations:	2279	2 AIC:				
1.645e+0 Df Resid	uals:	2269	7 BIC:				
1.721e+0 Df Model		9.	1				
Covariance Type:		nonrobus					
		=======================================					
P> t	[0.025	0.975]	coef std err t				
const	-0.327	0.060	-0.1296 0.101 -1.286				
age			0.1655 0.014 11.967				
	0.138	0.193	0.0400 0.011 4.460				
fnlwgt 0.000	0.027	0.070	0.0490 0.011 4.460				
capital-	-	4 00 4 1	5.437e-15 3.99e-15 1.361				
capital-			-7.774e-16 4.15e-16 -1.874				
0.061	-1.59e-15	3.59e-17					

education-num	0.0338	0.002	17.281
0.000 0.030 0.038			
workclass_Local-gov	-0.0963	0.016	-5.880
0.000 -0.128 -0.064			
workclass_Never-worked	-0.0240	0.174	-0.138
0.890 -0.365 0.317			
workclass_Private	-0.0712	0.014	-5.140
0.000 -0.098 -0.044			
workclass_Self-emp-inc	0.0287	0.019	1.543
0.123 -0.008 0.065			
workclass_Self-emp-not-inc	-0.1245	0.016	-7.694
0.000 -0.156 -0.093			
workclass_State-gov	-0.1166	0.018	-6.559
0.000 -0.151 -0.082			
workclass_Without-pay	-0.2704	0.106	-2.561
0.010 -0.477 -0.063			
education_11th	-0.0166	0.018	-0.932
0.351 -0.051 0.018			
education_12th	-0.0360	0.023	-1.546
0.122 -0.082 0.010			
education_1st-4th	0.0992	0.038	2.615
0.009 0.025 0.174			
education_5th-6th	0.0485	0.029	1.654
0.098 -0.009 0.106			
education_7th-8th	-0.0059	0.023	-0.258
0.796 -0.051 0.039			
education 9th	-0.0139	0.024	-0.591
0.555 -0.060 0.032			

# Appendix (11)

education Assoc-acdm	-0.0877	0.017	-5.064	occupation Protective-serv	0.0738	0.018	4.050
0.000 -0.122 -0.054				0.000 0.038 0.109			
education_Assoc-voc	-0.0542	0.016	-3.369	occupation_Sales	0.0386	0.010	3.862
0.001 -0.086 -0.023				0.000 0.019 0.058			
education_Bachelors	-0.0123	0.014	-0.853	occupation_Tech-support	0.0684	0.015	4.512
0.394 -0.040 0.016	0 1546	0.000	6 660	0.000 0.039 0.098			
education_Doctorate 0.000 0.109 0.200	0.1546	0.023	6.663	occupation_Transport-moving	-0.0245	0.013	-1.877
0.000 0.109 0.200 education HS-grad	-0.0642	0.013	-5.134	0.061 -0.050 0.001	0 1513	0 000	F 226
0.000 -0.089 -0.040	0.0042	0.013	3.134	relationship_Not-in-family 0.000 -0.207 -0.096	-0.1512	0.028	-5.326
education_Masters	0.0540	0.017	3.202	relationship Other-relative	-0.1263	0.028	-4.488
0.001 0.021 0.087			0.000	0.000 -0.181 -0.071	0.1203	0.020	4.400
education Preschool	0.1649	0.061	2.700	relationship Own-child	-0.1439	0.028	-5.080
0.007 0.045 0.285				0.000  -0.199  -0.088			
education_Prof-school	0.1727	0.021	8.137	relationship Unmarried	-0.1364	0.029	-4.633
0.000 0.131 0.214				0.000  -0.194  -0.079			
education_Some-college	-0.0542	0.013	-4.236	relationship_Wife	0.1166	0.013	9.017
0.000 -0.079 -0.029	0.0010	0 004	0.440	0.000 0.091 0.142			
marital-status_Married-AF-spouse	0.2818	0.091	3.113	race_Asian-Pac-Islander	0.0219	0.030	0.724
0.002 0.104 0.459	0.1326	0.029	4.641	0.469 -0.037 0.081	0.0442	0 005	1 770
marital-status_Married-civ-spouse 0.000 0.077 0.189	0.1326	0.029	4.041	race_Black	0.0443	0.025	1.772
marital-status Married-spouse-absent	0.0285	0.021	1.340	0.076 -0.005 0.093 race Other	0.0087	0.035	0.251
0.180 -0.013 0.070	0.0200	0.021	1.010	0.802 -0.059 0.076	0.0007	0.033	0.231
marital-status Never-married	-0.0040	0.009	-0.457	race White	0.0557	0.024	2.333
$0.648  -0.\overline{021}  0.013$				0.020 0.009 0.103			
marital-status_Separated	0.0147	0.014	1.020	sex Male	0.0613	0.007	8.891
0.308 -0.014 0.043				$0.0\overline{0}0$ $0.048$ $0.075$			
marital-status_Widowed	0.0097	0.015	0.638	native-country_Canada	-0.1027	0.105	-0.980
0.524 -0.020 0.039				0.327 -0.308 0.103			
occupation_Armed-Forces	-0.1780	0.132	-1.349	native-country_China	-0.1418	0.108	-1.313
0.177 -0.437 0.081	-0.0074	0 010	_0 727	0.189 -0.353 0.070	0.0565	0 115	0 001
occupation_Craft-repair 0.467 -0.027 0.013	-0.0074	0.010	-0.727	native-country_Columbia	-0.2565	0.115	-2.231
occupation Exec-managerial	0.1445	0.010	14.478	0.026 -0.482 -0.031	-0.1814	0.107	-1.698
0.000 0.125 0.164	0.1113	0.010	14.470	native-country_Cuba 0.090 -0.391 0.028	-0.1014	0.107	-1.090
0.000				0.030			

# Appendix (12)

sex Male	0.0613	0.007	8.891	native-country Honduras	-0.1529	0.143	-1.067
$0.0\overline{0}0$ $0.048$ $0.075$				$0.286  -0.\overline{4}34  0.128$			
native-country Canada	-0.1027	0.105	-0.980	native-country_Hong	-0.1906	0.131	-1.449
0.327 -0.308 0.103				$0.147  -0.\overline{4}48  0.067$			
native-country China	-0.1418	0.108	-1.313	native-country Hungary	-0.0349	0.157	-0.223
0.189 -0.353 0.070				$0.824  -0.\overline{3}42  0.272$			
native-country_Columbia	-0.2565	0.115	-2.231	native-country India	-0.1851	0.105	-1.768
0.026  -0.482  -0.031				$0.077  -0.\overline{3}90  0.020$			
native-country Cuba	-0.1814	0.107	-1.698	native-country Iran	-0.0489	0.115	-0.425
$0.090  -0.\overline{3}91  0.028$				0.671  -0.274  0.177			
native-country Dominican-Republic	-0.1611	0.110	-1.460	native-country Ireland	-0.0149	0.127	-0.117
$0.144  -0.\overline{377}  0.055$				$0.907  -0.\overline{2}64  0.235$			
native-country Ecuador	-0.1088	0.123	-0.885	native-country Italy	-0.0450	0.108	-0.415
0.376 -0.350 0.132				$0.678  -0.\overline{2}58  0.168$			
native-country_El-Salvador	-0.1188	0.106	-1.116	native-country Jamaica	-0.1514	0.109	-1.391
0.264 -0.327 0.090				$0.164  -0.\overline{3}65  0.062$			
native-country_England	-0.0827	0.107	-0.775	native-country Japan	-0.0193	0.109	-0.177
0.439 -0.292 0.127				$0.860  -0.\overline{2}34  0.195$			
native-country_France	-0.0679	0.123	-0.554	native-country Laos	-0.1963	0.130	-1.515
0.580 -0.308 0.172				0.130 -0.450 0.058			
native-country_Germany	-0.0972	0.103	-0.939	native-country Mexico	-0.1620	0.099	-1.630
0.348 -0.300 0.106				$0.103  -0.\overline{357}  0.033$			
native-country_Greece	-0.1648	0.122	-1.356	native-country Nicaragua	-0.1929	0.120	-1.609
0.175 -0.403 0.073				0.108  -0.428  0.042			
native-country_Guatemala	-0.0656	0.111	-0.591	native-country Outlying-US(Guam-USVI-etc)	-0.2829	0.151	-1.869
0.554 -0.283 0.152				$0.062  -0.\overline{5}80  0.014$			
native-country_Haiti	-0.1668	0.116	-1.443	native-country Peru	-0.1756	0.126	-1.393
0.149 -0.393 0.060				0.164  -0.423  0.071			
native-country_Holand-Netherlands	-0.0704	0.360	-0.195	native-country Philippines	-0.0691	0.101	-0.687
0.845 -0.777 0.636				0.492 -0.266 0.128			
				11111			

#### Appendix (13)

native-country_Peru		-0.1756	0.126	-1.393
0.164 -0.423				
native-country_Philippin		-0.0691	0.101	-0.687
0.492 -0.266	0.128			
native-country_Poland		-0.1724	0.111	-1.552
0.121 - 0.390	0.045			
native-country_Portugal		-0.1442	0.124	-1.167
$0.243  -0.\overline{387}$	0.098			
native-country_Puerto-Ri	co	-0.1472	0.105	-1.404
$0.160  -0.\overline{3}53$	0.058			
native-country_Scotland		-0.1217	0.157	-0.776
$0.438  -0.\overline{429}$	0.186			
native-country_South		-0.1094	0.107	-1.023
$0.306  -0.\overline{3}19$	0.100			
native-country_Taiwan		-0.1542	0.113	-1.367
$0.172  -0.\overline{375}$	0.067			
native-country_Thailand		-0.1692	0.142	-1.191
$0.234  -0.\overline{4}48$	0.109			
native-country_Trinadad&	Tobago	-0.1172	0.133	-0.883
$0.377 - 0.\overline{3}77$	0.143			
native-country_United-St	ates	-0.1107	0.098	-1.132
$0.258  -0.\overline{302}$	0.081			
native-country_Vietnam		-0.1276	0.108	-1.183
$0.237 - 0.\overline{3}39$	0.084			
native-country_Yugoslavi	a	-0.0940	0.147	-0.640
$0.522 - 0.\overline{3}82$	0.194			
=				
Omnibus:	991.186	Durbin-Watson:		

2.005

```
Prob (Omnibus):
                                       Jarque-Bera (JB):
1124.379
                                       Prob(JB):
Skew:
                               0.543
                                                                    6.98e-
245
                               2.922
                                       Cond. No.
Kurtosis:
1.03e+16
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 2.4e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```