Being a Prophet. Factors Predicting Occupations

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Introduction

Although every single human being is unique and has special character, people all over the world do share universal emotions, behaviors and personality traits. From 1930s, social psychologists started studying personalities and developed theories to predict behaviors. Until now, a lot of scales and measures of personality, like MBTI (The Myers-Briggs Type Indicator Instrument Personality assessment), have been established to apply in a wide range of areas, especially business and recruitment.

To understand the mechanism behind those inventories, we retrieved a data set of personality and vocational interest online. Our group plans to choose two response variables to do a thorough regression analysis to find the best model to predict each vocational interest. Also, we think it is very interesting to see if it is possible to generate a reasonable model when treating all vocational interest as predictor, cognitive and personality traits as response variables.

Data Set

The data set was retrieved from the website of Department of Psychology in University of Colorado. The data set contains 250 samples. All data were standardized.

The data set contains 33 variables in total. 3 variables are demographic variables including gender, education in years and age. 6 variables are cognitive traits. 6 variables are personality traits and 18 variables are different vocational interests. The variables are shown below:

Demographic

Educ='Education in years' age='Age in years'
Gender='Gender, 1 as male, 2 as female'

Coginitive Traits

vocab='Cognitive: vocabulary test'
reading='Cognitive: reading comprehension' sentcomp='Cognitive: sentence completion'
mathmtcs='Cognitive: mathematics' geometry='Cognitive: geometry'
analyrea='Cognitive: analytical reasoning'

Personality Traits

socdom='Personality: social dominance'
sociabty='Personality: sociability' stress='Personality: stress reaction'

worry='Personality: worry scale' impulsve='Personality: impulsivity'
thrillsk='Personality: thrill-seeking';

Vocational interests

carpentr='Interests: carpentry' forestr = 'Interests: forest ranger'
morticin = 'Interests: mortician' policemn = 'Interests: police'
fireman = 'Interests: fireman' salesrep = 'Interests: sales representative'
teacher = 'Interests: teacher' busexec = 'Interests: business executive'
stockbrk = 'Interests: stock broker' artist = 'Interests: artist'
socworkr = 'Interests: social worker' truckdvr = 'Interests: truck driver'
doctor = 'Interests: doctor' clergymn = 'Interests: clergyman'
lawyer = 'Interests: lawyer' actor = 'Interests: actor'
archtct = 'Interests: architect' landscpr = 'Interests: landscaper'

In our first analysis, we used demographic, cognitive traits and personality traits as predictor variables and chose "lawyer" in vocational interests as response variable. So there are 15 predictor variables.

In our second analysis, we used 18 vocational interests as predictor variables and chose "impulsve" in personality traits as response variable.

Data Analysis

Model 1 – Predicting interests on Lawyer

Main Effect Model

First of all, we examined the multicolinearity between response variables and correlation between predictor and each response variable.

To examine the multicolinearity, we calculated variance inflation factor (VIF) in R using command "vif()". As shown below, all vifs are much lower than 10, which suggest no multicolinearity.

Variance Inflation Factor (VIF)							
Gender	Educ	Age	Vocab	Reading	Sentcomp	Mathmtcs	Geometry
1.1697	1.5353	1.2231	4.8872	3.3499	3.3233	4.8127	2.8896
Analyrea	Socdom	Sociabty	Stress	Worry	Impulsve	Thrillsk	
3.5126	1.6048	1.5632	1.3648	1.3441	1.4811	1.4082	

The correlations between predictor and each response are shown below. As we can see, 4 variables (gender, age, stress & thrillsk) show very small correlation with predictor "Lawyer". However, psychologically speaking, we thought those variables had relationship with the occupations. For example, ability to handle stress (variable "stress") and courage to take risk (variable "thrillsk") are very crucial for lawyer to handle arguments and debated in courtroom. So we decided to keep those variables with low correlation.

Correlation between Predictor and Response							
Gender	Educ	Age	Vocab	Reading	Sentcomp	Mathmtcs	Geometry
0.02289	0.3942	0.0911	0.4242	0.3867	0.3492	0.3291	0.2767
Analyrea	Socdom	Sociabty	Stress	Worry	Impulsve	Thrillsk	
0.3532	0.2096	0.2163	0.0196	0.1256	-0.1130	-0.0117	

We then fit the model with only main effects. Summary of the full model are shown below. As we can see (Figure 1), clearly there were several variables with high p-value that should be considered eliminated.

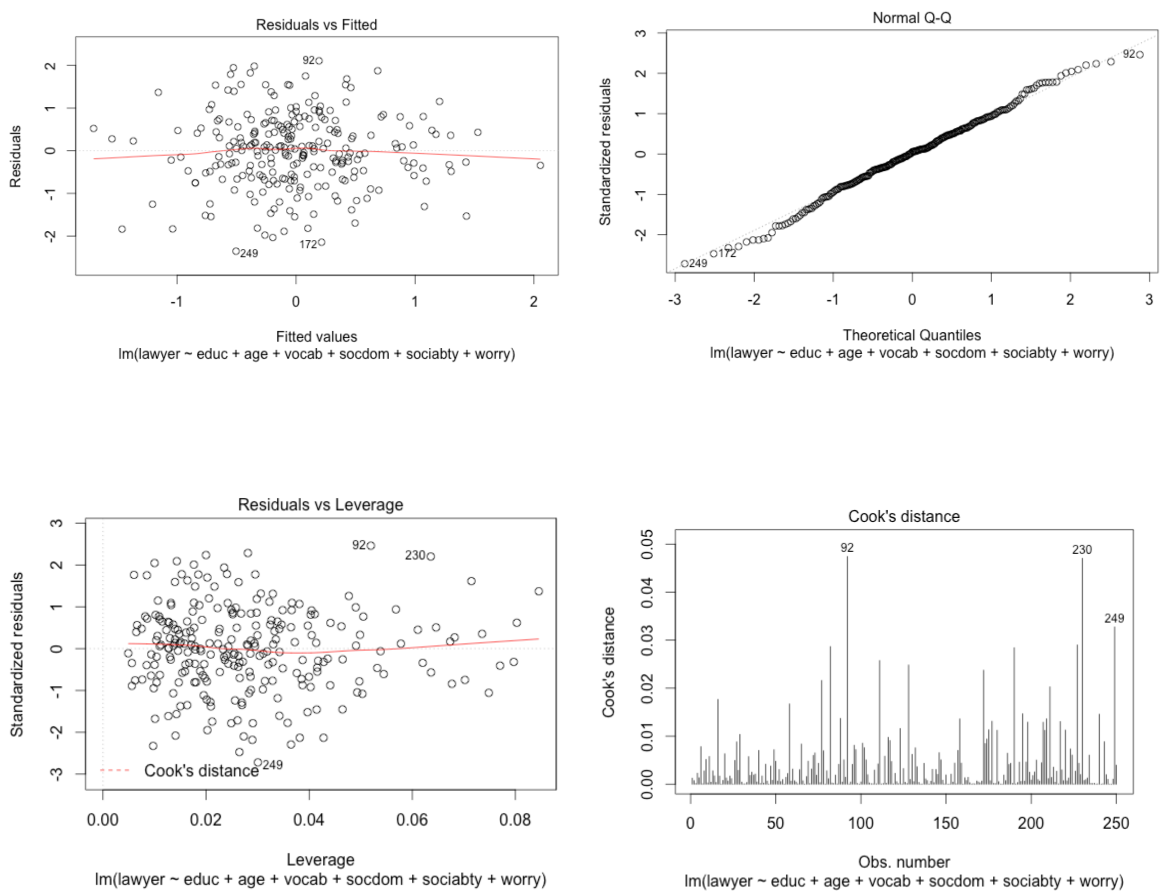
```
> summary(out2)

Call:
lm(formula = lawyer ~ gender + educ + age + vocab + reading +
    sentcomp + mathmtcs + geometry + analyrea + socdom + sociabty
    stress + worry + impulsve + thrillsk, data = a)

Residuals:
     Min       1Q   Median       3Q      Max
-2.09271 -0.47440  0.05115  0.56018  2.11774

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.793012   0.634384  -4.403 1.63e-05 ***
gender      -0.079517   0.120973  -0.657 0.511627
educ         0.168104   0.043001   3.909 0.000121 ***
age          0.019205   0.006170   3.112 0.002086 **
vocab        0.241054   0.124056   1.943 0.053203 .
reading      0.123075   0.103516   1.189 0.235665
sentcomp    -0.106179   0.102986  -1.031 0.303605
mathmtcs     0.002276   0.116562   0.020 0.984436
geometry    -0.066027   0.092122  -0.717 0.474255
analyrea     0.085826   0.099341   0.864 0.388498
socdom       0.147668   0.070712   2.088 0.037851 *
sociabty     0.124079   0.068418   1.814 0.071030 .
stress      -0.017164   0.069803  -0.246 0.805980
worry        0.169289   0.064535   2.623 0.009282 **
impulsve    -0.038078   0.068918  -0.553 0.581126
thrillsk     0.093211   0.064132   1.453 0.147445
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.884 on 234 degrees of freedom
Multiple R-squared:   0.32,     Adjusted R-squared:  0.2765
F-statistic: 7.343 on 15 and 234 DF,  p-value: 3.14e-13
```

Figure 1.

```
> summary(choose2)

Call:
lm(formula = lawyer ~ educ + age + vocab + socdom + sociabty +
    worry, data = a)

Residuals:
     Min       1Q   Median       3Q      Max
-2.35529 -0.55339  0.04513  0.55934  2.10683

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.828702   0.592403  -4.775 3.11e-06 ***
educ         0.169194   0.041149   4.112 5.37e-05 ***
age          0.017458   0.005762   3.030  0.00271 **
vocab        0.273803   0.066492   4.118 5.24e-05 ***
socdom       0.128538   0.068914   1.865  0.06336 .
sociabty     0.126220   0.067456   1.871  0.06253 .
worry        0.147572   0.055610   2.654  0.00849 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8793 on 243 degrees of freedom
Multiple R-squared:  0.3015,    Adjusted R-squared:  0.2842
F-statistic: 17.48 on 6 and 243 DF,  p-value: < 2.2e-16
```

Figure 2.

Then we used automated AIC to chose the best model from the full model with only main effects. The best model chosen by AIC method is shown above (Figure 2.). Examining the residual plots as shown below, normality and good model were confirmed.



We found 3 potential outliers in this model. However, by looking at cook's distance, we see that cook's distance of all 3 potential outliers are lower than 0.05, which are not significant. In addition, we performed test with

```
> outlierTest(choose2)

No Studentized residuals with Bonferonni p < 0.05
Largest |rstudent|:
     rstudent unadjusted p-value Bonferonni p
249 -2.756584          0.0062858           NA
```

Benferonni Correction to make sure the significance of outlier, as shown above. Result further proves that 3 potential outliers are not real outliers in this model.

Interaction Term

To consider interaction term, we first examined the correlations among 13 predictor variables. The correlation table is in Appendix. We only considered interactions with correlation higher than 0.5. A brief summary of full model with interactions terms is shown here.

```
Call:
lm(formula = lawyer ~ gender + educ + educ * vocab + educ * mathmtcs +
    age + vocab + vocab * reading + vocab * sentcomp + vocab *
    mathmtcs + vocab * geometry + vocab * analyrea + reading +
    reading * sentcomp + reading * mathmtcs + reading * geometry +
    reading * analyrea + sentcomp + sentcomp * mathmtcs + sentcomp *
    geometry + mathmtcs + mathmtcs * geometry + mathmtcs * analyrea +
    geometry + geometry * analyrea + analyrea + socdom + sociabty +
    socdom * sociabty + stress + worry + stress * worry + impulsve +
    thrillsk + impulsve * thrillsk, data = a)
```

```
Residual standard error: 0.8873 on 215 degrees of freedom
Multiple R-squared:  0.3705,    Adjusted R-squared:  0.271
F-statistic: 3.722 on 34 and 215 DF,  p-value: 2.08e-09
```

AIC method and backward elimination were used to select the best model. Applying AIC method, we got the best model as shown below (Figure 3). Using backward elimination, we eliminated variable or interaction terms that were much larger than 0.05 (Figure 4). Compared two models, we found that standard residual error, R-squared and p-value were all very close. However, the model chosen by AIC method has lower standard residual error and higher R-squared even though they are very little. We choose this as the best model.

Figure 3. AIC Method

```
Call:
lm(formula = lawyer ~ educ + vocab + mathmtcs + age + reading +
    sentcomp + geometry + analyrea + socdom + worry + thrillsk +
    educ:vocab + educ:mathmtcs + vocab:sentcomp + reading:geometry +
    reading:analyrea + mathmtcs:analyrea + geometry:analyrea,
    data = a)

Residuals:
     Min       1Q   Median       3Q      Max
-2.13927 -0.49768  0.05101  0.56789  2.20045

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -2.756562   0.651705  -4.230 3.37e-05 ***
educ               0.169017   0.045703   3.698 0.000271 ***
vocab              1.447846   0.707189   2.047 0.041758 *
mathmtcs          -0.960014   0.647205  -1.483 0.139352
age                0.016540   0.006081   2.720 0.007025 **
reading            0.133696   0.104128   1.284 0.200445
sentcomp          -0.138919   0.102616  -1.354 0.177132
geometry          -0.071993   0.095321  -0.755 0.450852
analyrea           0.078385   0.099470   0.788 0.431488
socdom             0.212688   0.059223   3.591 0.000402 ***
worry              0.143905   0.056560   2.544 0.011603 *
thrillsk           0.079758   0.055699   1.432 0.153508
educ:vocab        -0.099056   0.056016  -1.768 0.078325 .
educ:mathmtcs      0.081072   0.052473   1.545 0.123712
vocab:sentcomp     0.103406   0.069006   1.499 0.135366
reading:geometry  -0.185255   0.091526  -2.024 0.044113 *
reading:analyrea   0.158467   0.097010   1.634 0.103724
mathmtcs:analyrea -0.274154   0.085199  -3.218 0.001477 **
geometry:analyrea  0.147758   0.079077   1.869 0.062952 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘

Residual standard error: 0.8661 on 231 degrees of freedom
Multiple R-squared:  0.3557,    Adjusted R-squared:  0.3055
F-statistic: 7.086 on 18 and 231 DF,  p-value: 2.754e-14
```

Figure 4. Backward Elimination

```
Call:
lm(formula = lawyer ~ educ + age + vocab + vocab * sentcomp
    vocab * geometry + reading + sentcomp + mathmtcs + mathm
    analyrea + geometry + geometry * analyrea + analyrea + s
    worry, data = a)

Residuals:
     Min       1Q   Median       3Q      Max
-2.14561 -0.49116  0.02458  0.54926  2.14424

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -2.664076   0.597903  -4.456 1.29e-05 ***
educ               0.164680   0.041918   3.929 0.000112 ***
age                0.015614   0.005935   2.631 0.009076 **
vocab              0.219432   0.121993   1.799 0.073346 .
sentcomp          -0.132820   0.101410  -1.310 0.191565
geometry          -0.080319   0.095588  -0.840 0.401617
reading            0.150320   0.100240   1.500 0.135060
mathmtcs           0.009782   0.115798   0.084 0.932749
analyrea           0.116715   0.097056   1.203 0.230358
socdom             0.207002   0.058710   3.526 0.000507 ***
worry              0.136417   0.056173   2.429 0.015912 *
vocab:sentcomp     0.142710   0.072617   1.965 0.050564 .
vocab:geometry    -0.196231   0.102777  -1.909 0.057443 .
mathmtcs:analyrea -0.186846   0.068513  -2.727 0.006870 **
geometry:analyrea  0.165983   0.088069   1.885 0.060706 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’

Residual standard error: 0.8699 on 235 degrees of freedom
Multiple R-squared:  0.3387,    Adjusted R-squared:  0.2993
F-statistic: 8.598 on 14 and 235 DF,  p-value: 5.728e-15
```

Model 2 – Predicting impulsive trait

As looking at correlation table, it was interesting to find out that correlations exist among different occupations. So we decided to do an exploratory analysis trying to find the best model to predict traits.

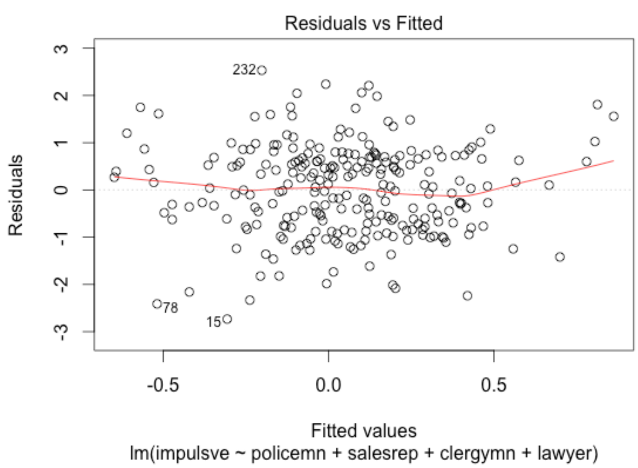
We chose “impulsve” as response variable and had 18 predictor variables. Using the same procedure as in Model 1, we examined the main effect model and models with interaction term.

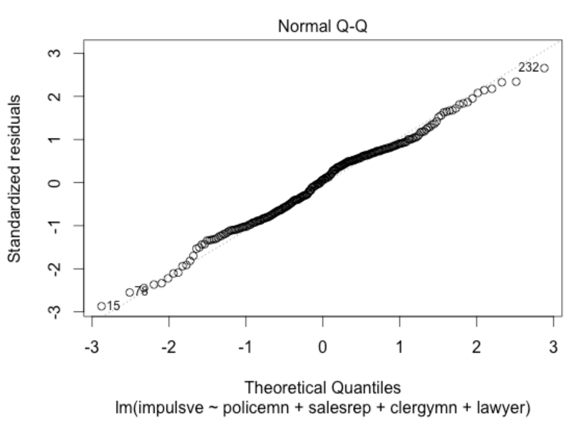
Main Effect Model

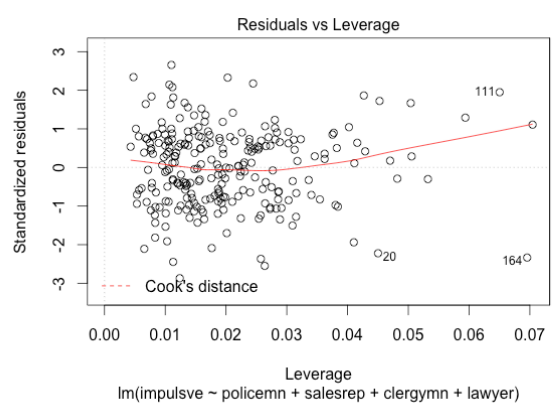
For main effect model, we first examined multicolinearity, no VIF was found larger than 5 suggesting no multicolinearity occurred. Applying AIC method, we got the model shown below.

Examining the residual plots, we found 3 potential outliers. Calculating cook’s distance, no one has cook's distance that is larger than 1, suggesting they are not influential.

```
> summary(choose5)

Call:
lm(formula = impulsve ~ policemn + salesrep + clergymn + lawyer,
    data = a)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.73331 -0.71750  0.06264  0.65895  2.53205 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.08364    0.06115   1.368 0.172605    
policemn     0.23678    0.06708   3.530 0.000497 ***
salesrep     0.13256    0.06708   1.976 0.049259 *  
clergymn     0.11512    0.06804   1.692 0.091924 .  
lawyer      -0.15972    0.06745  -2.368 0.018660 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9587 on 245 degrees of freedom
Multiple R-squared:  0.07605,	Adjusted R-squared:  0.06097 
F-statistic: 5.042 on 4 and 245 DF,  p-value: 0.0006386
```







However, the R-square in this model is very low. We expected that adding interaction terms, R-square might be higher.

Interaction Term

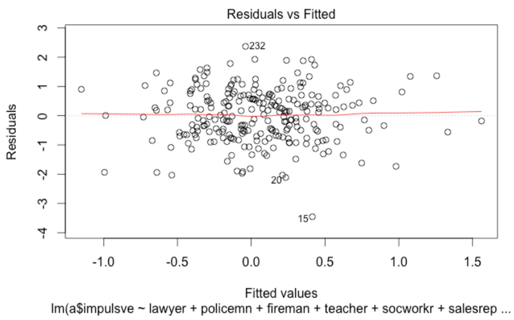
Before add interaction, we examined the correlation table of 18 predictor variables and eliminated correlations that were lower than 0.5. The full model with interaction terms was

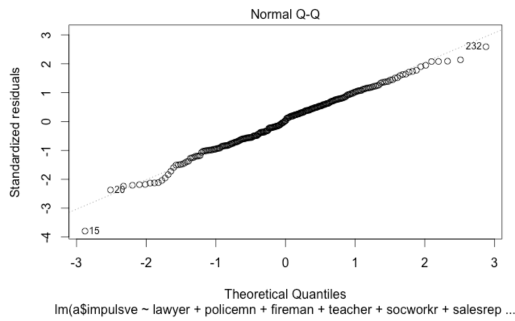
(impulsve = carpentr + forestr + morticin + morticin*lawyer + policemn + fireman + policemn*fireman + policemn*teacher + policemn*socworkr + salesrep + teacher + teacher*socworkr + busexec + stockbrk + busexec*stockbrk + busexec*lawyer + stockbrk*lawyer + artist + socworkr + socworkr*clergymn + truckdvr + doctor + doctor*lawyer + clergymn + actor + lawyer + archtct + landscpr)

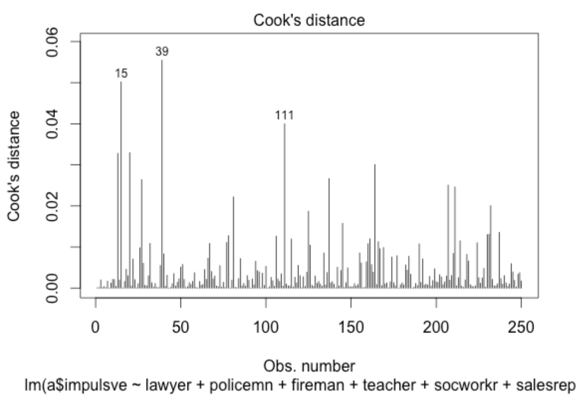
Same as we did in Model 1, we used AIC method to get a best model, as shown below. As we can see, R-square does imporove.

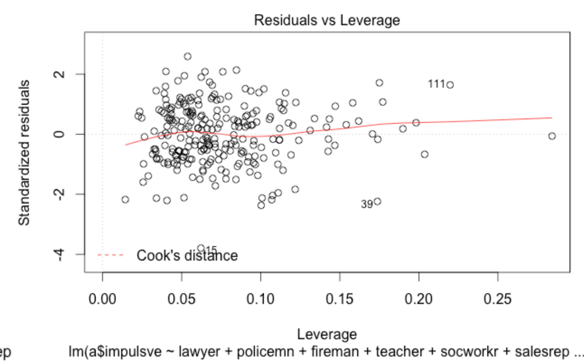
```
> summary(choose3)

Call:
lm(formula = a$impulsve ~ lawyer + policemn + fireman + teacher +
    socworkr + salesrep + busexec + stockbrk + artist + clergymn +
    doctor + archtct + landscpr + policemn:teacher + policemn:socworkr +
    busexec:stockbrk + lawyer:stockbrk + lawyer:doctor, data = a)

Residuals:
    Min      1Q  Median      3Q     Max
-3.4539 -0.6004  0.0265  0.6481  2.3687

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.006996   0.079184   0.088  0.92968
lawyer            -0.210661   0.099095  -2.126  0.03458 *
policemn           0.207263   0.085822   2.415  0.01651 *
fireman            0.113084   0.079723   1.418  0.15740
teacher            0.088409   0.093950   0.941  0.34767
socworkr           0.003119   0.116901   0.027  0.97874
salesrep           0.132511   0.068095   1.946  0.05287 .
busexec            0.034206   0.077084   0.444  0.65764
stockbrk           0.109191   0.086434   1.263  0.20776
artist            -0.136053   0.062140  -2.189  0.02957 *
clergymn           0.131143   0.080466   1.630  0.10451
doctor            -0.123297   0.079773  -1.546  0.12357
archtct            0.102233   0.072771   1.405  0.16141
landscpr           0.095540   0.068132   1.402  0.16218
policemn:teacher  -0.273438   0.102611  -2.665  0.00825 **
policemn:socworkr  0.198813   0.103088   1.929  0.05501 .
busexec:stockbrk   0.113321   0.071341   1.588  0.11355
lawyer:stockbrk   -0.227497   0.090640  -2.510  0.01276 *
lawyer:doctor      0.137271   0.069359   1.979  0.04899 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Residual standard error: 0.9401 on 231 degrees of freedom
Multiple R-squared:  0.1622,    Adjusted R-squared:  0.09691
F-statistic: 2.484 on 18 and 231 DF,  p-value: 0.001016
```

Examining residual plots, we found 3 potential outliers. Cook's distance plot suggested that those points were not influencial (all points are less than 0.5).









However, considering Bonferonni correction, we found that the 15th sample could be a outlier. So we delete the 15th sample and did the AIC again.

```
> outlierTest(choose3)
   rstudent unadjusted p-value Bonferonni p
15 -3.90908         0.00012192      0.03048
```

As we see below, the brief summary indicated a little bit higher R-square and lower standard residual error.

```
Residual standard error: 0.9124 on 230 degrees of freedom
Multiple R-squared:  0.1822,	Adjusted R-squared:  0.1182
F-statistic: 2.846 on 18 and 230 DF,  p-value: 0.00016
```

Conclusion and Discussion

In Model 1, we conclude that model (lawyer = educ + vocab + mathmtcs + age + reading + sentcomp + geometry + analyrea + socdom + worry + thrillsk + educ:vocab + educ:mathmtcs + vocab:sentcomp + reading:geometry + reading:analyrea + mathmtcs:analyrea + geometry:analyrea) is the best model. Multiple R-squared is 0.32. Standard residual error is 0.884. p-value is 2.754e-15.

Vocabulary has the highest estimate in the model, which suggests that vocabulary is the most important quality that a lawyer needs. However, mathematics, geometry and ability of sentence completion are all negatively related to the occupation of lawyer. A good lawyer requires excellent verbal skills and debating skills a lot, which are opposite to ability of sentence completion, mathematics and geometry. Because all the three qualities requires understanding and following other's thoughts.

In Model 2, we concluded that (impulsve ~ lawyer + policemn + fireman + teacher + socworkr + salesrep + busexec + stockbrk + artist + clergymn + doctor + archtct + landscpr + policemn:teacher + policemn:socworkr + busexec:stockbrk + lawyer:stockbrk + lawyer:doctor) is the best model to predict impulsive given all the variables we have. Multiple R-square is 0.1822. Standard residual error is 0.914. p-value is 0.00016.

Interests on lawyer, artist and doctor are all negatively related to the quality of impulsive. We reasoned that lawyer and doctor both required high neuroticism like the ability to keeping calm， making decisions and accomplishing goals under high pressure. Having clear mind and thinking thoroughly are required, which are opposite to impulsion. However, it is interesting to see artist is negatively related to impulsion as we think artist requires passion and imagination.

One problem in our analysis is that we got low R-square for both model, especially for model 2. We think that there are more personality traits and occupations in reality than we had, which makes our R-square very low. But it does not mean that our model is nor correct or useless. For future investigation, we believe that using more generalized personality traits like the Big Five traits and categorized occupation may help with increase R-square.

Appendix 1. Correlation Table

> trait.cor

	a.gender	a.educ	a.age	a.vocab	a.reading	a.sentcomp	a.mathmtcs	a.geometry
a.gender	1.00000000	0.03433217	0.034450863	0.06739080	0.08422738	0.08122627	-0.163947587	-0.10570105
a.educ	0.03433217	1.00000000	-0.145092082	0.51819779	0.46851404	0.45810789	0.500119456	0.41355956
a.age	0.03445086	-0.14509208	1.000000000	0.01846341	0.03702519	0.08691983	-0.123701002	-0.14241585
a.vocab	0.06739080	0.51819779	0.018463410	1.00000000	0.80309122	0.81327654	0.708355675	0.63251564
a.reading	0.08422738	0.46851404	0.037025192	0.80309122	1.00000000	0.72521551	0.660443825	0.52622783
a.sentcomp	0.08122627	0.45810789	0.086919829	0.81327654	0.72521551	1.00000000	0.618044026	0.57520368
a.mathmtcs	-0.16394759	0.50011946	-0.123701002	0.70835567	0.66044382	0.61804403	1.000000000	0.77404672
a.geometry	-0.10570105	0.41355956	-0.142415846	0.63251564	0.52622783	0.57520368	0.774046722	1.00000000
a.analyrea	-0.09695533	0.45828342	-0.092520525	0.67250828	0.63573280	0.61782519	0.817052688	0.71543156
a.socdom	0.11722972	0.05395887	-0.180120361	0.11610006	0.03466859	0.08781434	0.015101427	0.12212293
a.sociabty	0.09444753	0.07849930	-0.165419058	0.12562983	0.08470048	0.09708027	0.057166382	0.12668277
a.stress	0.12698567	-0.10196790	0.092808871	-0.02558073	-0.03054042	-0.02381294	-0.064008275	0.01434992
a.worry	0.05199878	0.02236982	-0.009428623	-0.05692623	-0.04172195	-0.02310027	0.003677557	0.05660412
a.impulsve	0.02607784	-0.14336001	-0.198196940	-0.17701107	-0.24411135	-0.20433707	-0.154611130	-0.13001233
a.thrillsk	0.02926081	-0.09525870	-0.154027454	-0.03752396	-0.09901077	-0.01511956	-0.029428182	-0.04339177

	a.analyrea	a.socdom	a.sociabty	a.stress	a.worry	a.impulsve	a.thrillsk
a.gender	-0.09695533	0.117229718	0.09444753	0.126985671	0.051998777	0.02607784	0.029260813
a.educ	0.45828342	0.053958874	0.07849930	-0.101967902	0.022369823	-0.14336001	-0.095258701
a.age	-0.09252052	-0.180120361	-0.16541906	0.092808871	-0.009428623	-0.19819694	-0.154027454
a.vocab	0.67250828	0.116100058	0.12562983	-0.025580733	-0.056926226	-0.17701107	-0.037523960
a.reading	0.63573280	0.034668589	0.08470048	-0.030540423	-0.041721951	-0.24411135	-0.099010773
a.sentcomp	0.61782519	0.087814339	0.09708027	-0.023812942	-0.023100271	-0.20433707	-0.015119558
a.mathmtcs	0.81705269	0.015101427	0.05716638	-0.064008275	0.003677557	-0.15461113	-0.029428182
a.geometry	0.71543156	0.122122927	0.12668277	0.014349923	0.056604120	-0.13001233	-0.043391770
a.analyrea	1.00000000	0.103552923	0.11866530	-0.039666423	0.011999137	-0.08419576	0.024243320
a.socdom	0.10355292	1.000000000	0.58329674	-0.001827869	-0.009709289	0.04394162	-0.004543251
a.sociabty	0.11866530	0.583296742	1.00000000	-0.093448018	-0.042862050	0.06409206	0.014380542
a.stress	-0.03966642	-0.001827869	-0.09344802	1.000000000	0.470277317	-0.04259686	-0.063889304
a.worry	0.01199914	-0.009709289	-0.04286205	0.470277317	1.000000000	-0.09235046	-0.122536578
a.impulsve	-0.08419576	0.043941618	0.06409206	-0.042596864	-0.092350460	1.00000000	0.504713293
a.thrillsk	0.02424332	-0.004543251	0.01438054	-0.063889304	-0.122536578	0.50471329	1.000000000

> occupation.cor

	carpentr	forestr	morticin	policemn	fireman	salesrep
carpentr	1.00000000	0.245828014	-0.30107109	0.04376280	-0.017024544	-0.014853076
forestr	0.24582801	1.000000000	-0.39343872	0.15544360	0.043894183	-0.009208963
morticin	-0.30107109	-0.393438716	1.00000000	-0.13753497	-0.080506643	0.329257271
policemn	0.04376280	0.155443603	-0.13753497	1.00000000	0.556832789	-0.024583008
fireman	-0.01702454	0.043894183	-0.08050664	0.55683279	1.000000000	-0.041336004
salesrep	-0.01485308	-0.009208963	0.32925727	-0.02458301	-0.041336004	1.000000000
teacher	-0.04553595	-0.067241286	0.11671120	-0.54419349	-0.368687750	0.033537787
busexec	-0.20489371	-0.251918635	0.58721679	-0.04747056	0.058952134	0.271105441
stockbrk	-0.29037295	-0.385837128	0.73924174	-0.09648669	0.009472041	0.273171478
artist	-0.04002375	-0.025049478	0.05713638	-0.02841041	-0.021652346	0.088672604
socworkr	-0.06193606	-0.104759809	0.22394285	-0.53177211	-0.422793160	0.069394027
truckdvr	0.32436971	0.354095209	-0.40753475	0.10569465	0.059864330	-0.096589101
doctor	-0.05969520	-0.099338463	0.49054882	-0.12198153	-0.062497604	0.280278936
clergymn	0.01407129	0.025241169	0.06217395	-0.31418418	-0.256071531	0.017774224
actor	-0.07358247	-0.013779099	0.05928042	-0.02344000	-0.018955133	0.001717670
lawyer	-0.20415794	-0.215925496	0.62135835	-0.13754637	-0.068737789	0.439053466
archtct	0.02387696	-0.048346326	0.33484635	-0.07771466	-0.077530149	0.242743694
landscpr	0.29876738	0.462603375	-0.47479250	0.08505183	-0.053690591	-0.057576598

	teacher	busexec	stockbrk	artist	socworkr	truckdvr
carpentr	-0.04553595	-0.20489371	-0.290372955	-0.040023748	-0.061936065	0.32436971
forestr	-0.06724129	-0.25191863	-0.385837128	-0.025049478	-0.104759809	0.35409521
morticin	0.11671120	0.58721679	0.739241743	0.057136378	0.223942848	-0.40753475
policemn	-0.54419349	-0.04747056	-0.096486693	-0.028410412	-0.531772108	0.10569465
fireman	-0.36868775	0.05895213	0.009472041	-0.021652346	-0.422793160	0.05986433
salesrep	0.03353779	0.27110544	0.273171478	0.088672604	0.069394027	-0.09658910
teacher	1.00000000	0.06559690	0.170639159	0.094340447	0.752935128	-0.12456666
busexec	0.06559690	1.00000000	0.552768682	0.087320176	0.076573593	-0.32677605
stockbrk	0.17063916	0.55276868	1.000000000	0.099489987	0.218602951	-0.34831413
artist	0.09434045	0.08732018	0.099489987	1.000000000	0.007488258	0.02024869
socworkr	0.75293513	0.07657359	0.218602951	0.007488258	1.000000000	-0.21511913
truckdvr	-0.12456666	-0.32677605	-0.348314132	0.020248689	-0.215119131	1.00000000
doctor	0.33483137	0.34205648	0.491095605	0.046438153	0.450515631	-0.14761978
clergymn	0.50962723	0.02502277	0.045244526	-0.005422429	0.615581369	-0.04784118
actor	0.09596972	0.11144516	0.057907424	0.269052005	0.135197559	-0.11675010
lawyer	0.32573974	0.50230305	0.613344472	0.111054679	0.439275919	-0.31708751
archtct	0.14243697	0.28342914	0.346583266	0.242641864	0.176240440	-0.10544252
landscpr	-0.08020921	-0.32805437	-0.452010084	0.063970512	-0.148618797	0.32795475