

Some Internet Data

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Introduction

Through this project, we seek to understand the relationship between internet access and inequality on a global scale before examining the factors in detail using American Census Data. We take this dual-pronged approach so that we can get a picture of Internet Inequality globally while using reliable US Census data to do the quantitaive analysis. We will use data from the United Nations to compare selected socio-economic indexes to international communication measurements.

Questions

What economic indicators (race, occupation, community poverty rate) are most strongly correlated with internet access rates? Can we build a model that accurately predicts said rates?

Are internet access rates a stronger predictor of poverty rates than other forms of social investment (ie roads, schools, hospitals)?

Do these effects extend across internet technologies (cell phones and broadband internet)? If not, which type of infrastructure investment is better.

Motivation

We are interested in this problem as data scientists because our field is a mixed bag. On one hand, big data can be used to influence elections, spread hateful propaganda, and be used to track every purchase and decision we make. These political consequences are well known. However, the Internet has a history of advancing economies, and those without the internet tend to be left behind. To speak about this in particular, we need to investigate the ways in which internet access influences occupational outlook while controlling for other confounding factors like geography, race, and infrastructure investment more generally.

Literature Review

Data

American Community Survey
Annual Survey of State Finances
World Bank Data
IEE MAC Address Blocks
List of Internet Exchange Points

Methodology

First we will examine the problem on a global scale using choropleth maps that will inform our future choices.

We will build several models for predicting poverty rate, using both the generalized logistic model and the generalized linear model. In this way, we'll see how things like internet access and infrastructure investment influence poverty rates. The American Community Survey includes internet access rates, poverty, race, industry, language, occupation, place of birth, and familial origin. Using this data alone, we should be able to see if race or occupation is a better indicator of aggregate poverty than internet access rates.

Hypothesis

Pew Research says that 20% of teens are unable to finish their homework due to the digital divide. The end result of this is likely low-skill careers and lower incomes. In fact, the internet tends to raise the tide for all, as a breadth study (also by Pew) showed that per capita income and access rates are highly correlated. We'd like to investigate the relationship between technology and the economy and see if we can build models resilient to the particle type of device. Previous work has used infrastructure investment to build logistic

models for poverty using satellite images of infrastructure. It is also well known that poverty and broadband access rates are highly correlated. However, it is unknown if there is an underlying causal factor or if internet can, *by itself*, lift people out of poverty. The McKinsey Global Institute did a massive study on the economic potential of internet investment in China that will inform our approach in this matter. Finally, the Internet Society, a global organization that builds internet infrastructure (mostly in the developing world), has compiled a list of internet penetration rates and other such metrics by country across the world. However, due to data collection limitations and the quality of data sources across continents, it would be impossible to investigate these things with respect to more generic features like race and infrastructure. Since the United States has a non-uniform income distribution across states, this should allow us to draw from a breadth of circumstances. Due to the multiplicative of effects in education, business opportunities, and spending opportunities available on the Internet, we suspect that governmental investment in digital infrastructure will have at least as much affect as road or school spending. Additionally, we suspect that this multiplier is reduced for cellular infrastructure relative to fixed (broadband) infrastructure because of the productivity gains associated with PCs over smartphones. This research will reveal to governments (both local and national) what kinds of infrastructure investment yields the most economic gains in the digital age. To our knowledge, this particular question has not been answered.

Executive Summary

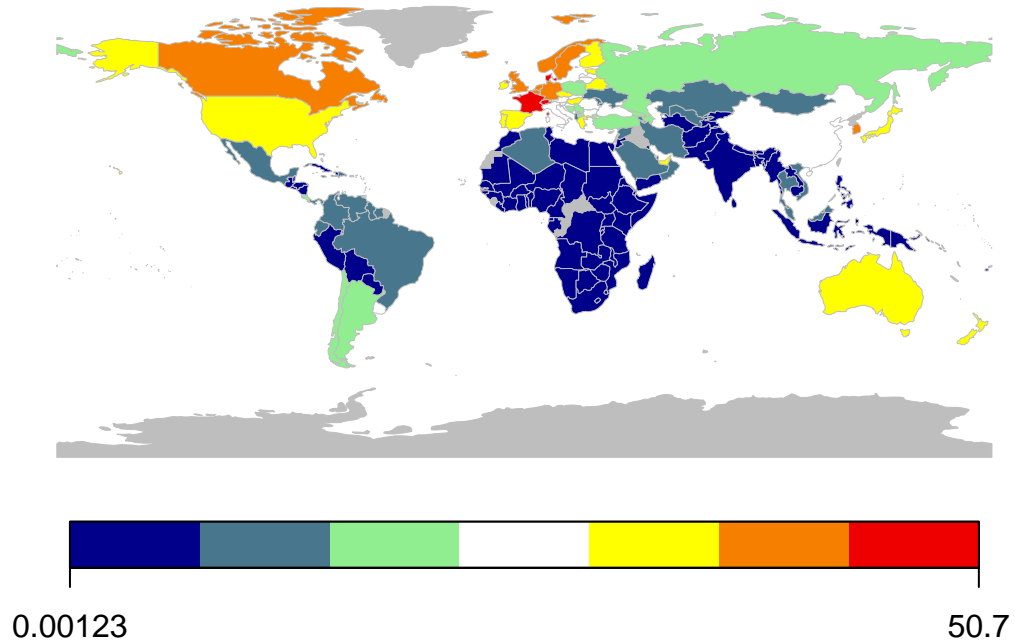
TODO

```
## [1] "tidycensus"    "rworldmap"    "sp"           "xlsx"
## [5] "forcats"      "stringr"      "dplyr"        "purrr"
## [9] "readr"        "tibble"       "tidyverse"    "tidyr"
## [13] "reshape2"     "readxl"       "randomForest" "nnet"
## [17] "ModelMetrics" "knitr"        "imputeTS"     "forecast"
## [21] "fastDummies"  "e1071"        "corrplot"     "caTools"
## [25] "caret"        "ggplot2"      "lattice"      "stats"
## [29] "graphics"     "grDevices"    "utils"        "datasets"
## [33] "methods"     "base"
```

Internet Inequality– A Global Persepective

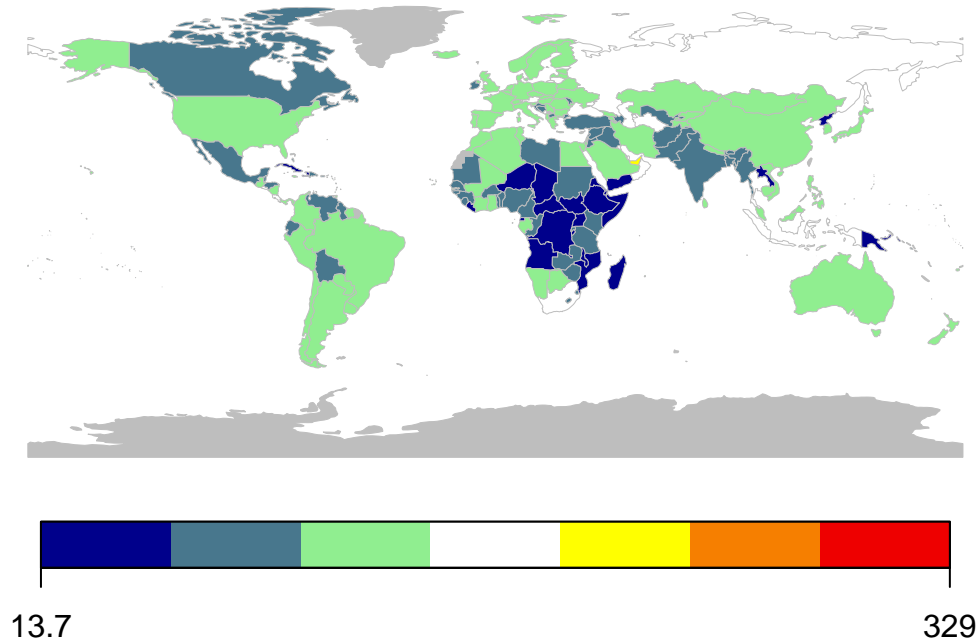
```
## 215 codes from your data successfully matched countries in the map
## 66 codes from your data failed to match with a country code in the map
## 28 codes from the map weren't represented in your data
```

Broadband Subscriptions per 100 people



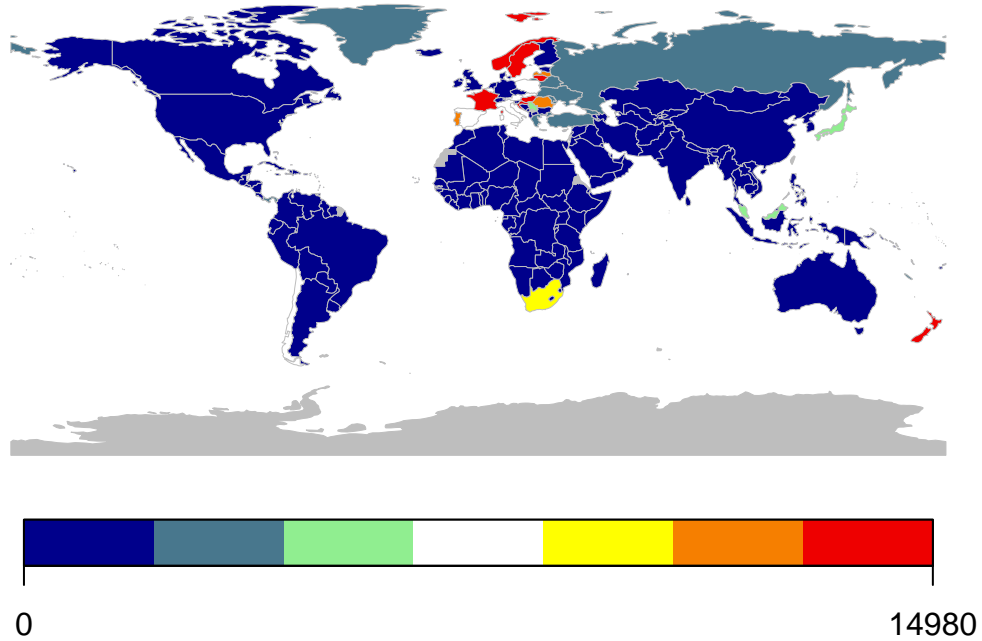
Immediately, we can see that broadband subscription rates are higher in strongly developed places like North America, Western Europe, and Australia. Conversely, poor countries across South America, Africa, and South Asia have significantly lower broadband access rates. Please note that countries in grey have unknown values.

Cell Phone Subscriptions per 100 People



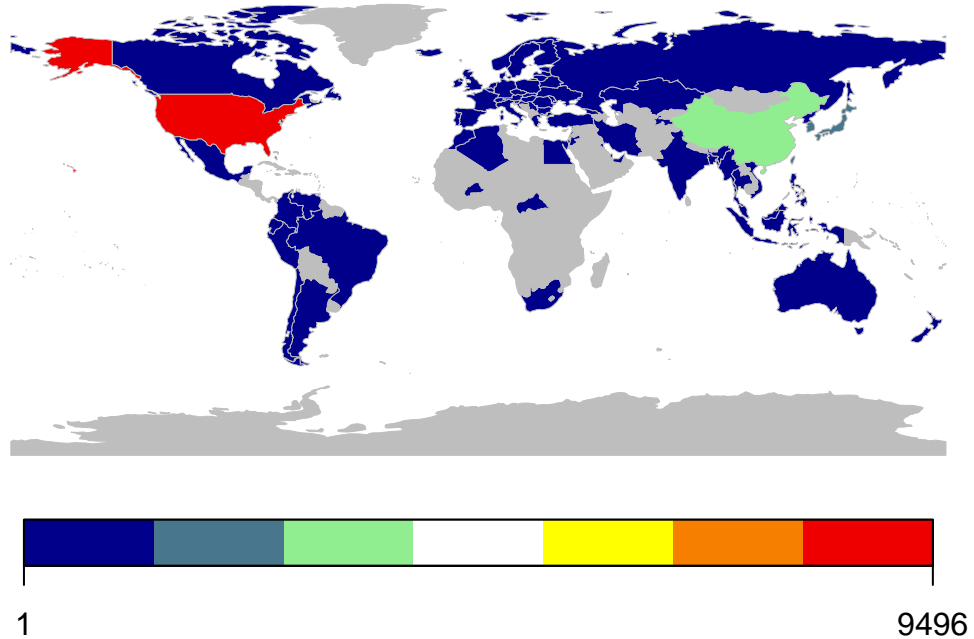
However, the number of cell phone subscriptions per 100 people is much more uniform. That is due to the lower cost of wireless network deployment compared to the capital-intensive processes of digging trenches to lay copper or fiber.

Servers per 10,000 people



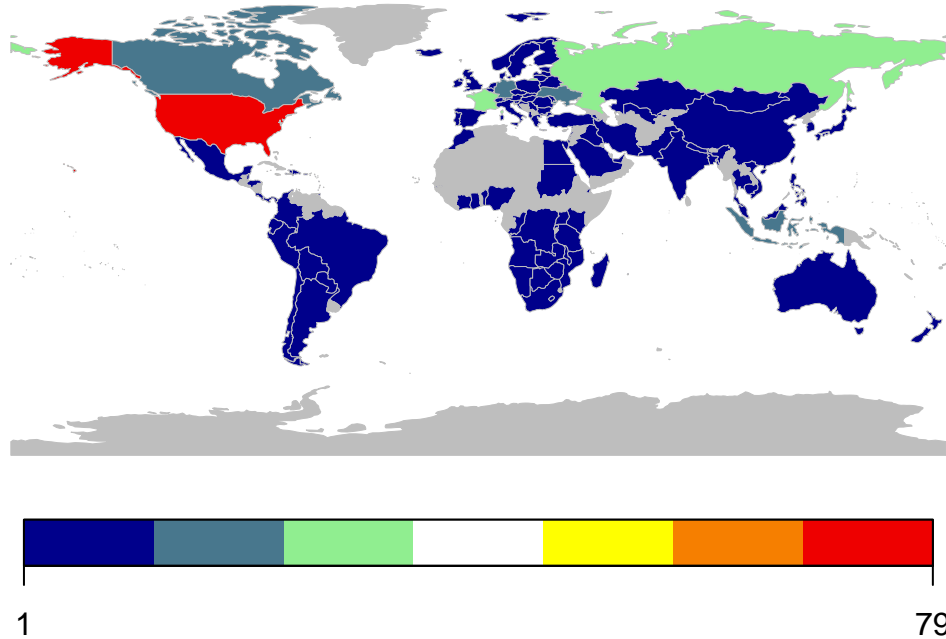
When we look at the number of servers available in each country, we find that Western Europe has the highest per capita server load. Countries like New Zealand and South Africa are also high because they are conveniently located for undersea cables that compose the back-bone of the internet. TODO Source

Mac Addresses Blocks Assigned per Country



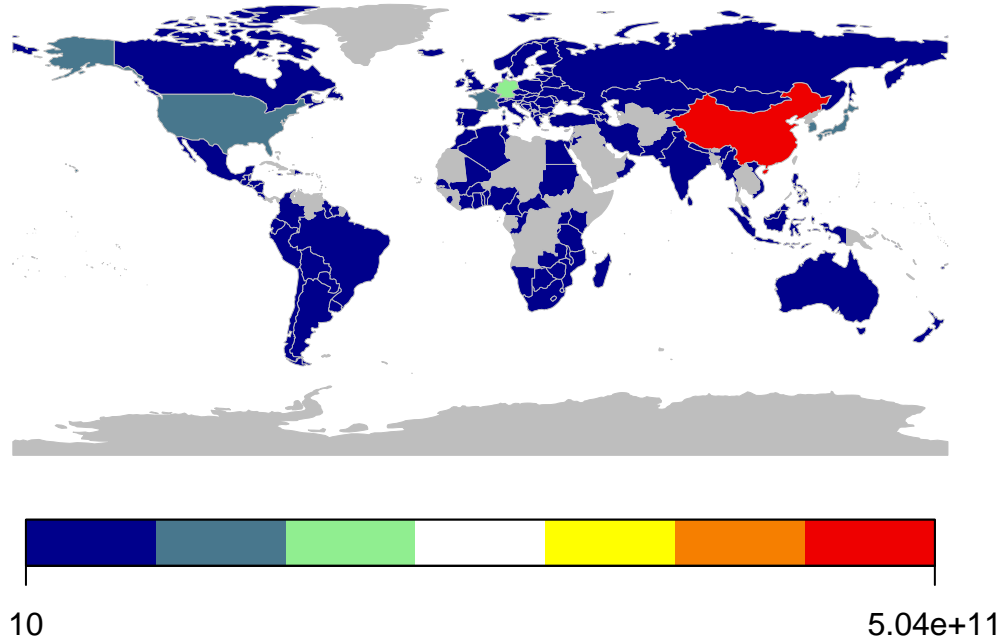
The IEEE is a global organization that manages technological standards, publishes and circulates literature about electronics and and electrical engineering. In addition, they allocate MAC addresses which are the physical address of every bluetooth/wifi radio, ethernet port, and fiber cable on the internet. As we can see, a relatively small number of countries have original electronics manufacturers, with the US registering more than twice the number of devices as the next country (China).

Internet Exchange Points by Country



The undersea cables mentioned earlier wind up at one of 600 buildings around the world where network operators connect their computers to their peers and create what we think of as the 'inter' net. These 600 buildings are not even distributed, with most countries only have a single access point to the Internet. In addition, regimes known for censorship (ie Egypt, Turkey, and China) have relatively few internet exchange points, allowing for centralized control and censorship. TODO: Source

High Tech Exports (2017 USD)



The net result of the modern Internet infrastructure is a centralized model with a few players making all of the profits. Above we see the total amount of high tech exports as measured in 2017 USD. Three countries account for the bulk of the profit here, seeming to indicate that a centralized Internet infrastructure does not raise the standards for everybody. It is apparent that today's paradigm encourages consumption over creation.

Correlation between Various Technology Indicators and Poverty Rates

Data Initialization and Preprocessing

```
## # A tibble: 6 x 28
##   Percent.Limited~ Percent.With.Br~ Percent.Occupie~ Percent.In.Serv~
##           <dbl>           <dbl>           <dbl>           <dbl>
## 1             1             82.2             85             68.3
## 2             2.1            88.7            79.5             58
## 3             4             87.7            82.3             68.2
## 4             1.5            77.1            86.6             64.2
## 5             9             90.2            82.4             65.7
## 6             2.7            90.9            83.4             70.1
## # ... with 24 more variables: Percent.STEM.education <dbl>,
## #   Percent.Computer.in.Household <dbl>,
## #   Percent.Smartphone.In.Household <dbl>,
## #   Percent.No.of.Internet.Subscriptions <dbl>, Employment.Rate <dbl>,
```

```
## # Median.Anual.Income <dbl>, Percent.in.Public.School <dbl>,
## # Percent.Foreign.Born <dbl>, White <dbl>, Black <dbl>, Native <dbl>,
## # Asian <dbl>, Other <dbl>, Two.or.more <dbl>, Population <dbl>,
## # Median.Age <dbl>, Percent.male <dbl>,
## # Percent.Less.Than.High.School <dbl>, Percent.High.School <dbl>,
## # Percent.Some.College <dbl>, Percent.Bachelors <dbl>,
## # Population.Graduate <dbl>, Percent.Below.Poverty.Line <dbl>,
## # Median.Monthly.Housing.Costs <dbl>
```

Fixing Missing Data

Below we impute the missing values using a monotone cubic approximator (known as a Stineman interpolation). It has a tendency to perform well on linear as well as higher-order data vectors.

##	Percent.Limited.English.Households	Percent.With.Broadband
## 1	1.0	82.2
## 2	2.1	88.7
## 3	4.0	87.7
## 4	1.5	77.1
## 5	9.0	90.2
## 6	2.7	90.9
## 7	5.3	89.6
## 8	2.4	89.3
## 9	3.6	84.1
## 10	6.9	85.6
## 11	2.8	85.6
## 12	5.5	88.3
## 13	2.1	88.3
## 14	4.5	88.0
## 15	1.7	85.1
## 16	1.9	86.6
## 17	2.4	87.2
## 18	1.2	83.3
## 19	2.1	80.6
## 20	0.8	87.0
## 21	3.2	90.7
## 22	6.1	90.7
## 23	1.6	87.0
## 24	2.4	90.0
## 25	0.7	78.3
## 26	1.2	84.9
## 27	0.4	84.8
## 28	3.0	88.8
## 29	5.8	86.4
## 30	1.3	91.8
## 31	7.2	90.0
## 32	5.5	79.2
## 33	8.2	86.9
## 34	2.4	85.4
## 35	0.8	84.5
## 36	1.3	87.3
## 37	1.9	83.6
## 38	2.5	90.5

## 39	2.5	86.3
## 40	68.2	65.8
## 41	6.3	90.1
## 42	1.3	83.1
## 43	1.1	84.8
## 44	1.6	83.3
## 45	7.9	85.7
## 46	2.4	91.0
## 47	0.5	85.4
## 48	2.7	88.2
## 49	3.8	92.1
## 50	0.4	81.6
## 51	1.5	87.4
## 52	1.5	87.8
##	Percent.Occupied.Single.Family.Homes	Percent.In.Service.Industry
## 1	85.0	68.3
## 2	79.5	58.0
## 3	82.3	68.2
## 4	86.6	64.2
## 5	82.4	65.7
## 6	83.4	70.1
## 7	83.8	67.2
## 8	76.3	69.9
## 9	25.7	66.4
## 10	73.7	71.9
## 11	86.0	67.3
## 12	72.8	72.5
## 13	90.4	65.2
## 14	79.6	68.3
## 15	92.0	69.0
## 16	90.5	67.6
## 17	92.2	65.4
## 18	85.2	67.6
## 19	83.8	67.4
## 20	83.5	61.6
## 21	71.0	65.3
## 22	77.2	66.7
## 23	88.8	71.5
## 24	85.8	68.7
## 25	83.0	66.8
## 26	89.5	67.9
## 27	84.7	60.7
## 28	93.1	65.0
## 29	84.2	83.5
## 30	83.2	64.8
## 31	78.1	70.8
## 32	78.2	64.8
## 33	69.4	66.4
## 34	82.7	67.2
## 35	83.0	58.6
## 36	89.6	70.4
## 37	88.8	64.4
## 38	84.1	66.3
## 39	75.6	69.1

## 40	81.1	54.9
## 41	83.0	70.2
## 42	80.2	70.2
## 43	86.5	65.2
## 44	87.0	70.6
## 45	88.7	69.5
## 46	87.5	67.7
## 47	83.3	60.2
## 48	79.7	65.4
## 49	84.5	66.2
## 50	83.4	67.7
## 51	88.8	68.5
## 52	81.3	62.0

##	Percent.STEM.education	Percent.Computer.in.Household
## 1	28.8	86.1
## 2	39.9	94.2
## 3	32.5	92.2
## 4	29.7	86.3
## 5	41.1	93.5
## 6	39.3	94.2
## 7	36.1	90.9
## 8	34.5	92.9
## 9	49.4	91.9
## 10	31.7	91.9
## 11	32.7	90.9
## 12	34.8	91.3
## 13	33.2	91.3
## 14	32.6	90.3
## 15	29.0	88.8
## 16	30.1	89.5
## 17	29.7	90.7
## 18	29.2	86.3
## 19	28.1	86.0
## 20	34.6	89.7
## 21	41.1	93.0
## 22	40.3	91.2
## 23	33.5	90.0
## 24	34.4	92.1
## 25	25.5	84.6
## 26	29.1	89.7
## 27	34.6	88.7
## 28	28.3	90.8
## 29	32.6	93.3
## 30	38.1	93.7
## 31	37.7	92.6
## 32	36.1	86.6
## 33	34.3	90.1
## 34	34.3	89.4
## 35	28.4	90.5
## 36	30.7	89.6
## 37	28.1	89.2
## 38	40.1	93.2
## 39	33.6	88.0
## 40	24.6	69.2

## 41	33.9	89.7
## 42	30.9	88.8
## 43	28.2	88.4
## 44	29.8	87.4
## 45	35.1	91.8
## 46	32.4	95.5
## 47	38.6	89.5
## 48	40.3	91.8
## 49	42.1	94.2
## 50	28.2	84.6
## 51	32.3	89.5
## 52	35.5	91.7
##	Percent.Smartphone.In.Household	Percent.No.of.Internet.Subscriptions
## 1	77.3	78.5
## 2	87.6	86.4
## 3	83.3	86.0
## 4	78.2	73.3
## 5	86.8	87.9
## 6	86.1	88.6
## 7	81.1	85.9
## 8	83.3	86.5
## 9	86.5	82.8
## 10	82.8	83.4
## 11	83.5	82.9
## 12	83.1	84.8
## 13	79.8	83.1
## 14	82.0	84.0
## 15	78.7	81.6
## 16	78.1	82.4
## 17	80.8	83.3
## 18	76.5	79.2
## 19	78.6	75.8
## 20	73.8	82.9
## 21	84.4	87.9
## 22	81.3	87.0
## 23	79.5	83.1
## 24	81.9	86.4
## 25	77.0	73.7
## 26	79.9	81.6
## 27	75.9	82.0
## 28	80.3	84.9
## 29	85.4	83.6
## 30	80.8	88.9
## 31	83.9	87.0
## 32	76.7	77.0
## 33	80.4	83.7
## 34	80.4	82.0
## 35	80.2	81.6
## 36	78.8	83.6
## 37	81.3	80.0
## 38	83.1	87.1
## 39	75.8	82.0
## 40	61.7	62.0
## 41	79.5	85.8

## 42	80.5	79.5
## 43	75.0	80.9
## 44	78.8	79.6
## 45	85.7	83.5
## 46	88.9	88.1
## 47	72.9	82.0
## 48	83.4	85.2
## 49	85.5	89.4
## 50	69.7	76.3
## 51	77.8	83.9
## 52	80.5	84.0

##	Employment.Rate	Median.Annual.Income	Percent.in.Public.School
## 1	52.9	48123	86.7
## 2	60.2	73181	88.3
## 3	56.1	56581	88.8
## 4	54.6	45869	88.6
## 5	59.5	71805	86.0
## 6	64.6	69117	88.4
## 7	61.4	74168	80.0
## 8	55.8	62852	84.4
## 9	65.3	82372	58.1
## 10	54.9	52594	82.1
## 11	59.1	56183	85.9
## 12	59.0	77765	77.9
## 13	59.2	52225	86.3
## 14	60.8	62992	81.7
## 15	60.4	54181	83.6
## 16	64.8	58570	84.4
## 17	63.0	56422	85.8
## 18	55.6	48375	83.9
## 19	54.7	46145	79.9
## 20	60.3	56277	82.4
## 21	63.8	80776	81.5
## 22	63.6	77385	72.8
## 23	57.8	54909	87.2
## 24	66.9	68388	84.7
## 25	52.2	43529	87.1
## 26	59.8	53578	81.2
## 27	61.3	53386	84.6
## 28	67.4	59970	82.0
## 29	59.6	58003	88.5
## 30	65.1	73381	79.2
## 31	61.8	80088	81.7
## 32	52.6	46744	90.5
## 33	59.6	64894	76.8
## 34	58.0	52752	85.1
## 35	67.9	61843	90.6
## 36	59.6	54021	82.1
## 37	57.2	50051	88.8
## 38	59.1	60212	84.9
## 39	59.0	59195	76.4
## 40	36.2	19343	65.4
## 41	61.3	63870	73.9
## 42	56.1	50570	86.2

## 43	65.1	56521	87.8		
## 44	58.1	51340	82.8		
## 45	60.7	59206	89.2		
## 46	66.0	68358	85.9		
## 47	62.8	57513	80.5		
## 48	61.1	71535	83.3		
## 49	60.6	70979	85.0		
## 50	48.8	43469	88.8		
## 51	63.9	59305	84.1		
## 52	61.9	60434	91.1		
##	Percent.Foreign.Born	White	Black	Native	Asian
## 1	0.03592806	0.6795672	0.268212279	0.005165601	0.013725430
## 2	0.09528630	0.6418751	0.029882603	0.148619550	0.066754979
## 3	0.15183776	0.7756852	0.043848797	0.045319522	0.033139688
## 4	0.04890648	0.7633469	0.152571382	0.006360927	0.015938932
## 5	0.36884416	0.5863362	0.057463564	0.007938431	0.145821777
## 6	0.10892523	0.8418700	0.040918441	0.010128489	0.031968268
## 7	0.17339947	0.7588833	0.106064238	0.003140307	0.045684391
## 8	0.11406967	0.6882806	0.218679147	0.002836978	0.040470342
## 9	0.17202826	0.4100108	0.458548760	0.002435257	0.041066498
## 10	0.26373535	0.7514303	0.161763405	0.003032491	0.028024961
## 11	0.11384398	0.5870873	0.315652639	0.003533767	0.039399757
## 12	0.22854662	0.2501601	0.016382051	0.001864048	0.382223801
## 13	0.06259426	0.9004440	0.006608839	0.012574092	0.013461717
## 14	0.16704535	0.7123805	0.142085825	0.002336349	0.054285795
## 15	0.05561369	0.8366656	0.093592025	0.001859508	0.022254395
## 16	0.05596809	0.8999765	0.034038728	0.003430385	0.025976321
## 17	0.07393627	0.8452149	0.057397851	0.007354993	0.029466658
## 18	0.03945879	0.8694445	0.081190313	0.001745997	0.014565615
## 19	0.04260093	0.6171248	0.324771744	0.005091013	0.018106313
## 20	0.09528630	0.9443854	0.012255344	0.006991505	0.011345850
## 21	0.18108750	0.5489732	0.298516220	0.003127965	0.064659047
## 22	0.20277076	0.7853576	0.077536594	0.002200787	0.065995473
## 23	0.07601724	0.7844340	0.137981539	0.005366325	0.030921741
## 24	0.09552226	0.8267511	0.064758027	0.010903227	0.048989296
## 25	0.02251864	0.5817121	0.380125666	0.004606414	0.009280520
## 26	0.04390081	0.8200819	0.114235110	0.004182034	0.020367604
## 27	0.09528630	0.8858203	0.004412214	0.061788132	0.007011946
## 28	0.08067055	0.8734508	0.046327333	0.008134574	0.024539654
## 29	0.24813241	0.6460420	0.091576527	0.012644932	0.085063937
## 30	0.06602505	0.9307087	0.016688325	0.001329317	0.026558782
## 31	0.29566761	0.6787119	0.135200992	0.001981313	0.098411729
## 32	0.10330335	0.7576470	0.021278501	0.095728113	0.014092918
## 33	0.29658212	0.6309187	0.158039243	0.003832307	0.087391210
## 34	0.08782462	0.6878669	0.214785263	0.011671772	0.028780292
## 35	0.09528630	0.8659281	0.030836929	0.055210996	0.016811117
## 36	0.04746414	0.8131394	0.123629929	0.002034548	0.022088227
## 37	0.06039497	0.7218494	0.072939690	0.076929652	0.022057237
## 38	0.10945679	0.8441784	0.018767609	0.011512088	0.043849583
## 39	0.07503244	0.8074232	0.112223408	0.001836940	0.034718419
## 40	0.02816030	0.6624545	0.120958223	0.002377459	0.001625326
## 41	0.16109298	0.8175029	0.062908217	0.005265944	0.035916005
## 42	0.05110673	0.6727649	0.270160293	0.002986843	0.015162302
## 43	0.09528630	0.8469700	0.019532786	0.087479561	0.012389814

## 44	0.05460764	0.7774871	0.167164633	0.002179427	0.017736046
## 45	0.20699555	0.7394255	0.120942585	0.004773006	0.048057496
## 46	0.09505033	0.8565945	0.012144110	0.010540219	0.024402023
## 47	0.09528630	0.9416474	0.013244460	0.003776114	0.018070831
## 48	0.14341525	0.6746972	0.192164954	0.003163157	0.064436211
## 49	0.16706926	0.7537881	0.036672080	0.012562953	0.085360240
## 50	0.09528630	0.9275626	0.039645743	0.001342617	0.007562820
## 51	0.05230243	0.8527634	0.063900627	0.008499896	0.027526610
## 52	0.09528630	0.9121359	0.009953134	0.024069807	0.008340885
##	Other	Two.or.more	Population	Median.Age	Percent.male
## 1	0.013807486	0.01726038	4874747	38.9	46.90
## 2	0.015246115	0.08069127	739795	34.5	54.50
## 3	0.061692751	0.03014907	7016270	37.7	49.40
## 4	0.030586374	0.02612540	3004279	38.1	48.55
## 5	0.149527149	0.03870770	39536653	36.5	49.40
## 6	0.039090954	0.02884387	5607154	36.8	50.60
## 7	0.053334221	0.02553325	3588184	40.9	47.65
## 8	0.019098924	0.02813380	961939	40.1	46.90
## 9	0.057806367	0.02568259	693972	34.0	45.10
## 10	0.028689503	0.02217709	20984400	42.0	47.80
## 11	0.026064160	0.02399932	10429379	36.8	47.30
## 12	0.015044083	0.22636455	1427538	39.2	50.35
## 13	0.034417567	0.02706846	1716943	36.3	50.50
## 14	0.062327337	0.02093255	12802023	38.0	48.35
## 15	0.018858322	0.02334442	6666818	37.7	48.60
## 16	0.013179532	0.01977740	3145711	38.3	49.35
## 17	0.024504630	0.03194681	2913123	36.7	49.75
## 18	0.009469064	0.02107252	4454189	38.9	48.55
## 19	0.016135915	0.01701800	4684333	36.8	47.80
## 20	0.001961963	0.02163624	1335907	44.6	48.05
## 21	0.050445154	0.02984876	6052177	38.7	47.10
## 22	0.038170249	0.02591934	6859819	39.5	47.25
## 23	0.011435901	0.02671729	9962311	39.8	48.55
## 24	0.019856701	0.02528850	5576606	37.9	49.75
## 25	0.010359572	0.01213130	2984100	37.5	47.05
## 26	0.013288063	0.02456730	6113532	38.5	48.25
## 27	0.007413662	0.03001353	1050493	40.0	50.20
## 28	0.020219512	0.02419488	1920076	36.5	49.90
## 29	0.111316431	0.03898482	2998039	38.0	50.50
## 30	0.003364624	0.01943707	1342795	43.2	49.15
## 31	0.059781510	0.01962514	9005644	39.8	47.70
## 32	0.077131514	0.02430857	2088070	37.7	49.05
## 33	0.089113932	0.02264865	19849399	38.7	47.20
## 34	0.030091345	0.02335941	10273419	38.8	47.40
## 35	0.010922791	0.01822627	755393	35.4	52.90
## 36	0.009499246	0.02686830	11658609	39.3	48.00
## 37	0.027349458	0.07325743	3930864	36.6	49.15
## 38	0.029822274	0.04303660	4142776	39.3	49.15
## 39	0.018976166	0.02188007	12805537	40.8	48.00
## 40	0.159899820	0.04754168	3337177	41.4	45.60
## 41	0.044640675	0.02486790	1059639	39.5	46.95
## 42	0.016312297	0.01949598	5024369	39.4	47.10
## 43	0.006493297	0.02458300	869666	36.9	50.85
## 44	0.013290681	0.01964284	6715984	38.6	47.50

## 45	0.059491893	0.02073101	28304596	34.7	49.35
## 46	0.058011827	0.02427565	3101833	31.0	50.80
## 47	0.002231996	0.01966947	623657	42.6	48.75
## 48	0.025915051	0.03535139	8470020	38.2	48.35
## 49	0.045908425	0.05350685	7405743	37.7	49.90
## 50	0.006887106	0.01549682	1815857	42.4	48.85
## 51	0.021873414	0.02117580	5795483	39.5	49.40
## 52	0.017263492	0.02434427	579315	37.5	52.15
##	Percent.Less.Than.High.School		Percent.High.School	Percent.Some.College	
## 1			9.4	31.1	21.4
## 2			5.4	27.6	26.4
## 3			7.4	24.1	25.0
## 4			8.7	34.0	22.1
## 5			7.5	20.8	21.1
## 6			5.0	21.3	20.9
## 7			5.5	27.1	16.5
## 8			6.0	32.4	19.0
## 9			5.5	17.2	12.5
## 10			6.9	28.8	19.9
## 11			8.4	28.1	20.2
## 12			4.3	28.1	20.5
## 13			5.9	28.2	26.3
## 14			6.0	26.1	20.6
## 15			7.7	32.7	20.2
## 16			4.8	30.5	21.0
## 17			5.5	25.8	22.7
## 18			8.2	33.0	21.3
## 19			10.0	34.0	21.4
## 20			5.1	30.9	19.0
## 21			6.1	24.5	18.9
## 22			4.9	24.3	15.5
## 23			6.3	28.9	23.4
## 24			3.9	24.8	20.9
## 25			10.8	30.4	22.0
## 26			7.2	30.8	22.0
## 27			4.8	28.1	23.5
## 28			4.8	26.3	23.1
## 29			8.0	28.7	25.1
## 30			5.1	28.0	17.9
## 31			5.3	27.2	16.3
## 32			8.1	26.6	24.0
## 33			7.3	26.3	15.4
## 34			7.7	25.8	21.3
## 35			4.3	26.4	22.4
## 36			7.0	33.3	20.2
## 37			7.9	31.1	23.3
## 38			5.5	23.2	25.2
## 39			6.3	35.0	15.8
## 40			8.1	27.9	12.2
## 41			6.6	29.9	16.9
## 42			8.6	29.5	20.3
## 43			5.4	30.8	22.0
## 44			7.8	32.4	20.8
## 45			8.2	25.1	21.7

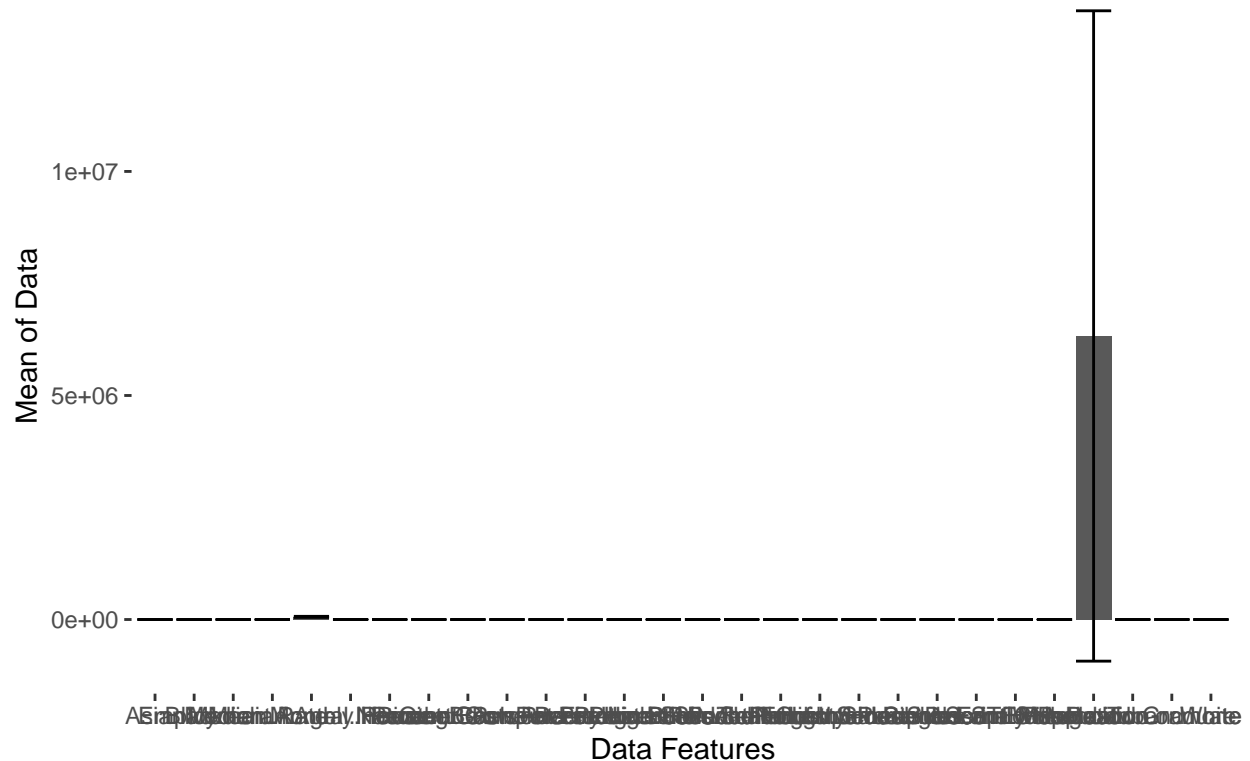
## 46	5.1	22.3	25.7
## 47	5.2	29.0	16.8
## 48	6.1	24.2	19.0
## 49	5.0	22.1	23.6
## 50	8.4	41.2	18.6
## 51	5.1	30.7	20.3
## 52	5.1	29.6	25.3
##	Percent.Bachelors	Population.Graduate	Percent.Below.Poverty.Line
## 1	16.0	9.6	29.1
## 2	18.0	10.8	21.0
## 3	18.3	11.0	24.6
## 4	15.0	8.4	30.7
## 5	21.1	12.6	25.5
## 6	26.0	15.2	21.0
## 7	21.4	17.3	20.1
## 8	18.0	13.5	26.7
## 9	23.9	33.4	19.4
## 10	18.9	10.8	24.9
## 11	19.0	11.9	26.0
## 12	21.7	11.2	23.4
## 13	18.2	8.5	27.8
## 14	21.0	13.4	23.4
## 15	17.0	9.8	26.5
## 16	19.4	9.5	23.6
## 17	21.2	12.6	25.2
## 18	14.0	9.9	31.0
## 19	15.5	8.3	31.8
## 20	19.9	12.1	25.0
## 21	21.3	18.3	20.1
## 22	23.9	19.5	21.2
## 23	17.6	11.5	26.2
## 24	23.5	12.5	20.7
## 25	13.5	8.3	34.1
## 26	17.9	11.1	25.2
## 27	21.7	10.6	24.8
## 28	20.9	10.8	21.8
## 29	16.5	8.4	23.1
## 30	22.6	14.3	17.5
## 31	24.2	15.6	21.2
## 32	15.2	11.8	28.8
## 33	20.2	15.8	24.5
## 34	20.1	11.2	25.8
## 35	21.8	9.0	22.7
## 36	17.3	10.6	25.4
## 37	16.9	8.6	27.9
## 38	21.0	12.7	25.8
## 39	18.9	12.5	25.6
## 40	18.3	7.4	56.6
## 41	20.3	13.1	22.7
## 42	17.6	10.4	26.9
## 43	19.1	9.0	22.9
## 44	17.2	10.1	26.5
## 45	19.3	10.3	24.9
## 46	22.8	11.8	26.4

## 47	22.5	15.8	22.2
## 48	22.0	16.7	22.7
## 49	22.2	13.3	22.5
## 50	12.2	8.0	33.7
## 51	19.8	10.6	23.2
## 52	17.4	10.3	23.0
##	Median.Monthly.Housing.Costs		
## 1	734		
## 2	1285		
## 3	1015		
## 4	691		
## 5	1567		
## 6	1300		
## 7	1390		
## 8	1126		
## 9	1641		
## 10	1047		
## 11	980		
## 12	1585		
## 13	880		
## 14	1081		
## 15	815		
## 16	825		
## 17	858		
## 18	743		
## 19	781		
## 20	884		
## 21	1456		
## 22	1464		
## 23	862		
## 24	1070		
## 25	672		
## 26	837		
## 27	816		
## 28	887		
## 29	1089		
## 30	1280		
## 31	1545		
## 32	782		
## 33	1291		
## 34	878		
## 35	799		
## 36	833		
## 37	770		
## 38	1164		
## 39	947		
## 40	329		
## 41	1190		
## 42	820		
## 43	774		
## 44	820		
## 45	1009		
## 46	1122		
## 47	1088		

```
## 48          1237
## 49          1319
## 50           585
## 51           913
## 52           890
```

Below we can see the mean and standard deviation for each data vector. As we can see, our data occurs across many orders of magnitude. For the best fit, the data should be centered and scaled.

Means of Various Features



These plots confirm the non-normality of most of our data. For the non-linear models, we must center and scale them. Additionally, we will need other data transformations (discussed below). TODO: Density Plots

```
#ggplot(data = gather(training), mapping = aes(x = value)) +
# geom_histogram(aes(y=..density..), colour="black", fill="white")+
# geom_density(alpha=.2, fill="lightgrey")+
# facet_wrap(~key, ncol = 1, scales = 'free')
```

Correlation Plot of Predictors

We can see significant covariance in the data. Additionally, many data points have near-zero variance. Excluding these confounding variables will improve our model.

Data Pre-processing

For preprocessing of data, we remove near zero predictors, fill in missing values with KNN method, and transform predictors using the Yeo-Johnson transformation method. We also center and scale the data. Additionally, we remove the covariant terms and the ones with near zero variance here, since they will not improve our models.

Support Vector Machine

Comparing SVM with Neural Networks (NN), both are non-linear algorithms. A Support Vector Machine with different kernels is comparable to a Neural Network with different layers. One advantage SVMs have over NNs is that NNs need large amounts of data to train, SVMs work with smaller-sized data with less computing power. Finally SVM usually only have 2-3 parameters to tune, they are easy to code, and the results are explainable. On the other hand, SVMs might not beat NNs on the accuracy metric.

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 39 samples
## 24 predictors
##
## No pre-processing
## Resampling: Cross-Validated (3 fold, repeated 3 times)
## Summary of sample sizes: 25, 27, 26, 26, 27, 25, ...
## Resampling results across tuning parameters:
##
##   C      RMSE      Rsquared    MAE
##   0.25  4.951241  0.4549275  2.878613
##   0.50  4.784790  0.4569550  2.712984
##   1.00  4.699560  0.4686361  2.695841
##   2.00  4.619132  0.4881648  2.666214
##   4.00  4.639514  0.4749878  2.689218
##   8.00  4.639514  0.4749878  2.689218
##  16.00  4.639514  0.4749878  2.689218
##  32.00  4.639514  0.4749878  2.689218
##
## Tuning parameter 'sigma' was held constant at a value of 0.04847725
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were sigma = 0.04847725 and C = 2.
```

Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
Support Vector Machine	2.848699	0.8712312	1.535414	0.5913622

Random Forest Model

Random forests are a modification of bagging that builds a large collection of de-correlated trees [1]. They are considered to belong in the category of non-parametric models since the number of parameters grows with the size of the training set. They are considered to be an improvement to the use of CART (Classification and Regression Tree) models because they do not suffer from some of the problems associated with CART models, such as the fact that CART models are unstable: small changes to the structure of the input data can have large effects on the CART model [2]. Random forests are designed to be low-variance estimators.

Random forests are based on the basic idea of aggregating uncorrelated sets of predictors, since one way to reduce the variance of an estimate is to average several estimates together [2]. A random forest trains a randomly chosen set of input variables over a randomly chosen subset of the data, and aggregates together several such trees to produce an overall estimator. Random forests have proven to be quite successful in a variety of real-world applications and often are seen to generalize very well to unseen real-world data.

##	Percent.Limited.English.Households	Percent.With.Broadband
## 1	1.0	82.2
## 3	4.0	87.7
## 6	2.7	90.9
## 7	5.3	89.6
## 9	3.6	84.1
## 10	6.9	85.6
## 12	5.5	88.3
## 13	2.1	88.3
## 14	4.5	88.0
## 15	1.7	85.1
## 17	2.4	87.2
## 18	1.2	83.3
## 19	2.1	80.6
## 22	6.1	90.7
## 23	1.6	87.0
## 25	0.7	78.3
## 26	1.2	84.9
## 27	0.4	84.8
## 28	3.0	88.8
## 29	5.8	86.4
## 30	1.3	91.8
## 33	8.2	86.9
## 35	0.8	84.5
## 36	1.3	87.3
## 37	1.9	83.6
## 38	2.5	90.5
## 39	2.5	86.3
## 40	68.2	65.8
## 41	6.3	90.1
## 42	1.3	83.1
## 43	1.1	84.8
## 44	1.6	83.3
## 45	7.9	85.7
## 46	2.4	91.0
## 47	0.5	85.4
## 48	2.7	88.2
## 49	3.8	92.1
## 51	1.5	87.4
## 52	1.5	87.8
##	Percent.Occupied.Single.Family.Homes	Percent.In.Service.Industry
## 1	85.0	68.3
## 3	82.3	68.2
## 6	83.4	70.1
## 7	83.8	67.2
## 9	25.7	66.4
## 10	73.7	71.9
## 12	72.8	72.5

## 13	90.4	65.2
## 14	79.6	68.3
## 15	92.0	69.0
## 17	92.2	65.4
## 18	85.2	67.6
## 19	83.8	67.4
## 22	77.2	66.7
## 23	88.8	71.5
## 25	83.0	66.8
## 26	89.5	67.9
## 27	84.7	60.7
## 28	93.1	65.0
## 29	84.2	83.5
## 30	83.2	64.8
## 33	69.4	66.4
## 35	83.0	58.6
## 36	89.6	70.4
## 37	88.8	64.4
## 38	84.1	66.3
## 39	75.6	69.1
## 40	81.1	54.9
## 41	83.0	70.2
## 42	80.2	70.2
## 43	86.5	65.2
## 44	87.0	70.6
## 45	88.7	69.5
## 46	87.5	67.7
## 47	83.3	60.2
## 48	79.7	65.4
## 49	84.5	66.2
## 51	88.8	68.5
## 52	81.3	62.0

##	Percent.STEM.education	Percent.Computer.in.Household
## 1	28.8	86.1
## 3	32.5	92.2
## 6	39.3	94.2
## 7	36.1	90.9
## 9	49.4	91.9
## 10	31.7	91.9
## 12	34.8	91.3
## 13	33.2	91.3
## 14	32.6	90.3
## 15	29.0	88.8
## 17	29.7	90.7
## 18	29.2	86.3
## 19	28.1	86.0
## 22	40.3	91.2
## 23	33.5	90.0
## 25	25.5	84.6
## 26	29.1	89.7
## 27	34.6	88.7
## 28	28.3	90.8
## 29	32.6	93.3
## 30	38.1	93.7

## 33	34.3	90.1
## 35	28.4	90.5
## 36	30.7	89.6
## 37	28.1	89.2
## 38	40.1	93.2
## 39	33.6	88.0
## 40	24.6	69.2
## 41	33.9	89.7
## 42	30.9	88.8
## 43	28.2	88.4
## 44	29.8	87.4
## 45	35.1	91.8
## 46	32.4	95.5
## 47	38.6	89.5
## 48	40.3	91.8
## 49	42.1	94.2
## 51	32.3	89.5
## 52	35.5	91.7
##	Percent.Smartphone.In.Household	Percent.No.of.Internet.Subscriptions
## 1	77.3	78.5
## 3	83.3	86.0
## 6	86.1	88.6
## 7	81.1	85.9
## 9	86.5	82.8
## 10	82.8	83.4
## 12	83.1	84.8
## 13	79.8	83.1
## 14	82.0	84.0
## 15	78.7	81.6
## 17	80.8	83.3
## 18	76.5	79.2
## 19	78.6	75.8
## 22	81.3	87.0
## 23	79.5	83.1
## 25	77.0	73.7
## 26	79.9	81.6
## 27	75.9	82.0
## 28	80.3	84.9
## 29	85.4	83.6
## 30	80.8	88.9
## 33	80.4	83.7
## 35	80.2	81.6
## 36	78.8	83.6
## 37	81.3	80.0
## 38	83.1	87.1
## 39	75.8	82.0
## 40	61.7	62.0
## 41	79.5	85.8
## 42	80.5	79.5
## 43	75.0	80.9
## 44	78.8	79.6
## 45	85.7	83.5
## 46	88.9	88.1
## 47	72.9	82.0

## 48	83.4	85.2
## 49	85.5	89.4
## 51	77.8	83.9
## 52	80.5	84.0

##	Employment.Rate	Median.Annual.Income	Percent.in.Public.School
## 1	52.9	48123	86.7
## 3	56.1	56581	88.8
## 6	64.6	69117	88.4
## 7	61.4	74168	80.0
## 9	65.3	82372	58.1
## 10	54.9	52594	82.1
## 12	59.0	77765	77.9
## 13	59.2	52225	86.3
## 14	60.8	62992	81.7
## 15	60.4	54181	83.6
## 17	63.0	56422	85.8
## 18	55.6	48375	83.9
## 19	54.7	46145	79.9
## 22	63.6	77385	72.8
## 23	57.8	54909	87.2
## 25	52.2	43529	87.1
## 26	59.8	53578	81.2
## 27	61.3	53386	84.6
## 28	67.4	59970	82.0
## 29	59.6	58003	88.5
## 30	65.1	73381	79.2
## 33	59.6	64894	76.8
## 35	67.9	61843	90.6
## 36	59.6	54021	82.1
## 37	57.2	50051	88.8
## 38	59.1	60212	84.9
## 39	59.0	59195	76.4
## 40	36.2	19343	65.4
## 41	61.3	63870	73.9
## 42	56.1	50570	86.2
## 43	65.1	56521	87.8
## 44	58.1	51340	82.8
## 45	60.7	59206	89.2
## 46	66.0	68358	85.9
## 47	62.8	57513	80.5
## 48	61.1	71535	83.3
## 49	60.6	70979	85.0
## 51	63.9	59305	84.1
## 52	61.9	60434	91.1

##	Percent.Foreign.Born	White	Black	Native	Asian
## 1	0.03592806	0.6795672	0.268212279	0.005165601	0.013725430
## 3	0.15183776	0.7756852	0.043848797	0.045319522	0.033139688
## 6	0.10892523	0.8418700	0.040918441	0.010128489	0.031968268
## 7	0.17339947	0.7588833	0.106064238	0.003140307	0.045684391
## 9	0.17202826	0.4100108	0.458548760	0.002435257	0.041066498
## 10	0.26373535	0.7514303	0.161763405	0.003032491	0.028024961
## 12	0.22854662	0.2501601	0.016382051	0.001864048	0.382223801
## 13	0.06259426	0.9004440	0.006608839	0.012574092	0.013461717
## 14	0.16704535	0.7123805	0.142085825	0.002336349	0.054285795

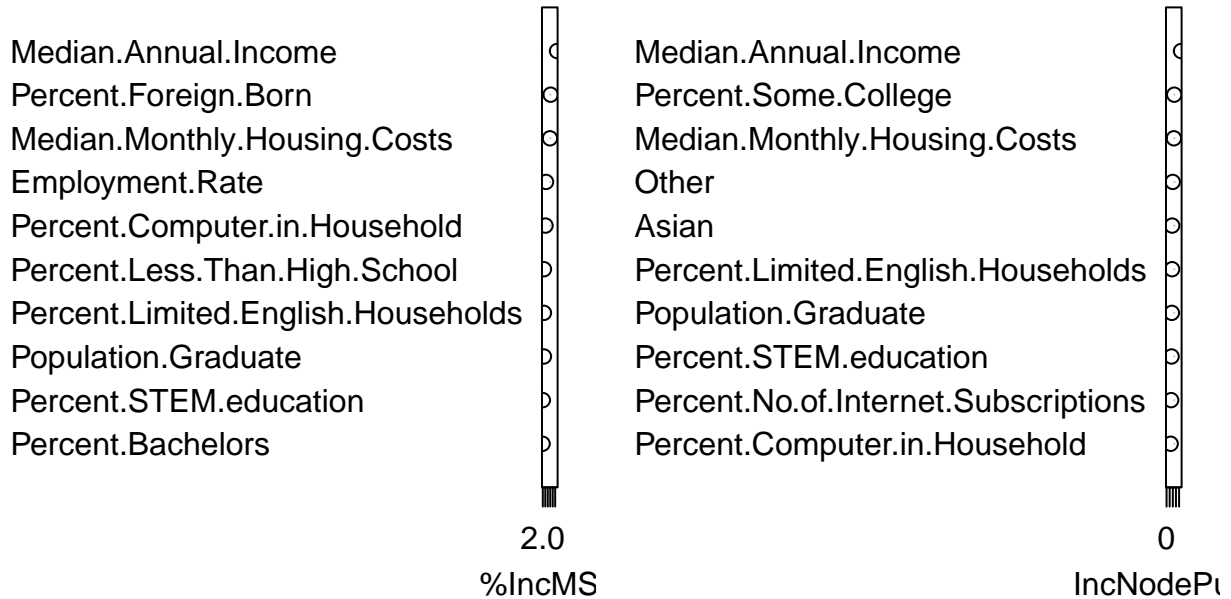
## 15	0.05561369	0.8366656	0.093592025	0.001859508	0.022254395
## 17	0.07393627	0.8452149	0.057397851	0.007354993	0.029466658
## 18	0.03945879	0.8694445	0.081190313	0.001745997	0.014565615
## 19	0.04260093	0.6171248	0.324771744	0.005091013	0.018106313
## 22	0.20277076	0.7853576	0.077536594	0.002200787	0.065995473
## 23	0.07601724	0.7844340	0.137981539	0.005366325	0.030921741
## 25	0.02251864	0.5817121	0.380125666	0.004606414	0.009280520
## 26	0.04390081	0.8200819	0.114235110	0.004182034	0.020367604
## 27	0.09528630	0.8858203	0.004412214	0.061788132	0.007011946
## 28	0.08067055	0.8734508	0.046327333	0.008134574	0.024539654
## 29	0.24813241	0.6460420	0.091576527	0.012644932	0.085063937
## 30	0.06602505	0.9307087	0.016688325	0.001329317	0.026558782
## 33	0.29658212	0.6309187	0.158039243	0.003832307	0.087391210
## 35	0.09528630	0.8659281	0.030836929	0.055210996	0.016811117
## 36	0.04746414	0.8131394	0.123629929	0.002034548	0.022088227
## 37	0.06039497	0.7218494	0.072939690	0.076929652	0.022057237
## 38	0.10945679	0.8441784	0.018767609	0.011512088	0.043849583
## 39	0.07503244	0.8074232	0.112223408	0.001836940	0.034718419
## 40	0.02816030	0.6624545	0.120958223	0.002377459	0.001625326
## 41	0.16109298	0.8175029	0.062908217	0.005265944	0.035916005
## 42	0.05110673	0.6727649	0.270160293	0.002986843	0.015162302
## 43	0.09528630	0.8469700	0.019532786	0.087479561	0.012389814
## 44	0.05460764	0.7774871	0.167164633	0.002179427	0.017736046
## 45	0.20699555	0.7394255	0.120942585	0.004773006	0.048057496
## 46	0.09505033	0.8565945	0.012144110	0.010540219	0.024402023
## 47	0.09528630	0.9416474	0.013244460	0.003776114	0.018070831
## 48	0.14341525	0.6746972	0.192164954	0.003163157	0.064436211
## 49	0.16706926	0.7537881	0.036672080	0.012562953	0.085360240
## 51	0.05230243	0.8527634	0.063900627	0.008499896	0.027526610
## 52	0.09528630	0.9121359	0.009953134	0.024069807	0.008340885
##	Other	Two.or.more	Population	Median.Age	Percent.male
## 1	0.013807486	0.01726038	4874747	38.9	46.90
## 3	0.061692751	0.03014907	7016270	37.7	49.40
## 6	0.039090954	0.02884387	5607154	36.8	50.60
## 7	0.053334221	0.02553325	3588184	40.9	47.65
## 9	0.057806367	0.02568259	693972	34.0	45.10
## 10	0.028689503	0.02217709	20984400	42.0	47.80
## 12	0.015044083	0.22636455	1427538	39.2	50.35
## 13	0.034417567	0.02706846	1716943	36.3	50.50
## 14	0.062327337	0.02093255	12802023	38.0	48.35
## 15	0.018858322	0.02334442	6666818	37.7	48.60
## 17	0.024504630	0.03194681	2913123	36.7	49.75
## 18	0.009469064	0.02107252	4454189	38.9	48.55
## 19	0.016135915	0.01701800	4684333	36.8	47.80
## 22	0.038170249	0.02591934	6859819	39.5	47.25
## 23	0.011435901	0.02671729	9962311	39.8	48.55
## 25	0.010359572	0.01213130	2984100	37.5	47.05
## 26	0.013288063	0.02456730	6113532	38.5	48.25
## 27	0.007413662	0.03001353	1050493	40.0	50.20
## 28	0.020219512	0.02419488	1920076	36.5	49.90
## 29	0.111316431	0.03898482	2998039	38.0	50.50
## 30	0.003364624	0.01943707	1342795	43.2	49.15
## 33	0.089113932	0.02264865	19849399	38.7	47.20
## 35	0.010922791	0.01822627	755393	35.4	52.90

## 36	0.009499246	0.02686830	11658609	39.3	48.00
## 37	0.027349458	0.07325743	3930864	36.6	49.15
## 38	0.029822274	0.04303660	4142776	39.3	49.15
## 39	0.018976166	0.02188007	12805537	40.8	48.00
## 40	0.159899820	0.04754168	3337177	41.4	45.60
## 41	0.044640675	0.02486790	1059639	39.5	46.95
## 42	0.016312297	0.01949598	5024369	39.4	47.10
## 43	0.006493297	0.02458300	869666	36.9	50.85
## 44	0.013290681	0.01964284	6715984	38.6	47.50
## 45	0.059491893	0.02073101	28304596	34.7	49.35
## 46	0.058011827	0.02427565	3101833	31.0	50.80
## 47	0.002231996	0.01966947	623657	42.6	48.75
## 48	0.025915051	0.03535139	8470020	38.2	48.35
## 49	0.045908425	0.05350685	7405743	37.7	49.90
## 51	0.021873414	0.02117580	5795483	39.5	49.40
## 52	0.017263492	0.02434427	579315	37.5	52.15
##	Percent.Less.Than.High.School	Percent.High.School	Percent.Some.College		
## 1		9.4	31.1		21.4
## 3		7.4	24.1		25.0
## 6		5.0	21.3		20.9
## 7		5.5	27.1		16.5
## 9		5.5	17.2		12.5
## 10		6.9	28.8		19.9
## 12		4.3	28.1		20.5
## 13		5.9	28.2		26.3
## 14		6.0	26.1		20.6
## 15		7.7	32.7		20.2
## 17		5.5	25.8		22.7
## 18		8.2	33.0		21.3
## 19		10.0	34.0		21.4
## 22		4.9	24.3		15.5
## 23		6.3	28.9		23.4
## 25		10.8	30.4		22.0
## 26		7.2	30.8		22.0
## 27		4.8	28.1		23.5
## 28		4.8	26.3		23.1
## 29		8.0	28.7		25.1
## 30		5.1	28.0		17.9
## 33		7.3	26.3		15.4
## 35		4.3	26.4		22.4
## 36		7.0	33.3		20.2
## 37		7.9	31.1		23.3
## 38		5.5	23.2		25.2
## 39		6.3	35.0		15.8
## 40		8.1	27.9		12.2
## 41		6.6	29.9		16.9
## 42		8.6	29.5		20.3
## 43		5.4	30.8		22.0
## 44		7.8	32.4		20.8
## 45		8.2	25.1		21.7
## 46		5.1	22.3		25.7
## 47		5.2	29.0		16.8
## 48		6.1	24.2		19.0
## 49		5.0	22.1		23.6

## 51	5.1	30.7	20.3
## 52	5.1	29.6	25.3
##	Percent.Bachelors	Population.Graduate	Percent.Below.Poverty.Line
## 1	16.0	9.6	29.1
## 3	18.3	11.0	24.6
## 6	26.0	15.2	21.0
## 7	21.4	17.3	20.1
## 9	23.9	33.4	19.4
## 10	18.9	10.8	24.9
## 12	21.7	11.2	23.4
## 13	18.2	8.5	27.8
## 14	21.0	13.4	23.4
## 15	17.0	9.8	26.5
## 17	21.2	12.6	25.2
## 18	14.0	9.9	31.0
## 19	15.5	8.3	31.8
## 22	23.9	19.5	21.2
## 23	17.6	11.5	26.2
## 25	13.5	8.3	34.1
## 26	17.9	11.1	25.2
## 27	21.7	10.6	24.8
## 28	20.9	10.8	21.8
## 29	16.5	8.4	23.1
## 30	22.6	14.3	17.5
## 33	20.2	15.8	24.5
## 35	21.8	9.0	22.7
## 36	17.3	10.6	25.4
## 37	16.9	8.6	27.9
## 38	21.0	12.7	25.8
## 39	18.9	12.5	25.6
## 40	18.3	7.4	56.6
## 41	20.3	13.1	22.7
## 42	17.6	10.4	26.9
## 43	19.1	9.0	22.9
## 44	17.2	10.1	26.5
## 45	19.3	10.3	24.9
## 46	22.8	11.8	26.4
## 47	22.5	15.8	22.2
## 48	22.0	16.7	22.7
## 49	22.2	13.3	22.5
## 51	19.8	10.6	23.2
## 52	17.4	10.3	23.0
##	Median.Monthly.Housing.Costs		
## 1	734		
## 3	1015		
## 6	1300		
## 7	1390		
## 9	1641		
## 10	1047		
## 12	1585		
## 13	880		
## 14	1081		
## 15	815		
## 17	858		

## 18	743
## 19	781
## 22	1464
## 23	862
## 25	672
## 26	837
## 27	816
## 28	887
## 29	1089
## 30	1280
## 33	1291
## 35	799
## 36	833
## 37	770
## 38	1164
## 39	947
## 40	329
## 41	1190
## 42	820
## 43	774
## 44	820
## 45	1009
## 46	1122
## 47	1088
## 48	1237
## 49	1319
## 51	913
## 52	890

Important Variables in Random Forest Model (top 10 shown)



We now compute RMSE values for the Random Forest model on both the training and the test (withheld) portion of the data set.

Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
Random Forest	1.732264	0.9750761	1.708613	0.8485353

Neural Network Model

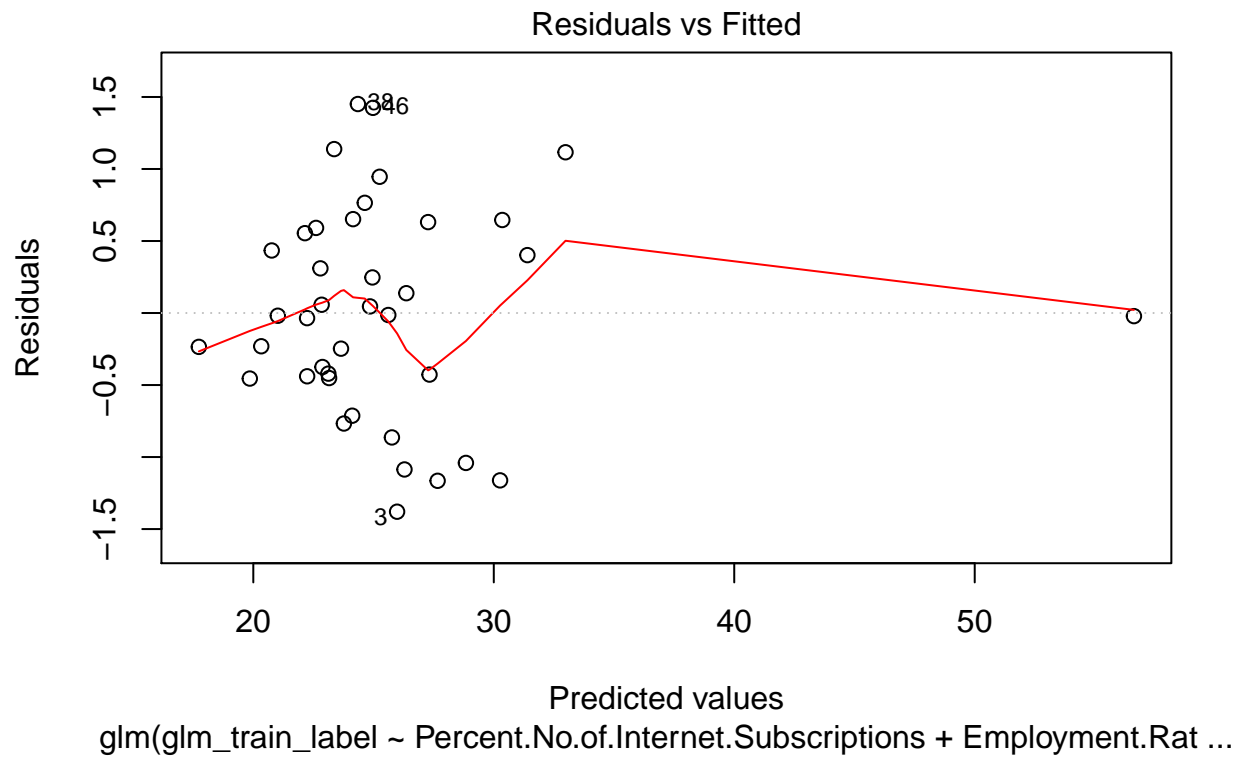
Neural Networks are a powerful nonlinear technique inspired by theories about how the human brain works [5]. Neural Networks can be classifiers (when the output variable is categorical) or regression (when the output variable is numeric). In this problem we use a regression artificial neural network (ANN) using the nnet package in R. Below we build and evaluate a Neural Network model of the regression problem.

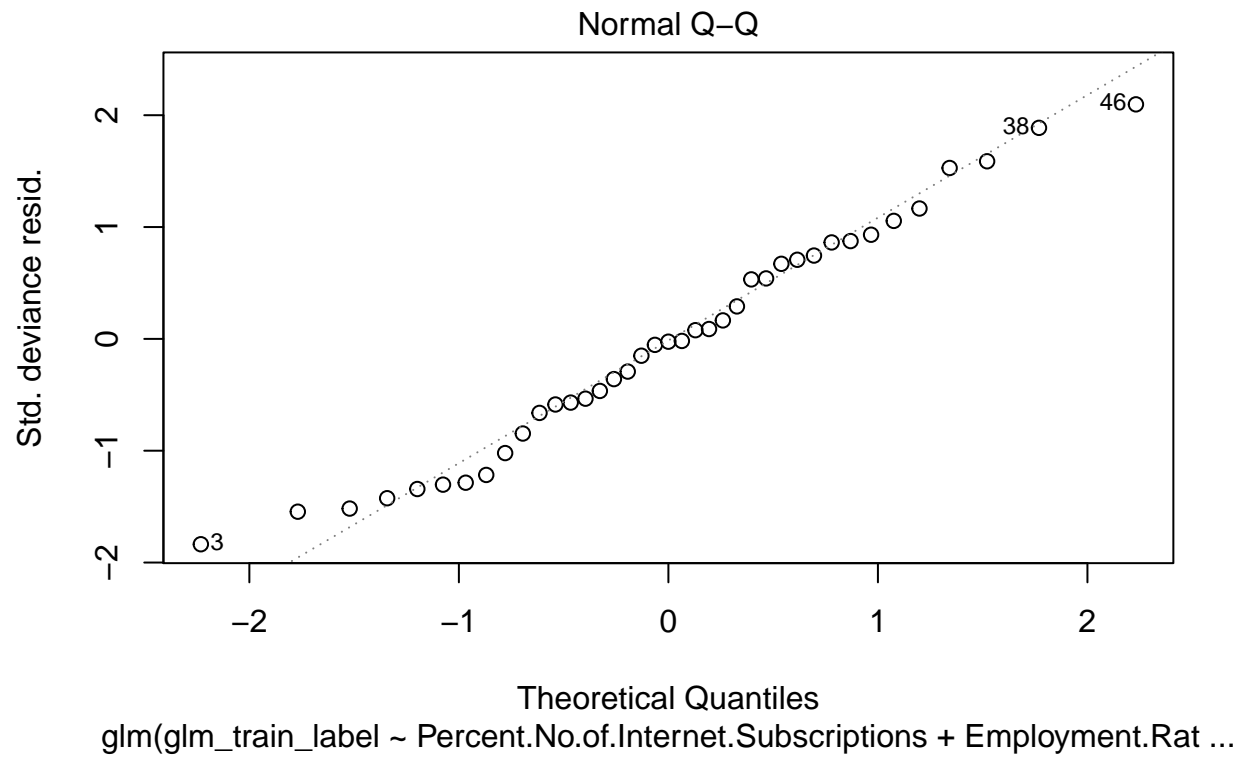
```
## a 27-4-1 network with 117 weights
## options were - linear output units decay=0.01
```

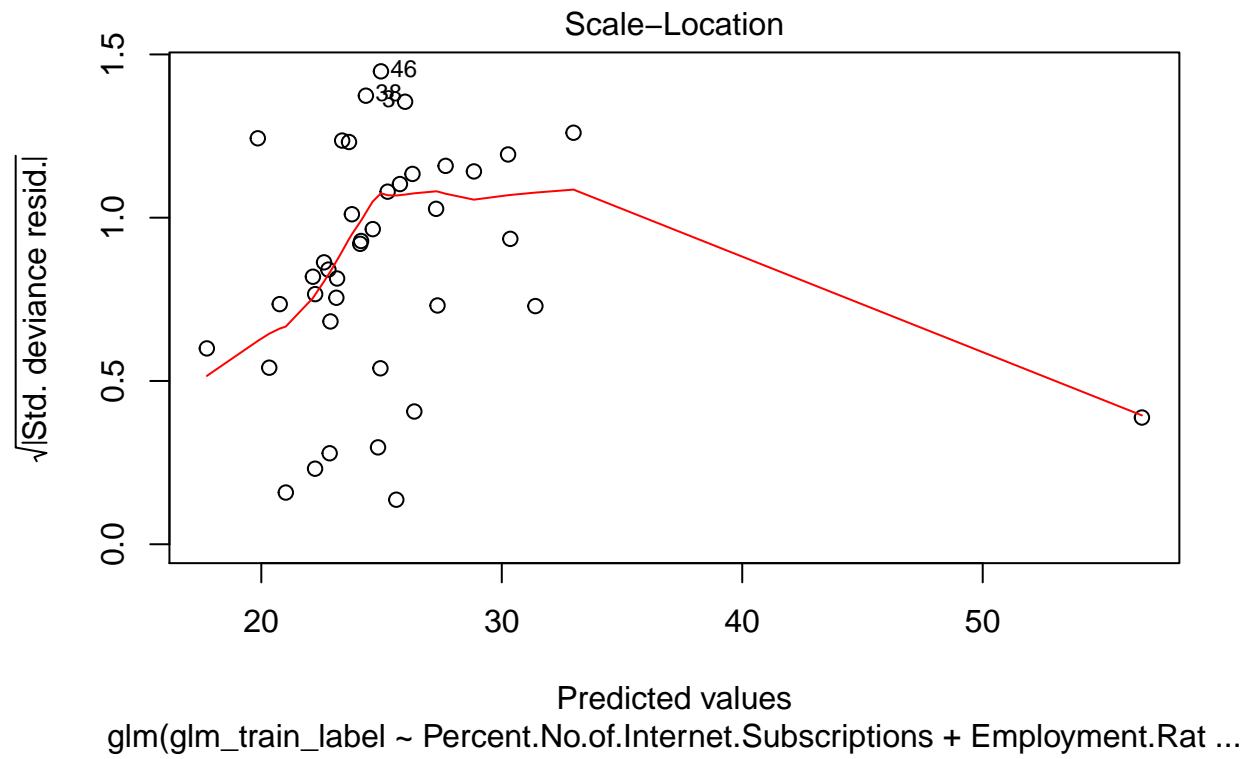
Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
NeuralNet	5.997393	0.2709523	3.939332	0.3219012

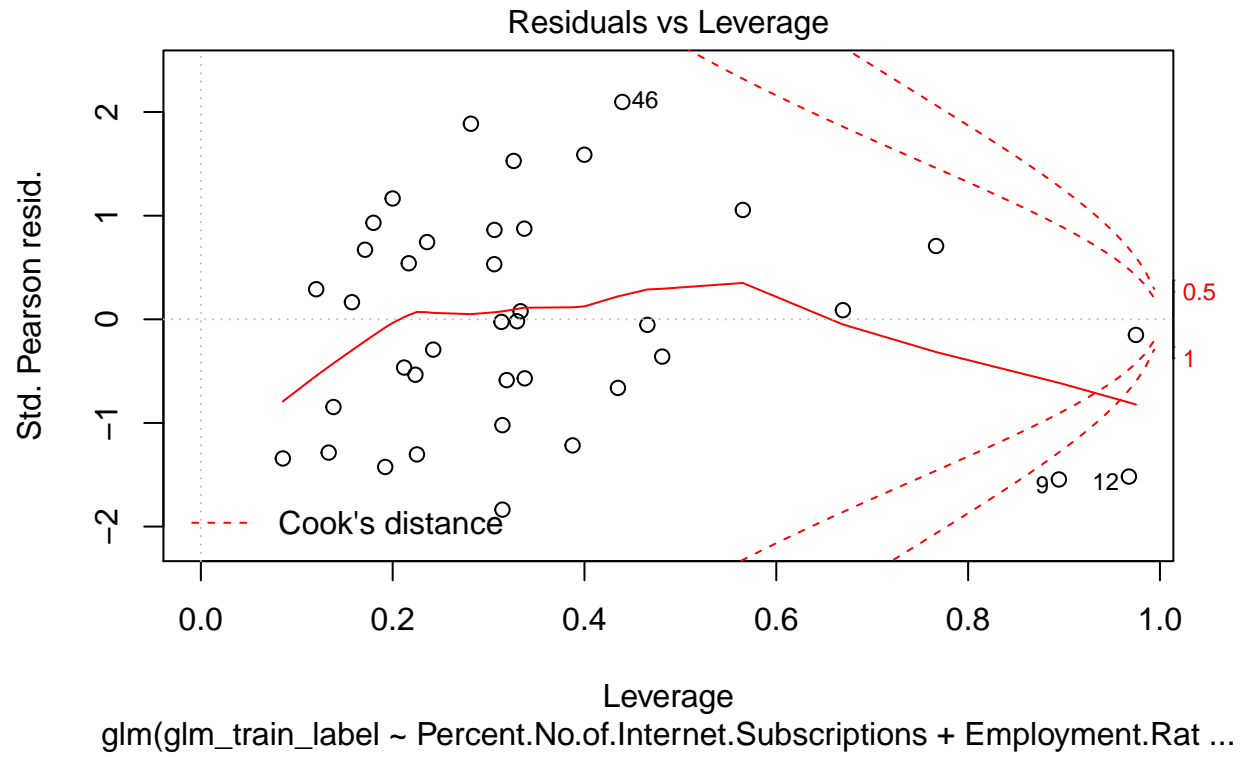
Generalized Linear Model

Because our output value is continuous and our data is numeric, we can use a generalized linear model to compute the pH. These models are generic and assume linearity in response. We will use the “Gaussian” type which assumes normally distributed variables





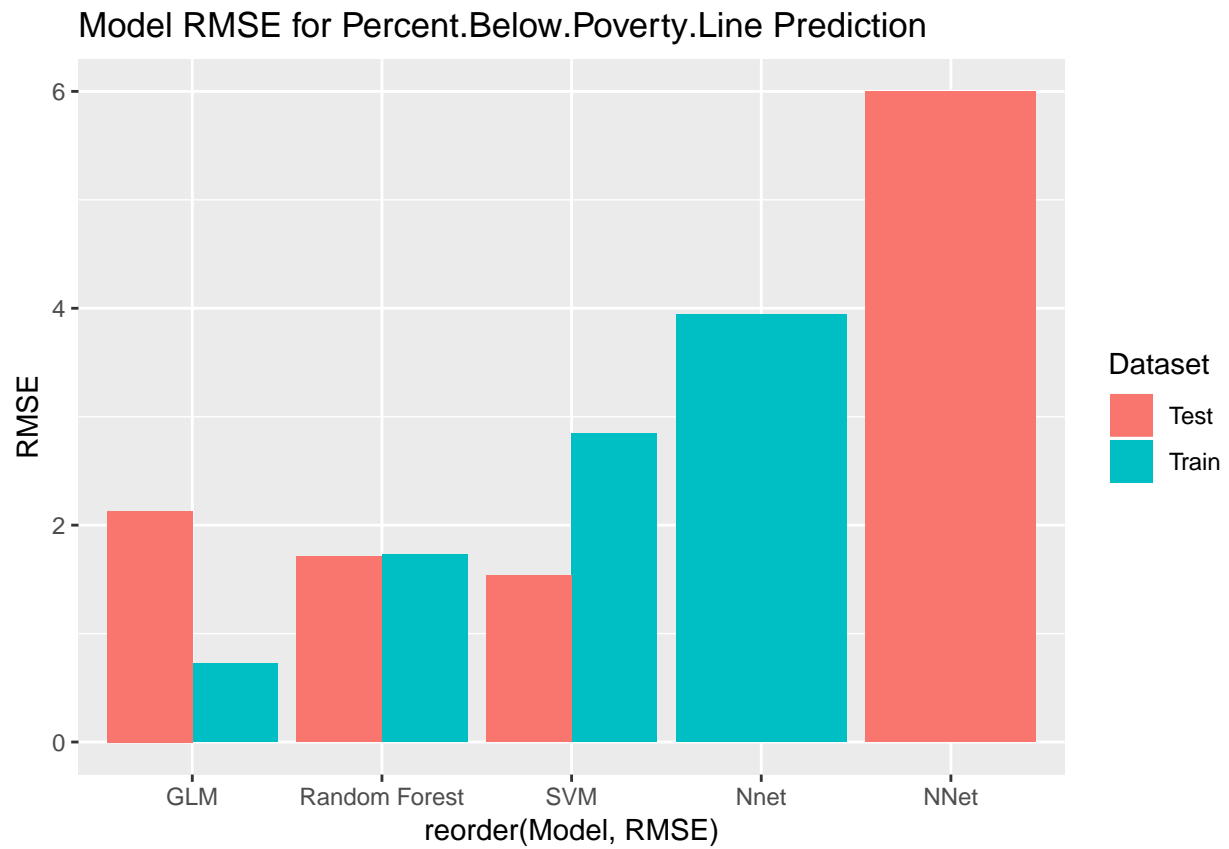


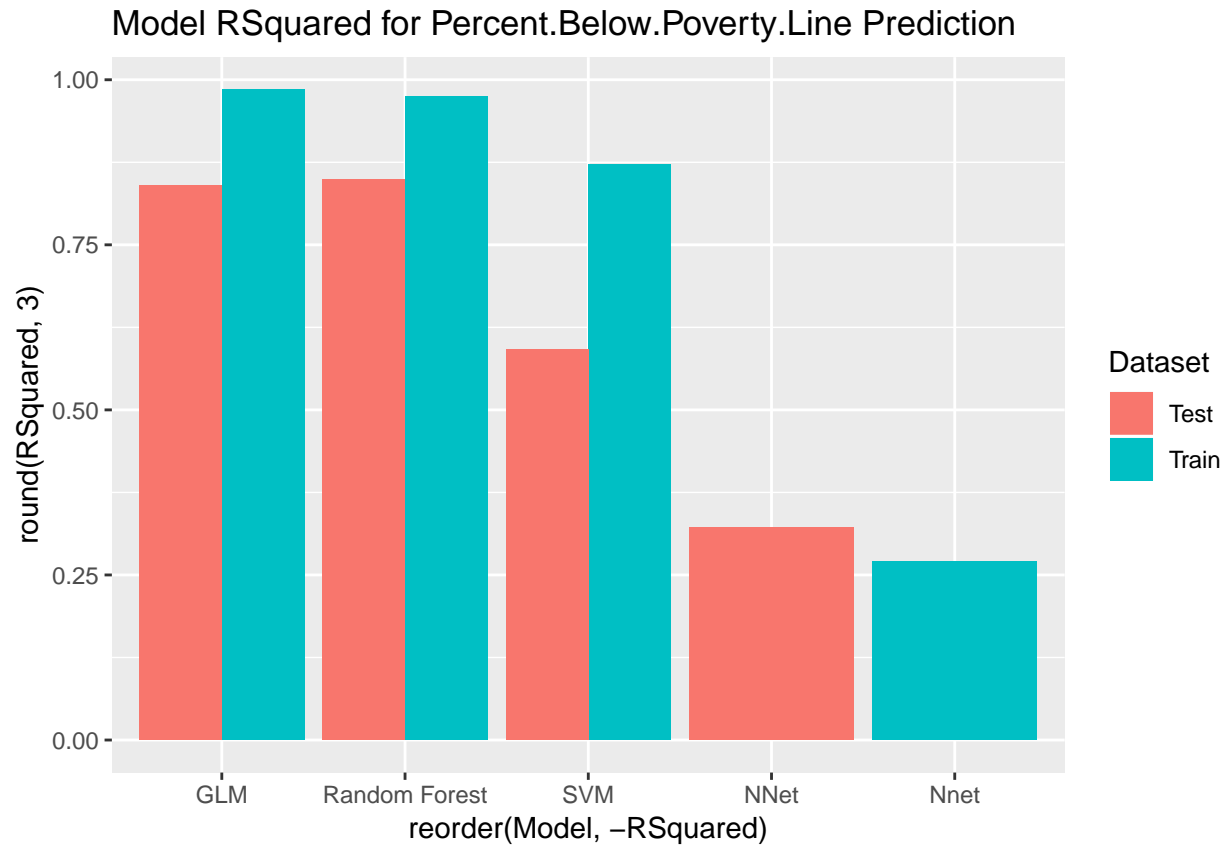


Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
GLM	0.7263871	0.9853306	2.130617	0.8400044

Conclusion: Social Indicators

Since we see that the Random Forest model produced the lowest RMSE on the withheld training data, we select it as the best model to predict poverty rates.





Finance Analysis

```
finances <- read.csv("Cleaned_Finance_Data.csv")

target <- finances$Poverty

finances$X <- NULL
finances <- as.data.frame(cbind(finances$Education,
finances$Hospitals,
finances$Health,
finances$Highways,
finances$Parks.and.recreation,
finances$Police.protection,
finances$Governmental.administration,
finances$Correction,
finances$Natural.resources,
finances$Internet,
finances$Smartphone,
finances$Computer,
finances$Public.welfare,
finances$Debt.at.end.of.fiscal.year))
```

```
preProcValues <- preProcess(finances, method = c("center", "scale", "YeoJohnson", "nzv", "corr"))
finances <- predict(preProcValues, finances)
finances
```

##	V1	V2	V3	V4	V5
## 1	2.0154243	1.995293447	-0.57917326	-0.37607281	-1.318307233
## 2	-0.6921255	-1.031508069	-0.18987493	2.12013592	-0.888184785
## 3	-0.2281786	-1.121100315	-0.91147296	-0.42041083	-0.634179079
## 4	0.3695117	0.429702237	-1.24800727	0.30664543	-0.213462852
## 5	-0.6090109	0.046418106	-0.43794742	-1.46012825	-0.840047742
## 6	1.0948297	-0.099757697	-0.64000412	-0.13220260	-0.022085522
## 7	-0.9449053	0.339346291	0.53420051	-0.50121098	-0.816401521
## 8	1.0882925	-0.954692149	1.65400025	1.18724434	1.262037746
## 9	-0.4758444	-0.734535829	1.12231946	0.93244090	-0.821404045
## 10	0.8877946	-0.294161185	0.19703717	-0.35646583	0.944460422
## 11	-1.1561363	0.209917748	0.88553354	-1.45732010	1.285614034
## 12	-0.8107949	-0.991535512	-1.08969846	-0.34368061	-0.047387939
## 13	-1.1680236	-0.471854888	-0.10885577	0.73422467	0.049957961
## 14	1.3363925	-1.014935148	-0.93683674	-0.17084199	-1.043243411
## 15	-0.1424361	1.326203588	-1.17930795	1.13491365	-1.057064104
## 16	1.0940404	3.233237492	-0.46016990	-0.10652287	-0.682004052
## 17	0.8917389	0.826890681	-0.78441524	-0.05035365	0.466663592
## 18	-0.4304863	-0.786799781	-1.06869688	-0.85446239	3.767803412
## 19	-1.3144301	-0.923366312	-0.86712647	0.21723748	-1.344646827
## 20	-0.2344486	-0.702979219	1.92329024	-0.28642860	0.523166930
## 21	-1.4248763	-0.756198929	-0.16307032	-0.60511580	0.005501044
## 22	0.7007226	0.773483277	-0.30105140	-1.00477241	-0.619671955
## 23	0.3103140	-0.916802633	-1.24044877	-0.37397036	1.399275038
## 24	0.6429537	1.386832267	-0.25164778	0.52263555	-0.301089472
## 25	-0.5041425	0.805776799	2.25272898	-1.11860816	-0.728901260
## 26	-1.1536972	-0.876079299	-0.09488102	0.31266284	-0.645250840
## 27	0.5697854	-0.585889462	0.11453195	0.32947220	0.806983763
## 28	-0.8477898	-0.708391860	-0.92437777	-0.69055746	-1.141784412
## 29	-2.1085096	-0.897297885	-1.16078953	-0.15831497	0.001935987
## 30	-0.7722884	-0.146465831	-0.47360064	-0.91213658	-0.303944381
## 31	-0.3826473	0.741768456	-0.46124763	-1.31907565	-0.197397082
## 32	-1.1655841	-0.272670706	1.52207715	-1.46558175	0.168356395
## 33	0.5733264	-0.002122108	-0.44487985	0.27668494	0.099507823
## 34	0.2880454	-1.007856216	2.03904603	2.74466665	1.236357456
## 35	-0.8343945	0.380088980	0.04985016	-0.88463889	-0.628522046
## 36	0.4373856	-0.789910604	1.24055759	0.86308333	0.045735800
## 37	-0.1606630	0.662527138	-0.13871884	-1.49646860	-0.433248286
## 38	-0.1169696	0.592914237	0.78905788	0.80412199	0.159638481
## 39	-0.7738107	-0.877925567	-0.32377570	-1.13042803	2.024461038
## 40	0.2502619	0.746588843	1.07928378	-0.03654031	0.733306341
## 41	-0.5317806	-0.992683041	0.27111750	2.13379193	2.246217986
## 42	0.3071960	-0.723995446	-0.26216792	-0.61308289	0.053815477
## 43	0.8429188	0.388689759	-0.48839725	0.04272500	-0.824584142
## 44	1.5536902	1.904277355	-0.78565440	-0.29803304	-0.367445381
## 45	3.4744730	0.186611523	0.31131526	0.58172332	0.240693473
## 46	-0.1662693	1.684191745	0.04560163	0.81788535	-0.170889884
## 47	0.5259314	1.311587033	0.62430844	-0.95668449	-0.420411919
## 48	-0.3134040	-0.809046850	-0.48930655	0.43553752	0.171599852

##	49	-0.2696155	0.627256610	-1.02830510	0.96583177	-1.466679953
##	50	0.4782341	-1.109041073	2.87805031	2.11644612	0.285150073
##		V6	V7	V8	V9	V11
##	1	-0.59410123	-0.75791548	-0.55676076	-0.36266083	-0.85303176
##	2	1.85240734	3.01156244	1.86329439	3.33086939	1.93771191
##	3	-0.27152845	-0.91904627	0.86681716	-0.63953822	0.70239950
##	4	-0.74938377	-0.40041892	-0.76180983	-0.14406542	-0.63189715
##	5	-0.76385300	-0.61690532	0.23056415	0.29802169	1.70006912
##	6	-0.16191293	-0.03613239	1.83022425	-0.01145203	1.49508438
##	7	-0.02416576	1.33087677	-0.42685611	-0.66134506	0.10971128
##	8	2.47991901	2.11032334	2.62276913	-0.02527469	0.70239950
##	9	-0.58766026	-0.50016523	0.38304152	0.22282186	0.56538944
##	10	0.52853123	-1.09515514	0.59713237	-0.32947755	0.75758616
##	11	-1.36685013	0.71652390	-1.14751869	-0.25803744	0.64743167
##	12	-0.74545340	0.04883803	0.13394956	0.75950823	-0.22825814
##	13	-0.69910206	-1.08535935	-0.90380542	-1.18479151	0.34900434
##	14	-0.36154047	-0.89395061	-0.76116252	-0.41352967	-0.50721092
##	15	-1.02893021	-0.56361856	-1.79416684	-0.13617862	-0.65667686
##	16	-0.63935413	-0.58090104	-0.72608331	-0.19893456	0.03091581
##	17	0.23735205	0.56752107	-0.08596006	-0.04318048	-1.04605564
##	18	0.75169916	-0.22995646	-0.36366934	1.23222813	-0.53225333
##	19	0.54226287	1.08275720	-0.93336875	0.15984422	-1.67322376
##	20	1.86991568	0.23783861	2.08525490	-0.02822486	1.00864341
##	21	1.90759655	0.99508841	-1.15126513	-1.03075005	0.16251022
##	22	-0.32488038	-1.34289675	0.64579864	-0.94625246	-0.30497163
##	23	0.51575115	-0.66490872	-1.60111721	0.07728868	0.32220027
##	24	0.03895392	-0.73984395	-0.39767235	-0.02321569	-0.92580483
##	25	-0.42518496	-1.27216956	0.10817477	-0.56814623	-0.20258070
##	26	-0.90236136	1.70983186	0.61511179	2.45125644	-1.18865140
##	27	0.03265672	-0.39405805	1.63175286	0.81129955	-0.09933847
##	28	-0.92327007	-0.78526135	-1.18934130	-0.73392482	1.29283995
##	29	0.11698448	0.33836887	-0.86858647	-0.74278139	0.03091581
##	30	0.52177298	-0.58264851	-0.51731393	-0.76833128	0.86861734
##	31	-0.12120995	-0.35126565	0.81702959	-0.01823167	-0.99811070
##	32	-0.79353826	-0.22302396	-0.86108737	-1.21195346	-0.07339456
##	33	1.08896125	-0.39514043	-0.05448927	-0.53569999	-0.07339456
##	34	-1.01084604	-0.25695192	-1.30897297	0.74615913	-0.12522899
##	35	-1.03666320	-0.64878324	-0.40806310	-0.97150844	-0.48211583
##	36	0.35262943	-0.20897394	0.18685437	-0.78075641	0.16251022
##	37	-0.86774909	0.86822785	-0.07962493	-0.03510225	0.64743167
##	38	0.96137692	-0.30003835	0.15516900	-0.63507192	-1.21223713
##	39	0.62551370	1.33694707	0.25469614	-0.84846475	-0.30497163
##	40	-0.42404783	-0.93559998	-1.00071121	-0.50426302	-0.04739722
##	41	0.12247398	0.40595219	-0.08167443	2.35835385	-1.39907740
##	42	0.15768827	-0.12776947	1.38836117	-0.26780207	-0.48211583
##	43	-0.03143178	-1.25859696	1.05763510	-0.88252867	1.37918154
##	44	-0.20606572	1.35581764	-0.71134587	-0.33519424	2.33161337
##	45	3.37827778	0.75158468	1.09547739	1.09977781	-1.87406020
##	46	0.21002152	0.43597798	0.92981759	-0.87717955	0.72996546
##	47	-0.15397262	-0.98309541	-0.82563575	0.28147220	1.32156480
##	48	-0.71537867	0.06846889	-0.34529625	0.57980253	-2.55553952
##	49	-1.87422591	-0.64645517	0.51013990	-0.08845452	-0.73070176
##	50	-0.48808431	2.42449933	-0.14570658	2.83360010	-0.04739722
##		V12	V13	V14		

```
## 1 -1.632990133 0.16697975 -0.78726521
## 2 1.498454015 0.04967626 0.72705235
## 3 0.725257929 1.13408690 -0.42789170
## 4 -1.555670525 0.47230536 -1.49297619
## 5 1.227835384 0.79072250 -0.11370728
## 6 1.498454015 -0.15100982 0.42880185
## 7 0.222680473 -1.82753251 2.08913427
## 8 0.995876559 0.17652525 0.37945612
## 9 0.609278516 -0.02981058 -0.82515543
## 10 0.222680473 -0.48896867 -1.12016955
## 11 0.377319690 -0.96577150 0.86696359
## 12 0.377319690 -0.95381859 -0.95368611
## 13 -0.009278353 0.14496921 1.20645470
## 14 -0.589175417 0.90323962 0.47677853
## 15 -0.318556787 -0.41884121 -1.11903977
## 16 0.145360864 -0.87522511 -0.27532700
## 17 -1.555670525 1.19963376 0.13425251
## 18 -1.671649938 0.73629662 0.45878342
## 19 -0.241237179 0.72280141 0.23545909
## 20 1.034536363 0.24291439 0.83423567
## 21 0.338659886 1.07810869 2.12384409
## 22 -0.125257766 -0.27975161 0.08236603
## 23 0.686598124 0.20706675 -0.57820823
## 24 -2.212887198 0.89890465 -0.22752550
## 25 -0.241237179 -0.40035316 0.30746652
## 26 -0.627835222 -0.21013417 -0.54816080
## 27 0.184020668 -0.37146466 -1.67192948
## 28 1.150515776 -1.12313659 -1.87007921
## 29 1.305154993 0.31446419 1.54114981
## 30 0.879897146 -0.27022332 1.55153681
## 31 -1.439691112 0.28392408 -0.41674187
## 32 -0.086597962 0.77229472 1.01366656
## 33 -0.357216592 -0.85260755 -1.02358326
## 34 0.068041256 -1.27672592 -0.20214919
## 35 -0.279896983 0.03198761 -0.39041950
## 36 -0.434536200 -0.08411378 -0.52849372
## 37 1.111855972 -0.32759027 -0.74973753
## 38 -0.898453852 0.65869411 0.28453876
## 39 -0.241237179 0.62138333 1.82768636
## 40 -0.589175417 -0.41675802 0.26184107
## 41 -0.743814635 -0.91169988 0.78884395
## 42 -1.130412678 1.34967250 -1.60198240
## 43 0.570618711 -0.31616946 -0.53172570
## 44 2.001031470 -1.22247846 -0.41397247
## 45 -0.318556787 4.39155127 0.82754974
## 46 0.570618711 -1.00769855 0.26601056
## 47 1.498454015 -0.84524193 0.60826476
## 48 -2.212887198 0.47946333 0.30136252
## 49 -0.318556787 -0.36081734 0.46539130
## 50 0.531958907 -1.83972360 -2.21896386
```

```
colnames(finances) <- c("Education", "Hospitals", "Health", "Highways", "Parks", "Police", "Administration")
finances$Poverty <- target
```


finances

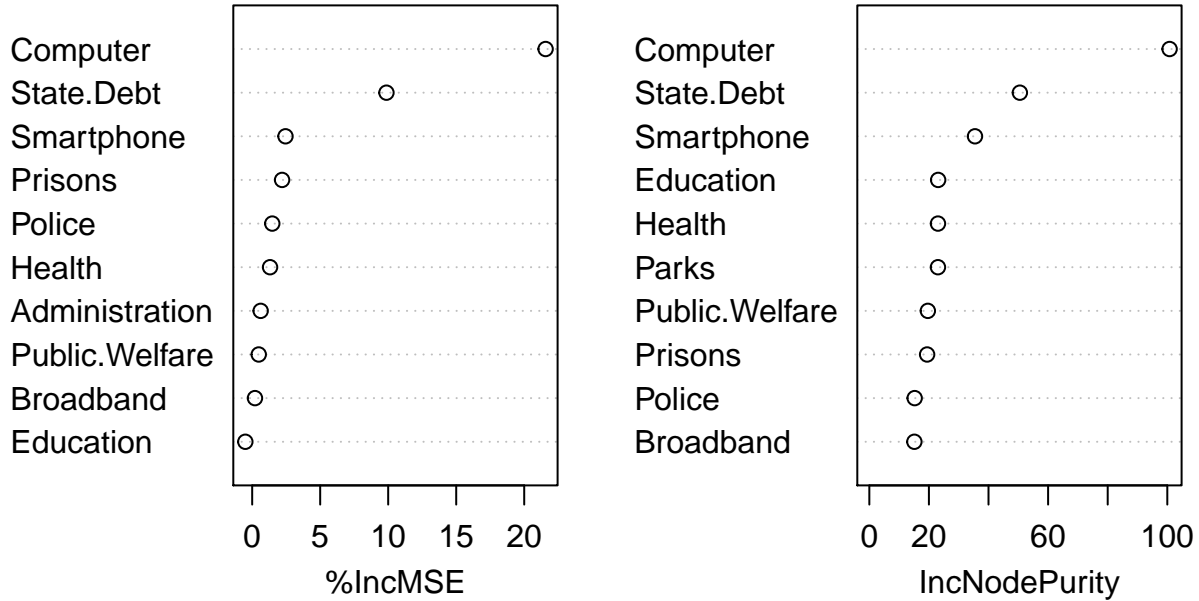
##	Education	Hospitals	Health	Highways	Parks
## 1	2.0154243	1.995293447	-0.57917326	-0.37607281	-1.318307233
## 2	-0.6921255	-1.031508069	-0.18987493	2.12013592	-0.888184785
## 3	-0.2281786	-1.121100315	-0.91147296	-0.42041083	-0.634179079
## 4	0.3695117	0.429702237	-1.24800727	0.30664543	-0.213462852
## 5	-0.6090109	0.046418106	-0.43794742	-1.46012825	-0.840047742
## 6	1.0948297	-0.099757697	-0.64000412	-0.13220260	-0.022085522
## 7	-0.9449053	0.339346291	0.53420051	-0.50121098	-0.816401521
## 8	1.0882925	-0.954692149	1.65400025	1.18724434	1.262037746
## 9	-0.4758444	-0.734535829	1.12231946	0.93244090	-0.821404045
## 10	0.8877946	-0.294161185	0.19703717	-0.35646583	0.944460422
## 11	-1.1561363	0.209917748	0.88553354	-1.45732010	1.285614034
## 12	-0.8107949	-0.991535512	-1.08969846	-0.34368061	-0.047387939
## 13	-1.1680236	-0.471854888	-0.10885577	0.73422467	0.049957961
## 14	1.3363925	-1.014935148	-0.93683674	-0.17084199	-1.043243411
## 15	-0.1424361	1.326203588	-1.17930795	1.13491365	-1.057064104
## 16	1.0940404	3.233237492	-0.46016990	-0.10652287	-0.682004052
## 17	0.8917389	0.826890681	-0.78441524	-0.05035365	0.466663592
## 18	-0.4304863	-0.786799781	-1.06869688	-0.85446239	3.767803412
## 19	-1.3144301	-0.923366312	-0.86712647	0.21723748	-1.344646827
## 20	-0.2344486	-0.702979219	1.92329024	-0.28642860	0.523166930
## 21	-1.4248763	-0.756198929	-0.16307032	-0.60511580	0.005501044
## 22	0.7007226	0.773483277	-0.30105140	-1.00477241	-0.619671955
## 23	0.3103140	-0.916802633	-1.24044877	-0.37397036	1.399275038
## 24	0.6429537	1.386832267	-0.25164778	0.52263555	-0.301089472
## 25	-0.5041425	0.805776799	2.25272898	-1.11860816	-0.728901260
## 26	-1.1536972	-0.876079299	-0.09488102	0.31266284	-0.645250840
## 27	0.5697854	-0.585889462	0.11453195	0.32947220	0.806983763
## 28	-0.8477898	-0.708391860	-0.92437777	-0.69055746	-1.141784412
## 29	-2.1085096	-0.897297885	-1.16078953	-0.15831497	0.001935987
## 30	-0.7722884	-0.146465831	-0.47360064	-0.91213658	-0.303944381
## 31	-0.3826473	0.741768456	-0.46124763	-1.31907565	-0.197397082
## 32	-1.1655841	-0.272670706	1.52207715	-1.46558175	0.168356395
## 33	0.5733264	-0.002122108	-0.44487985	0.27668494	0.099507823
## 34	0.2880454	-1.007856216	2.03904603	2.74466665	1.236357456
## 35	-0.8343945	0.380088980	0.04985016	-0.88463889	-0.628522046
## 36	0.4373856	-0.789910604	1.24055759	0.86308333	0.045735800
## 37	-0.1606630	0.662527138	-0.13871884	-1.49646860	-0.433248286
## 38	-0.1169696	0.592914237	0.78905788	0.80412199	0.159638481
## 39	-0.7738107	-0.877925567	-0.32377570	-1.13042803	2.024461038
## 40	0.2502619	0.746588843	1.07928378	-0.03654031	0.733306341
## 41	-0.5317806	-0.992683041	0.27111750	2.13379193	2.246217986
## 42	0.3071960	-0.723995446	-0.26216792	-0.61308289	0.053815477
## 43	0.8429188	0.388689759	-0.48839725	0.04272500	-0.824584142
## 44	1.5536902	1.904277355	-0.78565440	-0.29803304	-0.367445381
## 45	3.4744730	0.186611523	0.31131526	0.58172332	0.240693473
## 46	-0.1662693	1.684191745	0.04560163	0.81788535	-0.170889884
## 47	0.5259314	1.311587033	0.62430844	-0.95668449	-0.420411919
## 48	-0.3134040	-0.809046850	-0.48930655	0.43553752	0.171599852
## 49	-0.2696155	0.627256610	-1.02830510	0.96583177	-1.466679953
## 50	0.4782341	-1.109041073	2.87805031	2.11644612	0.285150073

##	Police	Administration	Prisons	Broadband	Smartphone
## 1	-0.59410123	-0.75791548	-0.55676076	-0.36266083	-0.85303176
## 2	1.85240734	3.01156244	1.86329439	3.33086939	1.93771191
## 3	-0.27152845	-0.91904627	0.86681716	-0.63953822	0.70239950
## 4	-0.74938377	-0.40041892	-0.76180983	-0.14406542	-0.63189715
## 5	-0.76385300	-0.61690532	0.23056415	0.29802169	1.70006912
## 6	-0.16191293	-0.03613239	1.83022425	-0.01145203	1.49508438
## 7	-0.02416576	1.33087677	-0.42685611	-0.66134506	0.10971128
## 8	2.47991901	2.11032334	2.62276913	-0.02527469	0.70239950
## 9	-0.58766026	-0.50016523	0.38304152	0.22282186	0.56538944
## 10	0.52853123	-1.09515514	0.59713237	-0.32947755	0.75758616
## 11	-1.36685013	0.71652390	-1.14751869	-0.25803744	0.64743167
## 12	-0.74545340	0.04883803	0.13394956	0.75950823	-0.22825814
## 13	-0.69910206	-1.08535935	-0.90380542	-1.18479151	0.34900434
## 14	-0.36154047	-0.89395061	-0.76116252	-0.41352967	-0.50721092
## 15	-1.02893021	-0.56361856	-1.79416684	-0.13617862	-0.65667686
## 16	-0.63935413	-0.58090104	-0.72608331	-0.19893456	0.03091581
## 17	0.23735205	0.56752107	-0.08596006	-0.04318048	-1.04605564
## 18	0.75169916	-0.22995646	-0.36366934	1.23222813	-0.53225333
## 19	0.54226287	1.08275720	-0.93336875	0.15984422	-1.67322376
## 20	1.86991568	0.23783861	2.08525490	-0.02822486	1.00864341
## 21	1.90759655	0.99508841	-1.15126513	-1.03075005	0.16251022
## 22	-0.32488038	-1.34289675	0.64579864	-0.94625246	-0.30497163
## 23	0.51575115	-0.66490872	-1.60111721	0.07728868	0.32220027
## 24	0.03895392	-0.73984395	-0.39767235	-0.02321569	-0.92580483
## 25	-0.42518496	-1.27216956	0.10817477	-0.56814623	-0.20258070
## 26	-0.90236136	1.70983186	0.61511179	2.45125644	-1.18865140
## 27	0.03265672	-0.39405805	1.63175286	0.81129955	-0.09933847
## 28	-0.92327007	-0.78526135	-1.18934130	-0.73392482	1.29283995
## 29	0.11698448	0.33836887	-0.86858647	-0.74278139	0.03091581
## 30	0.52177298	-0.58264851	-0.51731393	-0.76833128	0.86861734
## 31	-0.12120995	-0.35126565	0.81702959	-0.01823167	-0.99811070
## 32	-0.79353826	-0.22302396	-0.86108737	-1.21195346	-0.07339456
## 33	1.08896125	-0.39514043	-0.05448927	-0.53569999	-0.07339456
## 34	-1.01084604	-0.25695192	-1.30897297	0.74615913	-0.12522899
## 35	-1.03666320	-0.64878324	-0.40806310	-0.97150844	-0.48211583
## 36	0.35262943	-0.20897394	0.18685437	-0.78075641	0.16251022
## 37	-0.86774909	0.86822785	-0.07962493	-0.03510225	0.64743167
## 38	0.96137692	-0.30003835	0.15516900	-0.63507192	-1.21223713
## 39	0.62551370	1.33694707	0.25469614	-0.84846475	-0.30497163
## 40	-0.42404783	-0.93559998	-1.00071121	-0.50426302	-0.04739722
## 41	0.12247398	0.40595219	-0.08167443	2.35835385	-1.39907740
## 42	0.15768827	-0.12776947	1.38836117	-0.26780207	-0.48211583
## 43	-0.03143178	-1.25859696	1.05763510	-0.88252867	1.37918154
## 44	-0.20606572	1.35581764	-0.71134587	-0.33519424	2.33161337
## 45	3.37827778	0.75158468	1.09547739	1.09977781	-1.87406020
## 46	0.21002152	0.43597798	0.92981759	-0.87717955	0.72996546
## 47	-0.15397262	-0.98309541	-0.82563575	0.28147220	1.32156480
## 48	-0.71537867	0.06846889	-0.34529625	0.57980253	-2.55553952
## 49	-1.87422591	-0.64645517	0.51013990	-0.08845452	-0.73070176
## 50	-0.48808431	2.42449933	-0.14570658	2.83360010	-0.04739722
##	Computer	Public.Welfare	State.Debt	Poverty	
## 1	-1.632990133	0.16697975	-0.78726521	29.1	
## 2	1.498454015	0.04967626	0.72705235	21.0	

## 3	0.725257929	1.13408690	-0.42789170	24.6
## 4	-1.555670525	0.47230536	-1.49297619	30.7
## 5	1.227835384	0.79072250	-0.11370728	25.5
## 6	1.498454015	-0.15100982	0.42880185	21.0
## 7	0.222680473	-1.82753251	2.08913427	20.1
## 8	0.995876559	0.17652525	0.37945612	26.7
## 9	0.609278516	-0.02981058	-0.82515543	24.9
## 10	0.222680473	-0.48896867	-1.12016955	26.0
## 11	0.377319690	-0.96577150	0.86696359	23.4
## 12	0.377319690	-0.95381859	-0.95368611	27.8
## 13	-0.009278353	0.14496921	1.20645470	23.4
## 14	-0.589175417	0.90323962	0.47677853	26.5
## 15	-0.318556787	-0.41884121	-1.11903977	23.6
## 16	0.145360864	-0.87522511	-0.27532700	25.2
## 17	-1.555670525	1.19963376	0.13425251	31.0
## 18	-1.671649938	0.73629662	0.45878342	31.8
## 19	-0.241237179	0.72280141	0.23545909	25.0
## 20	1.034536363	0.24291439	0.83423567	20.1
## 21	0.338659886	1.07810869	2.12384409	21.2
## 22	-0.125257766	-0.27975161	0.08236603	26.2
## 23	0.686598124	0.20706675	-0.57820823	20.7
## 24	-2.212887198	0.89890465	-0.22752550	34.1
## 25	-0.241237179	-0.40035316	0.30746652	25.2
## 26	-0.627835222	-0.21013417	-0.54816080	24.8
## 27	0.184020668	-0.37146466	-1.67192948	21.8
## 28	1.150515776	-1.12313659	-1.87007921	23.1
## 29	1.305154993	0.31446419	1.54114981	17.5
## 30	0.879897146	-0.27022332	1.55153681	21.2
## 31	-1.439691112	0.28392408	-0.41674187	28.8
## 32	-0.086597962	0.77229472	1.01366656	24.5
## 33	-0.357216592	-0.85260755	-1.02358326	25.8
## 34	0.068041256	-1.27672592	-0.20214919	22.7
## 35	-0.279896983	0.03198761	-0.39041950	25.4
## 36	-0.434536200	-0.08411378	-0.52849372	27.9
## 37	1.111855972	-0.32759027	-0.74973753	25.8
## 38	-0.898453852	0.65869411	0.28453876	25.6
## 39	-0.241237179	0.62138333	1.82768636	22.7
## 40	-0.589175417	-0.41675802	0.26184107	26.9
## 41	-0.743814635	-0.91169988	0.78884395	22.9
## 42	-1.130412678	1.34967250	-1.60198240	26.5
## 43	0.570618711	-0.31616946	-0.53172570	24.9
## 44	2.001031470	-1.22247846	-0.41397247	26.4
## 45	-0.318556787	4.39155127	0.82754974	22.2
## 46	0.570618711	-1.00769855	0.26601056	22.7
## 47	1.498454015	-0.84524193	0.60826476	22.5
## 48	-2.212887198	0.47946333	0.30136252	33.7
## 49	-0.318556787	-0.36081734	0.46539130	23.2
## 50	0.531958907	-1.83972360	-2.21896386	23.0

NULL

Important Variables in Random Forest Model (top 10 shown)



##	Education	Hospitals	Health	Highways	Parks
## 1	2.0154243	1.995293447	-0.57917326	-0.37607281	-1.318307233
## 3	-0.2281786	-1.121100315	-0.91147296	-0.42041083	-0.634179079
## 6	1.0948297	-0.099757697	-0.64000412	-0.13220260	-0.022085522
## 7	-0.9449053	0.339346291	0.53420051	-0.50121098	-0.816401521
## 9	-0.4758444	-0.734535829	1.12231946	0.93244090	-0.821404045
## 10	0.8877946	-0.294161185	0.19703717	-0.35646583	0.944460422
## 12	-0.8107949	-0.991535512	-1.08969846	-0.34368061	-0.047387939
## 13	-1.1680236	-0.471854888	-0.10885577	0.73422467	0.049957961
## 14	1.3363925	-1.014935148	-0.93683674	-0.17084199	-1.043243411
## 15	-0.1424361	1.326203588	-1.17930795	1.13491365	-1.057064104
## 17	0.8917389	0.826890681	-0.78441524	-0.05035365	0.466663592
## 18	-0.4304863	-0.786799781	-1.06869688	-0.85446239	3.767803412
## 19	-1.3144301	-0.923366312	-0.86712647	0.21723748	-1.344646827
## 22	0.7007226	0.773483277	-0.30105140	-1.00477241	-0.619671955
## 23	0.3103140	-0.916802633	-1.24044877	-0.37397036	1.399275038
## 25	-0.5041425	0.805776799	2.25272898	-1.11860816	-0.728901260
## 26	-1.1536972	-0.876079299	-0.09488102	0.31266284	-0.645250840
## 27	0.5697854	-0.585889462	0.11453195	0.32947220	0.806983763
## 28	-0.8477898	-0.708391860	-0.92437777	-0.69055746	-1.141784412
## 29	-2.1085096	-0.897297885	-1.16078953	-0.15831497	0.001935987
## 30	-0.7722884	-0.146465831	-0.47360064	-0.91213658	-0.303944381
## 33	0.5733264	-0.002122108	-0.44487985	0.27668494	0.099507823
## 35	-0.8343945	0.380088980	0.04985016	-0.88463889	-0.628522046
## 36	0.4373856	-0.789910604	1.24055759	0.86308333	0.045735800
## 37	-0.1606630	0.662527138	-0.13871884	-1.49646860	-0.433248286

## 38	-0.1169696	0.592914237	0.78905788	0.80412199	0.159638481
## 39	-0.7738107	-0.877925567	-0.32377570	-1.13042803	2.024461038
## 40	0.2502619	0.746588843	1.07928378	-0.03654031	0.733306341
## 41	-0.5317806	-0.992683041	0.27111750	2.13379193	2.246217986
## 42	0.3071960	-0.723995446	-0.26216792	-0.61308289	0.053815477
## 43	0.8429188	0.388689759	-0.48839725	0.04272500	-0.824584142
## 44	1.5536902	1.904277355	-0.78565440	-0.29803304	-0.367445381
## 45	3.4744730	0.186611523	0.31131526	0.58172332	0.240693473
## 46	-0.1662693	1.684191745	0.04560163	0.81788535	-0.170889884
## 47	0.5259314	1.311587033	0.62430844	-0.95668449	-0.420411919
## 48	-0.3134040	-0.809046850	-0.48930655	0.43553752	0.171599852
## 49	-0.2696155	0.627256610	-1.02830510	0.96583177	-1.466679953
##	Police	Administration	Prisons	Broadband	Smartphone
## 1	-0.59410123	-0.75791548	-0.55676076	-0.36266083	-0.85303176
## 3	-0.27152845	-0.91904627	0.86681716	-0.63953822	0.70239950
## 6	-0.16191293	-0.03613239	1.83022425	-0.01145203	1.49508438
## 7	-0.02416576	1.33087677	-0.42685611	-0.66134506	0.10971128
## 9	-0.58766026	-0.50016523	0.38304152	0.22282186	0.56538944
## 10	0.52853123	-1.09515514	0.59713237	-0.32947755	0.75758616
## 12	-0.74545340	0.04883803	0.13394956	0.75950823	-0.22825814
## 13	-0.69910206	-1.08535935	-0.90380542	-1.18479151	0.34900434
## 14	-0.36154047	-0.89395061	-0.76116252	-0.41352967	-0.50721092
## 15	-1.02893021	-0.56361856	-1.79416684	-0.13617862	-0.65667686
## 17	0.23735205	0.56752107	-0.08596006	-0.04318048	-1.04605564
## 18	0.75169916	-0.22995646	-0.36366934	1.23222813	-0.53225333
## 19	0.54226287	1.08275720	-0.93336875	0.15984422	-1.67322376
## 22	-0.32488038	-1.34289675	0.64579864	-0.94625246	-0.30497163
## 23	0.51575115	-0.66490872	-1.60111721	0.07728868	0.32220027
## 25	-0.42518496	-1.27216956	0.10817477	-0.56814623	-0.20258070
## 26	-0.90236136	1.70983186	0.61511179	2.45125644	-1.18865140
## 27	0.03265672	-0.39405805	1.63175286	0.81129955	-0.09933847
## 28	-0.92327007	-0.78526135	-1.18934130	-0.73392482	1.29283995
## 29	0.11698448	0.33836887	-0.86858647	-0.74278139	0.03091581
## 30	0.52177298	-0.58264851	-0.51731393	-0.76833128	0.86861734
## 33	1.08896125	-0.39514043	-0.05448927	-0.53569999	-0.07339456
## 35	-1.03666320	-0.64878324	-0.40806310	-0.97150844	-0.48211583
## 36	0.35262943	-0.20897394	0.18685437	-0.78075641	0.16251022
## 37	-0.86774909	0.86822785	-0.07962493	-0.03510225	0.64743167
## 38	0.96137692	-0.30003835	0.15516900	-0.63507192	-1.21223713
## 39	0.62551370	1.33694707	0.25469614	-0.84846475	-0.30497163
## 40	-0.42404783	-0.93559998	-1.00071121	-0.50426302	-0.04739722
## 41	0.12247398	0.40595219	-0.08167443	2.35835385	-1.39907740
## 42	0.15768827	-0.12776947	1.38836117	-0.26780207	-0.48211583
## 43	-0.03143178	-1.25859696	1.05763510	-0.88252867	1.37918154
## 44	-0.20606572	1.35581764	-0.71134587	-0.33519424	2.33161337
## 45	3.37827778	0.75158468	1.09547739	1.09977781	-1.87406020
## 46	0.21002152	0.43597798	0.92981759	-0.87717955	0.72996546
## 47	-0.15397262	-0.98309541	-0.82563575	0.28147220	1.32156480
## 48	-0.71537867	0.06846889	-0.34529625	0.57980253	-2.55553952
## 49	-1.87422591	-0.64645517	0.51013990	-0.08845452	-0.73070176
##	Computer	Public.Welfare	State.Debt	Poverty	
## 1	-1.632990133	0.16697975	-0.78726521	29.1	
## 3	0.725257929	1.13408690	-0.42789170	24.6	
## 6	1.498454015	-0.15100982	0.42880185	21.0	

```

## 7  0.222680473 -1.82753251 2.08913427 20.1
## 9  0.609278516 -0.02981058 -0.82515543 24.9
## 10 0.222680473 -0.48896867 -1.12016955 26.0
## 12 0.377319690 -0.95381859 -0.95368611 27.8
## 13 -0.009278353 0.14496921 1.20645470 23.4
## 14 -0.589175417 0.90323962 0.47677853 26.5
## 15 -0.318556787 -0.41884121 -1.11903977 23.6
## 17 -1.555670525 1.19963376 0.13425251 31.0
## 18 -1.671649938 0.73629662 0.45878342 31.8
## 19 -0.241237179 0.72280141 0.23545909 25.0
## 22 -0.125257766 -0.27975161 0.08236603 26.2
## 23 0.686598124 0.20706675 -0.57820823 20.7
## 25 -0.241237179 -0.40035316 0.30746652 25.2
## 26 -0.627835222 -0.21013417 -0.54816080 24.8
## 27 0.184020668 -0.37146466 -1.67192948 21.8
## 28 1.150515776 -1.12313659 -1.87007921 23.1
## 29 1.305154993 0.31446419 1.54114981 17.5
## 30 0.879897146 -0.27022332 1.55153681 21.2
## 33 -0.357216592 -0.85260755 -1.02358326 25.8
## 35 -0.279896983 0.03198761 -0.39041950 25.4
## 36 -0.434536200 -0.08411378 -0.52849372 27.9
## 37 1.111855972 -0.32759027 -0.74973753 25.8
## 38 -0.898453852 0.65869411 0.28453876 25.6
## 39 -0.241237179 0.62138333 1.82768636 22.7
## 40 -0.589175417 -0.41675802 0.26184107 26.9
## 41 -0.743814635 -0.91169988 0.78884395 22.9
## 42 -1.130412678 1.34967250 -1.60198240 26.5
## 43 0.570618711 -0.31616946 -0.53172570 24.9
## 44 2.001031470 -1.22247846 -0.41397247 26.4
## 45 -0.318556787 4.39155127 0.82754974 22.2
## 46 0.570618711 -1.00769855 0.26601056 22.7
## 47 1.498454015 -0.84524193 0.60826476 22.5
## 48 -2.212887198 0.47946333 0.30136252 33.7
## 49 -0.318556787 -0.36081734 0.46539130 23.2

```

Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
Random Forest	1.083638	0.9656586	2.220804	0.8002246

Model	RMSE.train	RSquared.train	RMSE.test	RSquared.test
GLM	1.957209	0.6317318	2.005328	0.7493103

Next Steps

There are many ways we can continue improving the model performance, one method could be running more times of cross validation on more folds than 3 times 3-fold we have now for SVM and GBM models. It would take a longer time to compute, but the results would likely be better. Finally, more data would help us build a better model, in particular because the gap between the test and train sets tends to be relatively large across all of the models, with the exception of the Random Forest regressor because it builds its model over 1000 iterations.

We could also use time-series data to examine causal relationships between the data.

References

TO DO: APA format

1. Random Forests. https://uc-r.github.io/random_forests
2. Kevin Murphy (2012). Machine Learning a Probabilistic Perspective.
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5. Kuhn et al (2013). Applied Predictive Modeling