

Assessed Pratical 2 201482038

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1. (a) Fit a logistic regression model for the outputs using all of the available inputs. Explain your model and report your results. Identify the direction and magnitude of each effect from the fitted coefficients. Compare these with the plots shown on the Guardian website. Do your findings agree with these plots? Comment on your findings.

I created a logistic regression model attempts to predict an individuals voting choice for brexit ("voteBrexit") using the following input variables from the dataframe "brexit":

```
- "abc1": proportion of individuals who are in the ABC1 social classes (middle to upper class)
- "medianIncome": the median income of all residents
- "medianAge": median age of residents
- "withHigherEd": proportion of residents with any university-level education
- "notBornUK": the proportion of residents who were born outside the UK
```

As logistic regression is a special case of generalized linear models, the `glm()` function was used to create this model. Although logistic regression models such as this are non-linear, the `glm()` function implements a description of error distribution and the link function to be used, in this case, as the outcome is binary, the "binomial" function is used.

When considering the magnitude and direction of the coefficients, negative coefficients indicate there is an inverse relationship between an increase in a particular variable and voting "yes" to Brexit, whereas positive coefficients indicate a direct relationship between an increase in the variable and voting "yes" to Brexit. When comparing the direction and magnitude of each of these variables, they do seem to align with the plots on the guardian website. Higher education, which had the strongest inverse relationship with a "yes" vote in our regression is also reflected in the Guardians plot, this was also the case in our model and the guardian plot for median income, despite the magnitude of median income being smaller (-26.7443 vs. -6.3857).

In terms of explanatory variables with direct relationships, the median age also agrees with the guardian plot, which showed areas with increasing older populations also voted leave more frequently.

However, the coefficients for the proportion of individuals who are in the ABC1 social classes and the proportion of residents who were born outside the UK are inconsistent with the guardian plots. For notbornUK, there appears to be a direct relationship, although there is a wide spread of data in the guardian plot, it still seems that areas with greater percentages of residents not born in the UK had fewer votes to leave. For abc1, there was a strong positive coefficient indicating that an increase in an areas abc1 population were more likely to vote "leave". The guardian plot contradicts this, showing populations with a large percent of ABC1 grades were voted remain more often.

##	abc1	notBornUK	medianIncome	medianAge	withHigherEd	voteBrexit
## 1	0.13364055	0.012605042	0.25257732	0.50000000	0.08552632	TRUE
## 2	0.12903226	0.113445378	0.10824742	0.27272727	0.11184210	TRUE
## 3	0.16129032	0.004201681	0.12886598	0.63636364	0.11842105	TRUE
## 4	0.32258064	0.046218487	0.22680412	0.45454545	0.21710526	TRUE

## 5	0.34562212	0.058823529	0.20103093	0.54545455	0.24342105	TRUE
## 6	0.22119816	0.012605042	0.23195876	0.45454545	0.09210526	TRUE
## 7	0.51152074	0.067226891	0.30927835	0.50000000	0.33552632	TRUE
## 8	0.18433180	0.239495798	0.09278351	0.22727273	0.14473684	TRUE
## 9	0.18894009	0.063025210	0.00000000	0.59090909	0.03289474	TRUE
## 10	0.09677419	0.121848739	0.06701031	0.22727273	0.02631579	TRUE
## 11	0.43317972	0.033613445	0.21649484	0.77272727	0.29605263	TRUE
## 12	0.09216590	0.042016807	0.08247423	0.50000000	0.05263158	TRUE
## 13	0.17972350	0.084033613	0.29896907	0.59090909	0.13815790	TRUE
## 14	0.57603687	0.134453782	0.23711340	0.36363636	0.46052632	FALSE
## 15	0.32258064	0.222689076	0.32474227	0.27272727	0.25657895	TRUE
## 16	0.22580645	0.596638655	0.07216495	0.09090909	0.17763158	FALSE
## 17	0.64516129	0.079831933	0.40206186	0.68181818	0.47368421	TRUE
## 18	0.30875576	0.327731092	0.07731959	0.00000000	0.19736842	TRUE
## 19	0.34101382	0.084033613	0.08762887	0.68181818	0.33552632	TRUE
## 20	0.29953917	0.096638655	0.14432990	0.40909091	0.17105263	TRUE
## 21	0.10138249	0.117647059	0.13402062	0.36363636	0.03289474	TRUE
## 22	0.63594470	0.134453782	0.26288660	0.45454545	0.48684211	FALSE
## 23	0.53917051	0.239495798	0.35567010	0.13636364	0.47368421	FALSE
## 24	0.51152074	0.071428571	0.35051546	0.68181818	0.36184211	TRUE
## 25	0.55299539	0.084033613	0.30927835	0.50000000	0.31578947	TRUE
## 26	0.35023042	0.092436975	0.17525773	0.36363636	0.18421053	TRUE
## 27	0.26728111	0.063025210	0.08247423	0.77272727	0.16447368	TRUE
## 28	0.50230415	0.243697479	0.28350516	0.36363636	0.30921053	TRUE
## 29	0.47926267	0.113445378	0.25773196	0.59090909	0.28947368	TRUE
## 30	0.41935484	0.201680672	0.32474227	0.40909091	0.21710526	TRUE
## 31	0.28571429	0.546218487	0.26288660	0.09090909	0.20394737	TRUE
## 32	0.47465438	0.147058824	0.30927835	0.50000000	0.19736842	TRUE
## 33	0.30875576	0.184873950	0.36597938	0.27272727	0.08552632	TRUE
## 34	0.34562212	0.155462185	0.39175258	0.31818182	0.12500000	TRUE
## 35	0.65437788	0.210084034	0.47938144	0.36363636	0.40789474	TRUE
## 36	0.66820276	0.130252101	0.48969072	0.54545455	0.45394737	FALSE
## 37	0.60829493	0.428571429	0.43814433	0.13636364	0.52631579	FALSE
## 38	0.33640553	0.697478992	0.45876289	0.13636364	0.29605263	TRUE
## 39	0.82027650	0.289915966	0.67010309	0.50000000	0.61842105	FALSE
## 40	0.88018433	0.193277311	0.68041237	0.50000000	0.65789474	FALSE
## 41	0.52995392	0.310924370	0.39690722	0.27272727	0.35526316	TRUE
## 42	0.70506912	0.256302521	0.30412371	0.22727273	0.57894737	FALSE
## 43	0.45161290	0.189075630	0.25773196	0.18181818	0.24342105	TRUE
## 44	0.39631336	0.294117647	0.24226804	0.09090909	0.26315789	TRUE
## 45	0.32718894	0.058823529	0.15979381	0.81818182	0.21710526	TRUE
## 46	0.26728111	0.021008403	0.23711340	0.59090909	0.18421053	TRUE
## 47	0.57603687	0.063025210	0.25773196	0.63636364	0.45394737	TRUE
## 48	0.48387097	0.050420168	0.28350516	0.59090909	0.38815789	TRUE
## 49	0.39631336	0.050420168	0.18556701	0.68181818	0.34210526	TRUE
## 50	0.31336405	0.042016807	0.09793814	0.72727273	0.27631579	TRUE
## 51	0.54377880	0.109243697	0.23711340	0.59090909	0.38815789	TRUE
## 52	0.48847926	0.294117647	0.31443299	0.40909091	0.35526316	TRUE
## 53	0.56221198	0.109243697	0.42268041	0.50000000	0.33552632	TRUE
## 54	0.64055299	0.163865546	0.31443299	0.45454545	0.45394737	TRUE
## 55	0.67281106	0.243697479	0.48453608	0.40909091	0.49342105	FALSE
## 56	0.78801843	0.516806723	0.47422680	0.04545454	0.84210526	FALSE
## 57	0.52995392	0.147058824	0.37113402	0.54545455	0.37500000	TRUE
## 58	0.15668203	0.121848739	0.18556701	0.63636364	0.01973684	TRUE

## 59	0.56682028	0.142857143	0.38659794	0.54545455	0.34868421	TRUE
## 60	0.73732719	0.172268908	0.48969072	0.54545455	0.65789474	FALSE
## 61	0.20737327	0.008403361	0.14948454	0.72727273	0.21710526	TRUE
## 62	0.18433180	0.016806723	0.12886598	0.63636364	0.12500000	TRUE
## 63	0.23041475	0.054621849	0.14432990	0.59090909	0.20394737	TRUE
## 64	0.23041475	0.012605042	0.59278350	0.68181818	0.17105263	TRUE
## 65	0.27649770	0.025210084	0.06701031	0.81818182	0.33552632	TRUE
## 66	0.42396313	0.050420168	0.19587629	0.86363636	0.48684211	FALSE
## 67	0.32718894	0.016806723	0.23195876	0.63636364	0.23026316	TRUE
## 68	0.14746544	0.016806723	0.10824742	0.59090909	0.04605263	TRUE
## 69	0.27649770	0.033613445	0.20618557	0.59090909	0.17763158	TRUE
## 70	0.49308756	0.021008403	0.20103093	0.81818182	0.48684211	TRUE
## 71	0.31797235	0.029411765	0.26804124	0.54545455	0.16447368	TRUE
## 72	0.43778802	0.029411765	0.18556701	0.63636364	0.38815789	TRUE
## 73	0.34562212	0.004201681	0.13402062	0.72727273	0.20394737	TRUE
## 74	0.43317972	0.033613445	0.35567010	0.50000000	0.30263158	TRUE
## 75	0.45161290	0.054621849	0.22680412	0.90909091	0.38157895	TRUE
## 76	0.52534562	0.168067227	0.17010309	0.18181818	0.36842105	FALSE
## 77	0.34101382	0.054621849	0.20103093	0.68181818	0.30921053	TRUE
## 78	0.28571429	0.046218487	0.03608247	0.72727273	0.22368421	TRUE
## 79	0.44700461	0.046218487	0.16494845	0.81818182	0.34868421	TRUE
## 80	0.17050691	0.025210084	0.04123711	0.81818182	0.19078947	TRUE
## 81	0.41474654	0.050420168	0.17010309	0.86363636	0.40131579	TRUE
## 82	0.48847926	0.067226891	0.27319588	0.90909091	0.27631579	TRUE
## 83	0.59907834	0.050420168	0.30412371	0.95454545	0.34210526	TRUE
## 84	0.41935484	0.088235294	0.11340206	0.72727273	0.32236842	TRUE
## 85	0.46082949	0.067226891	0.28865979	0.90909091	0.42105263	TRUE
## 86	0.33179724	0.063025210	0.19587629	0.72727273	0.21052632	TRUE
## 87	0.41474654	0.184873950	0.15979381	0.63636364	0.26315789	TRUE
## 88	0.29953917	0.126050420	0.17010309	0.54545455	0.17763158	TRUE
## 89	0.53917051	0.100840336	0.28865979	0.72727273	0.38815789	FALSE
## 90	0.58525346	0.088235294	0.30927835	0.77272727	0.37500000	TRUE
## 91	0.39631336	0.096638655	0.28350516	0.40909091	0.11184210	TRUE
## 92	0.66359447	0.105042017	0.38659794	0.50000000	0.37500000	TRUE
## 93	0.54377880	0.172268908	0.24226804	0.36363636	0.32894737	TRUE
## 94	0.62211982	0.130252101	0.55154639	0.54545455	0.28289474	TRUE
## 95	0.48847926	0.033613445	0.45360825	0.77272727	0.24342105	TRUE
## 96	0.22580645	0.042016807	0.23195876	0.86363636	0.04605263	TRUE
## 97	0.69124424	0.096638655	0.41237113	0.59090909	0.45394737	TRUE
## 98	0.65898618	0.172268908	0.35567010	0.40909091	0.55921053	FALSE
## 99	0.32258064	0.033613445	0.20103093	0.72727273	0.25000000	TRUE
## 100	0.36405530	0.159663866	0.20103093	0.36363636	0.20394737	TRUE
## 101	0.51612903	0.063025210	0.31958763	0.68181818	0.47368421	FALSE
## 102	0.58064516	0.079831933	0.32989691	0.63636364	0.40789474	TRUE
## 103	0.63133641	0.163865546	0.52061856	0.45454545	0.41447368	TRUE
## 104	0.65437788	0.117647059	0.39690722	0.68181818	0.50000000	FALSE
## 105	0.57603687	0.100840336	0.31443299	0.50000000	0.34868421	TRUE
## 106	0.67741935	0.067226891	0.45360825	0.68181818	0.39473684	TRUE
## 107	0.39631336	0.075630252	0.28350516	0.50000000	0.18421053	TRUE
## 108	0.84792627	0.138655462	0.68556701	0.54545455	0.59210526	FALSE
## 109	0.34562212	0.058823529	0.28865979	0.68181818	0.20394737	TRUE
## 110	0.49769585	0.075630252	0.24742268	0.81818182	0.33552632	TRUE
## 111	0.51152074	0.289915966	0.38144330	0.31818182	0.26973684	TRUE
## 112	0.60829493	0.117647059	0.38144330	0.63636364	0.41447368	TRUE

## 113	0.40552995	0.184873950	0.50000000	0.45454545	0.13157895	TRUE
## 114	0.62672811	0.159663866	0.44329897	0.45454545	0.42763158	TRUE
## 115	0.66359447	0.281512605	0.38144330	0.45454545	0.42105263	TRUE
## 116	0.66359447	0.151260504	0.56701031	0.50000000	0.51315789	FALSE
## 117	0.70967742	0.222689076	0.47938144	0.50000000	0.50000000	TRUE
## 118	0.58525346	0.428571429	0.54639175	0.22727273	0.46052632	TRUE
## 119	0.44239631	0.134453782	0.30412371	0.50000000	0.26315789	TRUE
## 120	0.57603687	0.168067227	0.35051546	0.36363636	0.33552632	TRUE
## 121	0.45622120	0.172268908	0.45876289	0.31818182	0.19736842	TRUE
## 122	0.30875576	0.226890756	0.29896907	0.40909091	0.14473684	TRUE
## 123	0.53456221	0.134453782	0.37113402	0.50000000	0.28947368	TRUE
## 124	0.66820276	0.113445378	0.36082474	0.59090909	0.45394737	TRUE
## 125	0.37327189	0.134453782	0.28350516	0.68181818	0.19078947	TRUE
## 126	0.31797235	0.067226891	0.34536082	0.50000000	0.11842105	TRUE
## 127	0.27649770	0.121848739	0.05670103	0.59090909	0.13815790	TRUE
## 128	0.58986175	0.088235294	0.51030928	0.54545455	0.32894737	TRUE
## 129	0.14285714	0.105042017	0.17525773	0.40909091	0.11842105	TRUE
## 130	0.47926267	0.029411765	0.26804124	0.54545455	0.34868421	TRUE
## 131	0.61290323	0.054621849	0.22164949	0.81818182	0.39473684	TRUE
## 132	0.17511521	0.096638655	0.14948454	0.40909091	0.11842105	TRUE
## 133	0.16589862	0.163865546	0.22164949	0.40909091	0.15131579	TRUE
## 134	0.37327189	0.214285714	0.05670103	0.22727273	0.26315789	TRUE
## 135	0.55299539	0.029411765	0.37628866	0.72727273	0.50657895	TRUE
## 136	0.36866359	0.046218487	0.14948454	0.50000000	0.27631579	TRUE
## 137	0.49769585	0.029411765	0.25257732	0.59090909	0.30921053	TRUE
## 138	0.41013825	0.033613445	0.22680412	0.59090909	0.28289474	TRUE
## 139	0.42396313	0.021008403	0.16494845	0.81818182	0.22368421	TRUE
## 140	0.52073733	0.084033613	0.34020619	0.54545455	0.26973684	TRUE
## 141	0.50691244	0.155462185	0.31443299	0.40909091	0.32236842	TRUE
## 142	0.45161290	0.037815126	0.26804124	0.63636364	0.25000000	TRUE
## 143	0.39631336	0.033613445	0.20103093	0.59090909	0.25657895	TRUE
## 144	0.50691244	0.243697479	0.08762887	0.54545455	0.26973684	TRUE
## 145	0.05529954	0.247899160	0.06185567	0.54545455	0.02631579	TRUE
## 146	0.19354839	0.029411765	0.21134021	0.90909091	0.09868421	TRUE
## 147	0.27188940	0.147058824	0.07731959	0.18181818	0.18421053	TRUE
## 148	0.48847926	0.058823529	0.24742268	0.68181818	0.28947368	TRUE
## 149	0.18433180	0.138655462	0.23711340	0.68181818	0.03947368	TRUE
## 150	0.42857143	0.088235294	0.14948454	0.63636364	0.28947368	TRUE
## 151	0.38248848	0.037815126	0.21134021	0.72727273	0.28289474	TRUE
## 152	0.26267281	0.121848739	0.08762887	0.68181818	0.11184210	TRUE
## 153	0.47004608	0.037815126	0.15463917	0.77272727	0.23026316	TRUE
## 154	0.14746544	0.084033613	0.05670103	0.63636364	0.00000000	TRUE
## 155	0.23963134	0.105042017	0.13402062	0.72727273	0.12500000	TRUE
## 156	0.26267281	0.037815126	0.11340206	1.00000000	0.20394737	TRUE
## 157	0.41013825	0.201680672	0.18041237	0.13636364	0.34210526	FALSE
## 158	0.48847926	0.054621849	0.25773196	0.68181818	0.32894737	TRUE
## 159	0.54838710	0.071428571	0.38144330	0.63636364	0.37500000	TRUE
## 160	0.44700461	0.075630252	0.40721650	0.59090909	0.25657895	TRUE
## 161	0.37327189	0.121848739	0.22164949	0.45454545	0.23026316	TRUE
## 162	0.39170507	0.268907563	0.23195876	0.27272727	0.24342105	TRUE
## 163	0.65898618	0.071428571	0.40206186	0.63636364	0.42763158	TRUE
## 164	0.29953917	0.193277311	0.19072165	0.50000000	0.15789474	TRUE
## 165	0.48387097	0.037815126	0.18556701	0.81818182	0.44736842	TRUE
## 166	0.52995392	0.046218487	0.11855670	0.77272727	0.45394737	TRUE

## 167	0.62672811	0.126050420	0.25773196	0.68181818	0.50657895	FALSE
## 168	0.51152074	0.117647059	0.28350516	0.50000000	0.32236842	TRUE
## 169	0.33179724	0.037815126	0.11340206	0.81818182	0.33552632	TRUE
## 170	0.23041475	0.050420168	0.14948454	0.81818182	0.21710526	TRUE
## 171	0.16129032	0.016806723	0.16494845	0.54545455	0.02631579	TRUE
## 172	0.22119816	0.050420168	0.19587629	0.63636364	0.15789474	TRUE
## 173	0.51612903	0.105042017	0.39175258	0.54545455	0.35526316	TRUE
## 174	0.47465438	0.067226891	0.27319588	0.59090909	0.28289474	TRUE
## 175	0.16589862	0.067226891	0.07731959	0.50000000	0.05921053	TRUE
## 176	0.81105991	0.084033613	0.40206186	0.59090909	0.63157895	FALSE
## 177	0.51152074	0.176470588	0.39175258	0.45454545	0.35526316	TRUE
## 178	0.70046083	0.500000000	0.45360825	0.00000000	0.72368421	FALSE
## 179	0.70967742	0.134453782	0.50000000	0.59090909	0.57236842	FALSE
## 180	0.60368664	0.113445378	0.41237113	0.59090909	0.47368421	FALSE
## 181	0.38709677	0.079831933	0.15463917	0.68181818	0.34868421	FALSE
## 182	0.28110599	0.054621849	0.16494845	0.68181818	0.20394737	TRUE
## 183	0.34562212	0.071428571	0.14432990	0.68181818	0.27631579	TRUE
## 184	0.44239631	0.092436975	0.24742268	0.63636364	0.35526316	TRUE
## 185	0.21658986	0.008403361	0.26288660	0.50000000	0.07894737	TRUE
## 186	0.29493088	0.121848739	0.11340206	0.50000000	0.23684210	TRUE
## 187	0.56221198	0.033613445	0.36597938	0.68181818	0.36184211	TRUE
## 188	0.33179724	0.054621849	0.17010309	0.54545455	0.21052632	TRUE
## 189	0.52073733	0.012605042	0.32474227	0.72727273	0.27631579	TRUE
## 190	0.56221198	0.075630252	0.24742268	0.63636364	0.40789474	TRUE
## 191	0.34562212	0.004201681	0.22680412	0.72727273	0.24342105	TRUE
## 192	0.28110599	0.029411765	0.19072165	0.45454545	0.08552632	TRUE
## 193	0.46543779	0.054621849	0.18556701	0.77272727	0.29605263	TRUE
## 194	0.28110599	0.184873950	0.19072165	0.31818182	0.16447368	TRUE
## 195	0.47465438	0.050420168	0.29381443	0.72727273	0.30921053	TRUE
## 196	0.43317972	0.121848739	0.27319588	0.59090909	0.26315789	TRUE
## 197	0.20737327	0.033613445	0.09278351	0.72727273	0.09210526	TRUE
## 198	0.91244240	0.306722689	0.64432990	0.50000000	0.75657895	FALSE
## 199	0.77880184	0.268907563	0.56701031	0.45454545	0.55263158	FALSE
## 200	0.79723502	0.252100840	0.55154639	0.36363636	0.64473684	FALSE
## 201	0.77880184	0.147058824	0.44845361	0.68181818	0.60526316	FALSE
## 202	0.74193548	0.189075630	0.50000000	0.45454545	0.50000000	TRUE
## 203	0.63133641	0.226890756	0.62886598	0.50000000	0.30263158	TRUE
## 204	0.80184332	0.210084034	0.58247423	0.54545455	0.51315789	TRUE
## 205	0.73732719	0.126050420	0.51546392	0.59090909	0.48026316	TRUE
## 206	0.80184332	0.159663866	0.57731959	0.59090909	0.65789474	FALSE
## 207	0.74193548	0.336134454	0.48453608	0.40909091	0.61184211	FALSE
## 208	0.35023042	0.016806723	0.28350516	0.63636364	0.14473684	TRUE
## 209	0.23963134	0.088235294	0.28350516	0.50000000	0.11184210	TRUE
## 210	0.45161290	0.180672269	0.45360825	0.50000000	0.35526316	TRUE
## 211	0.64055299	0.075630252	0.31958763	0.77272727	0.48684211	TRUE
## 212	0.73271889	0.176470588	0.42268041	0.40909091	0.61842105	FALSE
## 213	0.43778802	0.075630252	0.23195876	0.63636364	0.19736842	TRUE
## 214	0.40552995	0.121848739	0.18041237	0.81818182	0.21710526	TRUE
## 215	0.58986175	0.113445378	0.17010309	0.81818182	0.46052632	TRUE
## 216	0.41013825	0.344537815	0.31443299	0.27272727	0.19078947	TRUE
## 217	0.72350230	0.142857143	0.51030928	0.59090909	0.49342105	FALSE
## 218	0.52995392	0.138655462	0.27835052	0.59090909	0.30263158	TRUE
## 219	0.64516129	0.033613445	0.35051546	0.68181818	0.41447368	TRUE
## 220	0.55299539	0.054621849	0.09793814	0.86363636	0.50000000	TRUE

## 221	0.30875576	0.109243697	0.04123711	0.40909091	0.16447368	TRUE
## 222	0.45622120	0.113445378	0.27319588	0.36363636	0.34210526	TRUE
## 223	0.49769585	0.067226891	0.22680412	0.72727273	0.36842105	TRUE
## 224	0.30875576	0.033613445	0.11855670	0.68181818	0.20394737	TRUE
## 225	0.30875576	0.172268908	0.16494845	0.36363636	0.20394737	TRUE
## 226	0.45622120	0.126050420	0.37113402	0.45454545	0.28947368	TRUE
## 227	0.41935484	0.436974790	0.20103093	0.00000000	0.37500000	FALSE
## 228	0.21658986	0.180672269	0.14432990	0.31818182	0.11184210	TRUE
## 229	0.21198157	0.172268908	0.17525773	0.36363636	0.13157895	TRUE
## 230	0.36405530	0.180672269	0.19072165	0.22727273	0.20394737	TRUE
## 231	0.55299539	0.088235294	0.30927835	0.54545455	0.39473684	FALSE
## 232	0.24884793	0.092436975	0.15979381	0.45454545	0.08552632	TRUE
## 233	0.64055299	0.172268908	0.39690722	0.45454545	0.50000000	FALSE
## 234	0.24884793	0.025210084	0.25257732	0.50000000	0.13815790	TRUE
## 235	0.14285714	0.004201681	0.19072165	0.45454545	0.03289474	TRUE
## 236	0.34101382	0.147058824	0.22164949	0.22727273	0.21052632	FALSE
## 237	0.24884793	0.012605042	0.21649484	0.54545455	0.17105263	TRUE
## 238	0.41474654	0.037815126	0.22164949	0.68181818	0.25000000	FALSE
## 239	0.37327189	0.037815126	0.27319588	0.59090909	0.28289474	FALSE
## 240	0.17511521	0.025210084	0.18556701	0.54545455	0.07894737	TRUE
## 241	0.15668203	0.075630252	0.10824742	0.50000000	0.07236842	TRUE
## 242	0.18894009	0.054621849	0.15979381	0.54545455	0.08552632	TRUE
## 243	0.43317972	0.180672269	0.17525773	0.22727273	0.28947368	TRUE
## 244	0.45161290	0.214285714	0.23195876	0.13636364	0.32894737	FALSE
## 245	0.44700461	0.033613445	0.20103093	0.54545455	0.28289474	TRUE
## 246	0.21658986	0.025210084	0.18041237	0.59090909	0.13157895	TRUE
## 247	0.22119816	0.037815126	0.18041237	0.54545455	0.10526316	TRUE
## 248	0.32258064	0.378151261	0.21649484	0.09090909	0.22368421	TRUE
## 249	0.33640553	0.361344538	0.25257732	0.13636364	0.22368421	TRUE
## 250	0.29032258	0.058823529	0.22680412	0.54545455	0.12500000	TRUE
## 251	0.12442396	0.260504202	0.18041237	0.27272727	0.03289474	TRUE
## 252	0.58525346	0.100840336	0.37628866	0.59090909	0.36184211	TRUE
## 253	0.16589862	0.147058824	0.13402062	0.36363636	0.07236842	TRUE
## 254	0.17050691	0.268907563	0.18041237	0.36363636	0.13815790	TRUE
## 255	0.29032258	0.285714286	0.16494845	0.22727273	0.19736842	TRUE
## 256	0.39631336	0.100840336	0.19587629	0.50000000	0.27631579	TRUE
## 257	0.34101382	0.163865546	0.19587629	0.40909091	0.25000000	TRUE
## 258	0.47926267	0.176470588	0.26804124	0.22727273	0.32236842	FALSE
## 259	0.20737327	0.063025210	0.15979381	0.54545455	0.10526316	TRUE
## 260	0.22119816	0.546218487	0.34536082	0.09090909	0.17105263	TRUE
## 261	0.70506912	0.693277311	0.44845361	0.22727273	0.66447368	FALSE
## 262	0.49769585	0.226890756	0.43814433	0.36363636	0.19078947	TRUE
## 263	0.41935484	1.000000000	0.39690722	0.18181818	0.48684211	FALSE
## 264	0.73732719	0.235294118	0.69587629	0.45454545	0.48026316	FALSE
## 265	0.87096774	0.764705882	0.77319588	0.13636364	0.92105263	FALSE
## 266	0.58064516	0.521008403	0.46907216	0.27272727	0.44736842	FALSE
## 267	0.55299539	0.869747899	0.46391753	0.22727273	0.57894737	FALSE
## 268	0.45161290	0.621848739	0.38144330	0.22727273	0.36842105	FALSE
## 269	0.50691244	0.546218487	0.55154639	0.13636364	0.48684211	FALSE
## 270	0.58064516	0.697478992	0.57731959	0.04545454	0.70394737	FALSE
## 271	0.82949309	0.768907563	0.84536082	0.13636364	0.90131579	FALSE
## 272	0.57142857	0.802521008	0.51546392	0.13636364	0.67763158	FALSE
## 273	0.64516129	0.806722689	0.48969072	0.27272727	0.57236842	FALSE
## 274	0.47465438	0.155462185	0.49484536	0.45454545	0.13157895	TRUE

## 275	0.51612903	0.525210084	0.46391753	0.22727273	0.35526316	TRUE
## 276	0.52534562	0.777310924	0.44329897	0.18181818	0.51973684	FALSE
## 277	0.76036866	0.630252101	0.77835051	0.09090909	0.86184211	FALSE
## 278	0.82488479	0.495798319	0.67525773	0.27272727	0.69078947	FALSE
## 279	0.68663595	0.693277311	0.57731959	0.09090909	0.82236842	FALSE
## 280	0.60368664	0.596638655	0.52061856	0.18181818	0.60526316	FALSE
## 281	0.72350230	0.672268908	0.57731959	0.22727273	0.68421053	FALSE
## 282	0.29953917	0.974789916	0.26288660	0.00000000	0.40789474	FALSE
## 283	0.61290323	0.659663866	0.59278350	0.18181818	0.50000000	FALSE
## 284	1.00000000	0.420168067	0.86597938	0.40909091	0.98684211	FALSE
## 285	0.64516129	0.705882353	0.63402062	0.09090909	0.73684211	FALSE
## 286	0.59907834	0.336134454	0.46391753	0.36363636	0.40131579	TRUE
## 287	0.65437788	0.773109244	0.61855670	0.00000000	0.68421053	FALSE
## 288	0.45622120	0.689075630	0.42783505	0.13636364	0.40131579	FALSE
## 289	0.89861751	0.630252101	0.90206186	0.13636364	1.00000000	FALSE
## 290	0.87557604	0.966386555	1.00000000	0.22727273	0.91447368	FALSE
## 291	0.26728111	0.084033613	0.18041237	0.31818182	0.23684210	FALSE
## 292	0.24423963	0.037815126	0.27835052	0.59090909	0.19736842	FALSE
## 293	0.12903226	0.025210084	0.11340206	0.77272727	0.18421053	FALSE
## 294	0.17511521	0.004201681	0.22164949	0.59090909	0.09868421	FALSE
## 295	0.42857143	0.058823529	0.34020619	0.59090909	0.32894737	FALSE
## 296	0.73271889	0.050420168	0.55154639	0.59090909	0.53289474	FALSE
## 297	0.21658986	0.016806723	0.13917526	0.77272727	0.30921053	FALSE
## 298	0.30414747	0.029411765	0.27835052	0.54545455	0.15789474	FALSE
## 299	0.35023042	0.067226891	0.24226804	0.59090909	0.24342105	FALSE
## 300	0.28571429	0.067226891	0.23711340	0.68181818	0.30921053	FALSE
## 301	0.27188940	0.008403361	0.20103093	0.63636364	0.14473684	FALSE
## 302	0.33179724	0.037815126	0.25773196	0.54545455	0.17763158	FALSE
## 303	0.23502304	0.058823529	0.10309278	0.59090909	0.21710526	FALSE
## 304	0.20276498	0.008403361	0.21134021	0.63636364	0.13815790	FALSE
## 305	0.19354839	0.021008403	0.23711340	0.72727273	0.31578947	FALSE
## 306	0.44239631	0.092436975	0.29896907	0.68181818	0.41447368	FALSE
## 307	0.29953917	0.058823529	0.22164949	0.77272727	0.32894737	FALSE
## 308	0.19815668	0.054621849	0.34020619	0.54545455	0.31578947	FALSE
## 309	0.36405530	0.025210084	0.29896907	0.77272727	0.27631579	FALSE
## 310	0.37327189	0.025210084	0.35051546	0.59090909	0.19736842	FALSE
## 311	0.52995392	0.092436975	0.32989691	0.54545455	0.48684211	FALSE
## 312	0.52995392	0.260504202	0.41237113	0.27272727	0.48026316	FALSE
## 313	0.37327189	0.071428571	0.30412371	0.54545455	0.32236842	FALSE
## 314	0.36405530	0.050420168	0.26288660	0.77272727	0.37500000	FALSE
## 315	0.71889401	0.260504202	0.38144330	0.27272727	0.69078947	FALSE
## 316	0.39170507	0.042016807	0.28865979	0.59090909	0.22368421	FALSE
## 317	0.23041475	0.021008403	0.19587629	0.54545455	0.05921053	FALSE
## 318	0.35023042	0.067226891	0.27319588	0.45454545	0.18421053	FALSE
## 319	0.30875576	0.046218487	0.19587629	0.68181818	0.24342105	FALSE
## 320	0.38248848	0.130252101	0.19587629	0.31818182	0.26973684	FALSE
## 321	0.22580645	0.016806723	0.27319588	0.45454545	0.07894737	FALSE
## 322	0.67741935	0.042016807	0.41752577	0.68181818	0.52631579	FALSE
## 323	0.35944700	0.193277311	0.25257732	0.22727273	0.29605263	FALSE
## 324	0.27188940	0.025210084	0.25257732	0.72727273	0.30263158	TRUE
## 325	0.30875576	0.050420168	0.06701031	0.59090909	0.30921053	FALSE
## 326	0.32258064	0.042016807	0.15463917	0.77272727	0.28947368	TRUE
## 327	0.28571429	0.037815126	0.15979381	0.68181818	0.25657895	TRUE
## 328	0.29032258	0.037815126	0.22680412	0.59090909	0.21052632	TRUE

```
## 329 0.23502304 0.079831933 0.23711340 0.50000000 0.21710526 TRUE
## 330 0.41013825 0.075630252 0.14432990 0.59090909 0.34868421 FALSE
## 331 0.22119816 0.046218487 0.04639175 0.72727273 0.26973684 TRUE
## 332 0.25345622 0.037815126 0.14432990 0.68181818 0.25000000 TRUE
## 333 0.41013825 0.096638655 0.17010309 0.45454545 0.29605263 TRUE
## 334 0.17050691 0.008403361 0.18556701 0.59090909 0.11842105 TRUE
## 335 0.26728111 0.029411765 0.17525773 0.54545455 0.21052632 TRUE
## 336 0.51612903 0.050420168 0.25773196 0.59090909 0.39473684 FALSE
## 337 0.58064516 0.210084034 0.24226804 0.13636364 0.46052632 FALSE
## 338 0.21198157 0.021008403 0.20618557 0.45454545 0.13815790 TRUE
## 339 0.21198157 0.004201681 0.21649484 0.50000000 0.11184210 TRUE
## 340 0.00000000 0.000000000 0.13917526 0.54545455 0.02631579 TRUE
## 341 0.21658986 0.012605042 0.23711340 0.54545455 0.15789474 TRUE
## 342 0.51612903 0.042016807 0.37113402 0.77272727 0.48026316 FALSE
## 343 0.25806452 0.037815126 0.13917526 0.81818182 0.30921053 TRUE
## 344 0.12442396 0.046218487 0.16494845 0.45454545 0.09210526 TRUE
```

```
##
## Call:
## glm(formula = voteBrexit ~ abc1 + notBornUK + medianIncome +
##     medianAge + withHigherEd, family = binomial, data = brexit)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.9793  -0.2296   0.3073   0.6032   2.0177
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.1386     0.8477  -0.164 0.870122
## abc1          17.5780     2.9114   6.038 1.56e-09 ***
## notBornUK      5.6861     1.8033   3.153 0.001615 **
## medianIncome  -6.3857     1.9217  -3.323 0.000891 ***
## medianAge      5.9209     1.4066   4.209 2.56e-05 ***
## withHigherEd -26.7443     3.5762  -7.478 7.52e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 426.52  on 343  degrees of freedom
## Residual deviance: 247.39  on 338  degrees of freedom
## AIC: 259.39
##
## Number of Fisher Scoring iterations: 6
```

- (b) Present the value of each coefficient estimate with a 95% confidence interval. Which inputs would you say have strong effects? Order the inputs in terms of decreasing effect. Comment on your findings and justify your reasoning.

In logistic regression, the standard errors are approximated by assuming that the likelihood is normally distributed, meaning the CI's are approximate, therefore, we assume that the data is large and use the appropriate value from the normal distribution (z-distribution). The variables, ranked from strongest to weakest effect were:

Higher education:	-26.74	(95 CI: -33.75 to -19.74)
Middle to upper class:	17.58	(95 CI: 11.87 to 23.28)
Median income:	- 6.39	(95 CI: -10.15 to -2.62)
Median age:	5.92	(95 CI: 3.16 to 8.68)
Not born in the UK:	5.69	(95 CI: 2.15 to 9.22)

with the following ranking (magnitudes):

```
withHigherEd abc1 medianIncome medianAge notBornUK (Intercept) 26.7442592 17.5779980 6.3857396
5.9208767 5.6861383 0.1385963
```

The variables with “strong” effects are those with a greater magnitude, or absolute value of their estimate. For instance, although higher education status is negative, its absolute value is 26.74, and so an increase in higher education has the strongest effect on whether or not someone voted, irrespective of its direction. When interpreting the results, higher education having the strongest effect is somewhat expected. For example, the guardian article mentions that the best predictor of a vote for remain is the proportion of residents who have a degree. It also also worth noting that although Median age appears to be a stronger predictor than Not born in the UK, their confidence intervals overlap, meaning that Not born in the UK could potentially be a better predictor.

- (c) Using aic, perform model selection to determine which factors are useful to predict the result of the vote. Use a ‘greedy’ input selection procedure, as follows: (i) select the best model with 1 input; (ii) fixing that input, select the best two-input model (i.e. try all the other 4 inputs with the one you selected first); (iii) select the best three-input model containing the first two inputs you chose, etc. At each stage evaluate the quality of fit using aic and stop if this gets worse. Report your results and comment on your findings. Are your findings consistent with the Task 1.(b)?

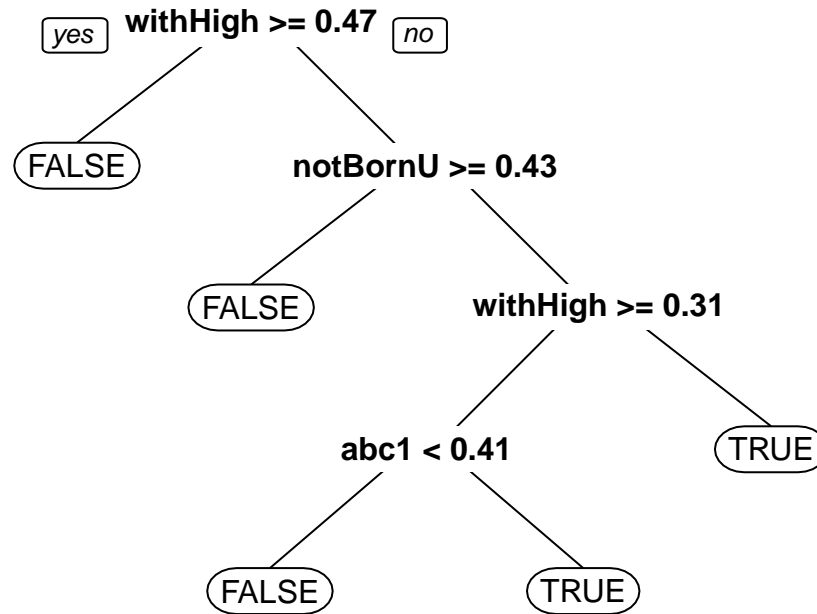
In order to perform model selection to determine which factors are useful in predicting the result of the vote, I used the “MuMIn” package. This allowed me to create models using all possible combinations of the 5 explanatory variables (32 models in total) and perform greedy selection by simply extracting AIC values from the table produced. From this, the best model with 1 input was the model using the Higher education status (AIC = 313.5956). Fixing this, the model containing 2 inputs was Higher Education + abc1 (AIC = 286.6160). Following this pattern, the 3-parameter model was Higher Education, abc1, and Median Age (AIC = 272.0497) and the 4 Parameter model, was Higher Education, abc1, Median Age, and median income. The model with all the input had the lowest AIC (259.6344). It is notable how the AIC continues to decrease even up to 5 parameters, however, these inputs were likely identified first place as having a meaningful relationship with how people voted for Brexit, meaning this result isn’t as surprising as it initially seemed.

The results of greedy input selection somewhat reflect the results of 1b. Firstly, the best-one input model used higher education status, which has the strongest effect as seen in 1b. The two-input model used higher education and income, which have the 1st and 2nd largest effects respectively. The 3 input model deviates from 1b slightly, if we were expecting additional inputs to be based on the strength of their individual effects alone, then based on the results from 1b, we would expect the next input to be median Income, instead, it is median age. However, median income is included in the 4-input model, meaning the 4-input model from the greedy selection is consistent with the results in 1b.

2. Use the rpart package to create a decision tree classification model. Explain and visualize your model and interpret the fitted model.

The top node of the decision tree checks if higher education ≥ 0.47 , if it is then we assume that they voted to remain (FALSE). If it lower than 0.47, we then check if their notBornUK status is ≥ 0.43 . If it is, we conclude they voted to remain. Otherwise, we look at higher education again, if less than 0.31, we assume

true (Voted to leave). Finally, we determine if median income ≥ 0.41 , if it is, then we assume they voted to remain and if < 0.41 conclude they voted to leave. Although this model is arguably more intuitive than the logistic regression model we have used so far, it does consider all of the input variables in the Brexit dataset.



3. Compare your decision tree model and your logistic regression model. Do they attribute high importance to the same factors? Interpret each model to explain the referendum vote.

To some degree, these models attribute importance to the same factors. For instance, two of the decision nodes in the decision tree rely on higher education status, which as mentioned displays the strongest effect in the logistic regression model. The decision tree also uses `abc1` status as a decision node, which displayed the 2nd strongest effect in the regression model. However, the decision tree also uses `notbornUK` as a decision node, which ranks as the input with the smallest effect in the regression model. In parallel, the decision tree model doesn't appear to place any value on median income or median age in decision-making process.

In terms of how each model works to make a prediction about the referendum, the decision tree bisect the space into smaller and smaller regions, whereas our Logistic Regression model fits a line (or equivalent in the 5-dimensional space we have in our model). A key aspect of our logistic regression model is that it also assumes that the probability of a true output (voted to leave) compared to false (voted to remain) changes monotonically as the inputs decrease or increase, which means that the logistic regression model use of a single decision boundary is good at capturing gradually changing functions. Conversely, our decision tree's partitioning of the input space into distinct areas means they are better suited for single partition (e.g. step wise functions, such as the top hat function mentioned). Determining which is better for predicting the outcome could be approached with methods such as cross validation.

4. Which model would you use if you were explaining the results for a newspaper article, and why?

If I were explaining the results in a newspaper article, my goal would arguably be to communicate as much important information to the general public as simply as possible. Although the logistic regression models may be better at modeling how each of the explanatory variables contributes to how an individual voted (e.g. less chance of overfitting), for someone who does not have a strong knowledge of statistics, they would have trouble using this to gain meaningful insight about how people actually voted. For this reason, I would use the decision tree, as it provides an intuitive and understandable result. That being said, decision trees in isolation are often unstable, with small changes in the data leading to a large change in their structures, as well as poor predictors. Although their poor predictive power could be rectified through a random forest, this again creates an issue of interpretability. It is also worth mentioning that although this decision tree is easier to interpret than the logistic regression model, the normalized values also hinder interpretability (i.e. a higher education status of ≥ 0.47 has no real meaning to the reader) and so could be changed for publication in the newspaper.

R code:

1) a

```
as.data.frame(brexit)
brexitglm <- glm(formula = voteBrexit~abc1+notBornUK+medianIncome+medianAge+withHigherEd,
                 family = binomial, data = brexit) #performing the logistic regression
summary(brexitglm)
```

1) b

```
zc = qnorm(0.975) #Get critical value of z at 2.5% (should be 1.96)

#Extract estimate and standard error of coefficient from model summary and get the 95% CIs

#middle to upper class
abc_estimate = summary(brexitglm)$coefficients[2,1]
abc_standard_error = summary(brexitglm)$coefficients[2,2]
abc_min = abc_estimate - zc*abc_standard_error
abc_max = abc_estimate + zc*abc_standard_error

#not born in the UK
notBornUK_estimate = summary(brexitglm)$coefficients[3,1]
notBornUK_standard_error = summary(brexitglm)$coefficients[3,2]
notBornUK_min = notBornUK_estimate - zc*notBornUK_standard_error
notBornUK_max = notBornUK_estimate + zc*notBornUK_standard_error

#median income
medianIncome_estimate = summary(brexitglm)$coefficients[4,1]
medianIncome_standard_error = summary(brexitglm)$coefficients[4,2]
medianIncome_min = medianIncome_estimate - zc*medianIncome_standard_error
medianIncome_max = medianIncome_estimate + zc*medianIncome_standard_error

#median age
medianAge_estimate = summary(brexitglm)$coefficients[5,1]
medianAge_standard_error = summary(brexitglm)$coefficients[5,2]
medianAge_min = medianAge_estimate - zc*medianAge_standard_error
medianAge_max = medianAge_estimate + zc*medianAge_standard_error
```

```

#higher education status
withHigherEd_estimate = summary(brexitglm)$coefficients[6,1]
WithHigherEd_standard_error = summary(brexitglm)$coefficients[6,2]
WithHigherEd_min = withHigherEd_estimate - zc*WithHigherEd_standard_error
WithHigherEd_max = withHigherEd_estimate + zc*WithHigherEd_standard_error

#confirming which estimates from largest to smallest effect

sort(abs(summary(brexitglm)$coefficient[,1]), decreasing = TRUE) # Estimate and 95 CI's (ordered from l

sprintf("higher education: %e (95 CI: %f to %g)",
        withHigherEd_estimate, WithHigherEd_min, WithHigherEd_max)
sprintf("Middle to upper class: %e (95 CI: %f to %g)",
        abc_estimate, abc_min, abc_max)
sprintf("Median income: %e (95 CI: %f to %g)",
        medianIncome_estimate, medianIncome_min, medianIncome_max)
sprintf("Median age: %e (95 CI: %f to %g)",
        medianAge_estimate, medianAge_min, medianAge_max)
sprintf("Not born in the UK: %e (95 CI: %f to %g)",
        notBornUK_estimate, notBornUK_min, notBornUK_max)

```

1) c

```

library(MuMIn) # creates all possible models and puts into table
allvariables <- glm(voteBrexit~., family=binomial(), na.action = "na.fail", data=brexit)
dd <-dredge(allvariables)
dd <-as.data.frame(dd) #makes it easier to manipulate and order
dd

```

2)

```

library(fields)
library(rpart)
library(rpart.plot)
brexittree = rpart (voteBrexit ~ ., data = brexit, method = 'class')
prp(brexittree)

#just a probability field out of interest.
prediction = predict(brexittree, newdata = brexit)
prediction = prediction[,2]
#fields::image.plot(matrix(prediction, 20,20))

#echo=FALSE #prevents the code showing
#results="hide" # prevents the results printing

```