ps1

October 22, 2024

#Predicting Happiness

In this problem set you will work with a data set from the World Happiness Website.

You will use the data in the file, WHR2018Chapter2OnlineData.xls.

Our goal will be to develop a model for happiness.

1 [DSLC Stage 1]: Domain Problem and Data Collection

Read the description of the data at the World Happiness Website.

TODO: Add a text cell to answer the following questions:

1. From your new domain knowledge, what variable will you use as a response or dependent variable for your model of happiness?

The response variable is average self-reported happiness (SWB, subjective well being) per capita as measured by the Cantril Ladder, in which 10 means the best possible life and 0 means the worst.

2. From your new domain knowledge, what variables will you consider as potential predictor (or independent) variables?

The predictor variables are

- GDP per capita as reported by the World Bank in September 2017, social support (average response to the question "If you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?", with 1 meaning yes and 0 meaning no, as reported by Gallup World Poll)
- healthy life expectancy at birth (extrapolated from WHO and WDI life and healthy life expectancy data)
- freedom (average response to "Are you satisfied or dissatisfied with your freedom to choose what you do with your life?")
- corruption (average response to 2 GWP questions: "Is corruption widespread throughout the government or not?" and "Is corruption widespread within businesses or not?", with the latter used if the former is missing)
- generosity (average donations to charity, regressed to average GDP).
- positive affect (GWP measures for previous-day happiness, laughter, and enjoyment)
- negative affect (GWP measures for previous-day worry, sadness, and anger)
- inequality of household income (from GWP and World Bank, based on self reported income in both and government statistics in the latter)

- confidence in national government (GWP, "Do you have confidence in [the national government]")
- demoncratic and delivery quality of governance (WGI, based 6 other variables and transformed to have STD 1 and mean 0)
- trust (World Value Surveys, "...would you say that most people can be trusted or that you need to be very careful in dealing with people?")

Country and year could also act as predictor variables, but are used as primary keys in the dataset.

3. From your new domain knowledge, can you identify any variables that are cofounders?

All of the variables may, in theory, confound one another. Affect may be a confounded variable, since things that affect happiness likely also affect affect. Confidence, trust, government quality, and corruption may all confound one another. GDP also likely confounds many variables, like life expectancy, freedom, corruption, and trust.

4. Please share one question that you still have about the data collection process.

A question I have is how the generosity is regressed on GDP per capita. Does this eliminate the confound, or would it still exist? In addition, the GINI index was poorly defined in the report and appendices, what does it actually measure?

2 [DSLC stage 2]: Data cleaning, pre-processing, and exploratory data analysis

In this section you will load and clean the data. Please run the code provide and complete modifications as specified.

[1]:
```
# Installing scikit-lego package
%pip install scikit-lego kaleido
import plotly.io as pio
pio.renderers.default = "pdf"
```

```
Requirement already satisfied: scikit-lego in ./.venv/lib/python3.12/site-
packages (0.9.1)
Requirement already satisfied: kaleido in ./.venv/lib/python3.12/site-packages
(0.1.0)
Requirement already satisfied: narwhals>=1.0.0 in ./.venv/lib/python3.12/site-
packages (from scikit-lego) (1.10.0)
Requirement already satisfied: pandas>=1.1.5 in ./.venv/lib/python3.12/site-
packages (from scikit-lego) (2.2.3)
Requirement already satisfied: scikit-learn>=1.0 in ./.venv/lib/python3.12/site-
packages (from scikit-lego) (1.5.2)
Requirement already satisfied: numpy>=1.26.0 in ./.venv/lib/python3.12/site-
packages (from pandas>=1.1.5->scikit-lego) (2.1.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
./.venv/lib/python3.12/site-packages (from pandas>=1.1.5->scikit-lego)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in ./.venv/lib/python3.12/site-
packages (from pandas>=1.1.5->scikit-lego) (2024.2)
```

```
Requirement already satisfied: tzdata>=2022.7 in ./.venv/lib/python3.12/site-
packages (from pandas>=1.1.5->scikit-lego) (2024.2)
Requirement already satisfied: scipy>=1.6.0 in ./.venv/lib/python3.12/site-
packages (from scikit-learn>=1.0->scikit-lego) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in ./.venv/lib/python3.12/site-
packages (from scikit-learn>=1.0->scikit-lego) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
./.venv/lib/python3.12/site-packages (from scikit-learn>=1.0->scikit-lego)
(3.5.0)
Requirement already satisfied: six>=1.5 in ./.venv/lib/python3.12/site-packages
(from python-dateutil>=2.8.2->pandas>=1.1.5->scikit-lego) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[2]:
```
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
from sklego.linear_model import LADRegression



pd.set_option('display.max_columns', None)
pd.options.display.max_colwidth = 500
pd.options.display.max_rows = 100
```

[3]:
```
# load the happiness data in file WHR2018Chapter2OnlineData.xls
# Upload this file using the folder to left
happiness_orig = pd.read_excel("WHR2018Chapter2OnlineData.xls", sheet_name=0)
happiness_orig
```

[3]:

	country	year	Life Ladder	Log GDP per capita	Social support	\
0	Afghanistan	2008	3.723590	7.168690	0.450662	
1	Afghanistan	2009	4.401778	7.333790	0.552308	
2	Afghanistan	2010	4.758381	7.386629	0.539075	
3	Afghanistan	2011	3.831719	7.415019	0.521104	
4	Afghanistan	2012	3.782938	7.517126	0.520637	
…	…	…	…	…	…	
1557	Zimbabwe	2013	4.690188	7.565154	0.799274	
1558	Zimbabwe	2014	4.184451	7.562753	0.765839	
1559	Zimbabwe	2015	3.703191	7.556052	0.735800	
1560	Zimbabwe	2016	3.735400	7.538829	0.768425	
1561	Zimbabwe	2017	3.638300	7.538187	0.754147	

Healthy life expectancy at birth	Freedom to make life choices	\

0	49.209663	0.718114
1	49.624432	0.678896
2	50.008961	0.600127
3	50.367298	0.495901
4	50.709263	0.530935
…	…	…
1557	48.949745	0.575884
1558	50.051235	0.642034
1559	50.925652	0.667193
1560	51.800068	0.732971
1561	52.674484	0.752826

	Generosity	Perceptions of corruption	Positive affect	Negative affect	\
0	0.181819	0.881686	0.517637	0.258195	
1	0.203614	0.850035	0.583926	0.237092	
2	0.137630	0.706766	0.618265	0.275324	
3	0.175329	0.731109	0.611387	0.267175	
4	0.247159	0.775620	0.710385	0.267919	
…	…	…	…	…	
1557	-0.076716	0.830937	0.711885	0.182288	
1558	-0.045885	0.820217	0.725214	0.239111	
1559	-0.094585	0.810457	0.715079	0.178861	
1560	-0.065283	0.723612	0.737636	0.208555	
1561	-0.066005	0.751208	0.806428	0.224051	

	Confidence in national government	Democratic Quality	Delivery Quality	\
0	0.612072	-1.929690	-1.655084	
1	0.611545	-2.044093	-1.635025	
2	0.299357	-1.991810	-1.617176	
3	0.307386	-1.919018	-1.616221	
4	0.435440	-1.842996	-1.404078	
…	…	…	…	
1557	0.527755	-1.026085	-1.526321	
1558	0.566209	-0.985267	-1.484067	
1559	0.590012	-0.893078	-1.357514	
1560	0.699344	-0.863044	-1.371214	
1561	0.682647	NaN	NaN	

	Standard deviation of ladder by country-year	\
0	1.774662	
1	1.722688	
2	1.878622	
3	1.785360	
4	1.798283	
…	…	
1557	1.964805	
1558	2.079248	

```
1559                                    2.198865
1560                                    2.776363
1561                                    2.656848

      Standard deviation/Mean of ladder by country-year  \
0                                                0.476600
1                                                0.391362
2                                                0.394803
3                                                0.465942
4                                                0.475367
…                                                   …
1557                                             0.418918
1558                                             0.496899
1559                                             0.593776
1560                                             0.743257
1561                                             0.730244

      GINI index (World Bank estimate)  \
0                                  NaN
1                                  NaN
2                                  NaN
3                                  NaN
4                                  NaN
…                                  …
1557                               NaN
1558                               NaN
1559                               NaN
1560                               NaN
1561                               NaN

      GINI index (World Bank estimate), average 2000-15  \
0                                                   NaN
1                                                   NaN
2                                                   NaN
3                                                   NaN
4                                                   NaN
…                                                   …
1557                                              0.432
1558                                              0.432
1559                                              0.432
1560                                              0.432
1561                                              0.432

      gini of household income reported in Gallup, by wp5-year
0                                                          NaN
1                                                     0.441906
2                                                     0.327318
```

```
3                                                    0.336764
4                                                    0.344540
…                                                         …
1557                                                 0.555439
1558                                                 0.601080
1559                                                 0.655137
1560                                                 0.596690
1561                                                 0.581484

[1562 rows x 19 columns]
```

[4]:
```
# Examine the first 10 rows
happiness_orig.head(10)
```

[4]:

	country	year	Life Ladder	Log GDP per capita	Social support	\
0	Afghanistan	2008	3.723590	7.168690	0.450662	
1	Afghanistan	2009	4.401778	7.333790	0.552308	
2	Afghanistan	2010	4.758381	7.386629	0.539075	
3	Afghanistan	2011	3.831719	7.415019	0.521104	
4	Afghanistan	2012	3.782938	7.517126	0.520637	
5	Afghanistan	2013	3.572100	7.503376	0.483552	
6	Afghanistan	2014	3.130896	7.484583	0.525568	
7	Afghanistan	2015	3.982855	7.466215	0.528597	
8	Afghanistan	2016	4.220169	7.461401	0.559072	
9	Afghanistan	2017	2.661718	7.460144	0.490880	

	Healthy life expectancy at birth	Freedom to make life choices	Generosity	\
0	49.209663	0.718114	0.181819	
1	49.624432	0.678896	0.203614	
2	50.008961	0.600127	0.137630	
3	50.367298	0.495901	0.175329	
4	50.709263	0.530935	0.247159	
5	51.042980	0.577955	0.074735	
6	51.370525	0.508514	0.118579	
7	51.693527	0.388928	0.094686	
8	52.016529	0.522566	0.057072	
9	52.339527	0.427011	-0.106340	

	Perceptions of corruption	Positive affect	Negative affect	\
0	0.881686	0.517637	0.258195	
1	0.850035	0.583926	0.237092	
2	0.706766	0.618265	0.275324	
3	0.731109	0.611387	0.267175	
4	0.775620	0.710385	0.267919	
5	0.823204	0.620585	0.273328	
6	0.871242	0.531691	0.374861	
7	0.880638	0.553553	0.339276	

8	0.793246	0.564953	0.348332
9	0.954393	0.496349	0.371326

	Confidence in national government	Democratic Quality	Delivery Quality
0	0.612072	-1.929690	-1.655084
1	0.611545	-2.044093	-1.635025
2	0.299357	-1.991810	-1.617176
3	0.307386	-1.919018	-1.616221
4	0.435440	-1.842996	-1.404078
5	0.482847	-1.879709	-1.403036
6	0.409048	-1.773257	-1.312503
7	0.260557	-1.844364	-1.291594
8	0.324990	-1.917693	-1.432548
9	0.261179	NaN	NaN

	Standard deviation of ladder by country-year
0	1.774662
1	1.722688
2	1.878622
3	1.785360
4	1.798283
5	1.223690
6	1.395396
7	2.160618
8	1.796219
9	1.454051

	Standard deviation/Mean of ladder by country-year
0	0.476600
1	0.391362
2	0.394803
3	0.465942
4	0.475367
5	0.342569
6	0.445686
7	0.542480
8	0.425627
9	0.546283

	GINI index (World Bank estimate)
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN

```
7                                NaN
8                                NaN
9                                NaN

   GINI index (World Bank estimate), average 2000-15  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN
5                                                NaN
6                                                NaN
7                                                NaN
8                                                NaN
9                                                NaN

   gini of household income reported in Gallup, by wp5-year
0                                                        NaN
1                                                   0.441906
2                                                   0.327318
3                                                   0.336764
4                                                   0.344540
5                                                   0.304368
6                                                   0.413974
7                                                   0.596918
8                                                   0.418629
9                                                   0.286599
```

[5]:
```
happiness_orig.sample(10)
```

[5]:
```
                country  year  Life Ladder  Log GDP per capita  \
539              Guinea  2017     4.873723            7.527477
678             Jamaica  2017     5.889759            9.025865
280               China  2009     4.454361            9.065514
142              Bhutan  2013     5.569092            8.863728
1252  Somaliland region  2011     4.930572                 NaN
36            Argentina  2012     6.468387            9.863960
1002          Nicaragua  2011     5.385705            8.350311
240              Canada  2009     7.487824           10.594738
855             Malaysia  2009     5.384702            9.908088
472               Gabon  2016     4.831764            9.728300

      Social support  Healthy life expectancy at birth  \
539         0.634026                         51.151817
678         0.913030                         65.818794
280         0.798034                         68.057518
142         0.818949                         59.889400
```

```
1252       0.787962                            NaN
36         0.901776                      66.836693
1002       0.800305                      64.795502
240        0.942845                      71.074837
855        0.791666                      64.084656
472        0.780049                      56.713547

      Freedom to make life choices  Generosity  Perceptions of corruption  \
539                       0.738213    0.054308                   0.750026
678                       0.860676   -0.130833                   0.882796
280                       0.771143   -0.177194                        NaN
142                       0.810201    0.360623                   0.802428
1252                      0.858104         NaN                   0.357341
36                        0.747498   -0.148023                   0.816546
1002                      0.778591   -0.017413                   0.760243
240                       0.915058    0.232484                   0.412622
855                       0.874320   -0.027878                   0.858095
472                       0.698942   -0.226151                   0.816564

      Positive affect  Negative affect  Confidence in national government  \
539          0.704477         0.422461                           0.639981
678          0.769282         0.243400                           0.348202
280          0.785806         0.161650                                NaN
142          0.778723         0.217350                           0.979501
1252         0.748686         0.122244                           0.760764
36           0.856516         0.272219                           0.418255
1002         0.791432         0.309019                           0.539968
240          0.867433         0.247633                           0.608264
855          0.821611         0.163550                           0.818659
472          0.640117         0.432405                           0.378070

      Democratic Quality  Delivery Quality  \
539                  NaN               NaN
678                  NaN               NaN
280            -1.075259         -0.263004
142             0.312921          0.128376
1252                 NaN               NaN
36              0.199125         -0.572653
1002           -0.423233         -0.673453
240             1.264292          1.827809
855            -0.273138          0.421721
472            -0.516068         -0.730402

      Standard deviation of ladder by country-year  \
539                                       2.969935
678                                       2.399338
280                                       1.828763
```

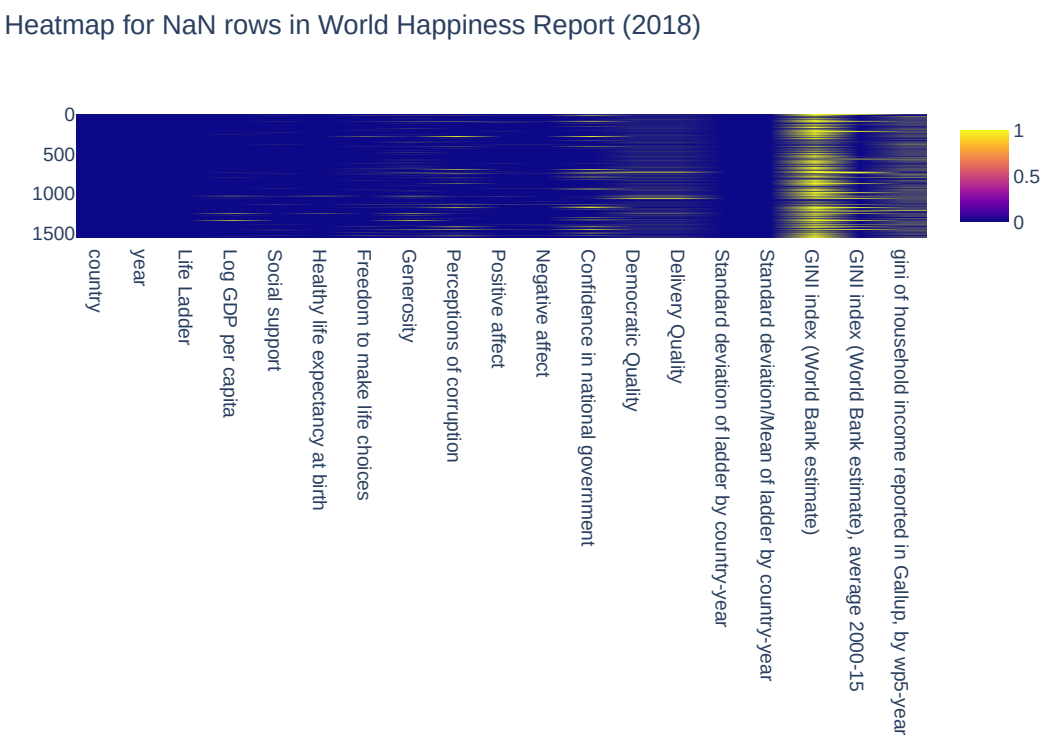
```
142                                        1.283989
1252                                       1.967024
36                                         2.098197
1002                                       2.703564
240                                        1.612508
855                                        1.593053
472                                        2.214464

      Standard deviation/Mean of ladder by country-year  \
539                                             0.609377
678                                             0.407375
280                                             0.410556
142                                             0.230556
1252                                            0.398944
36                                              0.324377
1002                                            0.501989
240                                             0.215351
855                                             0.295848
472                                             0.458314

      GINI index (World Bank estimate)  \
539                                NaN
678                                NaN
280                                NaN
142                                NaN
1252                               NaN
36                               0.425
1002                               NaN
240                                NaN
855                              0.463
472                                NaN

      GINI index (World Bank estimate), average 2000-15  \
539                                             0.387000
678                                             0.469000
280                                             0.425000
142                                             0.412333
1252                                                 NaN
36                                              0.476067
1002                                            0.482750
240                                             0.336800
855                                             0.461000
472                                             0.422000

      gini of household income reported in Gallup, by wp5-year
539                                                   0.618353
678                                                   0.564535
```

280	0.566069
142	0.359662
1252	0.537145
36	0.317217
1002	0.507107
240	0.663210
855	0.471126
472	0.557237

Edit this cell to answer the following question: 5. Please share one question that you still have about the data itself 6. What is the observational unit in the data?

[6]:
```
# 1. Calculate the percent of missingness of each variable in the data
happiness_orig_na = happiness_orig.isna().sum() / len(happiness_orig)
print(happiness_orig_na * 100)

# 2. Visualize the percent of missingness of each variable in a heatmap
px.imshow(
    happiness_orig.isna().astype(np.float64),
    title="Heatmap for NaN rows in World Happiness Report (2018)"
)
```

```
country                                                 0.000000
year                                                    0.000000
Life Ladder                                             0.000000
Log GDP per capita                                      1.728553
Social support                                          0.832266
Healthy life expectancy at birth                        0.576184
Freedom to make life choices                            1.856594
Generosity                                              5.121639
Perceptions of corruption                               5.761844
Positive affect                                         1.152369
Negative affect                                         0.768246
Confidence in national government                      10.307298
Democratic Quality                                     10.947503
Delivery Quality                                       10.947503
Standard deviation of ladder by country-year            0.000000
Standard deviation/Mean of ladder by country-year       0.000000
GINI index (World Bank estimate)                       62.676056
GINI index (World Bank estimate), average 2000-15      11.267606
gini of household income reported in Gallup, by wp5-year    22.855314
dtype: float64
```



[7]:
```
# This is a data cleaning function that is provided for you.
# Please feel free to modify this based on decisions you make
# during the pre-processing step. Document any changes you make and why.
def clean_happiness(happiness_orig, predictor_variable = None):
  # rename column names
  happiness_clean = happiness_orig.rename(columns={
    "Life Ladder": "happiness",
    "Log GDP per capita": "log_gdp_per_capita",
    "Social support": "social_support",
    "Healthy life expectancy at birth": "life_expectancy",
    "Freedom to make life choices": "freedom_choices",
    "Generosity": "generosity",
    "Perceptions of corruption": "corruption",
    "Positive affect": "positive_affect",
    "Negative affect": "negative_affect",
    "Confidence in national government": "government_confidence",
    "gini of household income reported in Gallup, by wp5-year": "gini_index"})
  # filter to relevant columns
  happiness_clean = happiness_clean[["country", "year", "happiness",␣
 ↪"log_gdp_per_capita",
                                     "social_support", "life_expectancy",
```

```
                                    "freedom_choices", "generosity",
                                    "corruption", "positive_affect",
                                    "negative_affect", "government_confidence",
                                    "gini_index"]]

  if (predictor_variable is not None):
    happiness_clean = happiness_clean[["country", "year", "happiness",␣
 ↪predictor_variable]]

  happiness_clean = happiness_clean.dropna(subset=["log_gdp_per_capita"])

  return(happiness_clean)
```

[8]:
```
def impute(happiness_orig: pd.DataFrame):
    happiness_imputed = happiness_orig.copy()
    happiness_imputed["gini of household income reported in Gallup, by␣
 ↪wp5-year"] = (
        happiness_imputed["gini of household income reported in Gallup, by␣
 ↪wp5-year"]
            .fillna(happiness_imputed["GINI index (World Bank estimate)"])
            .fillna(happiness_imputed["GINI index (World Bank estimate),␣
 ↪average 2000-15"])
    )
    return happiness_imputed
```

[9]:
```
# Cleaning the data
happiness_clean = clean_happiness(impute(happiness_orig))
happiness_clean
```

[9]:

	country	year	happiness	log_gdp_per_capita	social_support	\
0	Afghanistan	2008	3.723590	7.168690	0.450662	
1	Afghanistan	2009	4.401778	7.333790	0.552308	
2	Afghanistan	2010	4.758381	7.386629	0.539075	
3	Afghanistan	2011	3.831719	7.415019	0.521104	
4	Afghanistan	2012	3.782938	7.517126	0.520637	
…	…	…	…	…	…	
1557	Zimbabwe	2013	4.690188	7.565154	0.799274	
1558	Zimbabwe	2014	4.184451	7.562753	0.765839	
1559	Zimbabwe	2015	3.703191	7.556052	0.735800	
1560	Zimbabwe	2016	3.735400	7.538829	0.768425	
1561	Zimbabwe	2017	3.638300	7.538187	0.754147	

	life_expectancy	freedom_choices	generosity	corruption	\
0	49.209663	0.718114	0.181819	0.881686	
1	49.624432	0.678896	0.203614	0.850035	
2	50.008961	0.600127	0.137630	0.706766	
3	50.367298	0.495901	0.175329	0.731109	

```
4           50.709263         0.530935    0.247159    0.775620
…              …               …          …          …
1557        48.949745         0.575884   -0.076716    0.830937
1558        50.051235         0.642034   -0.045885    0.820217
1559        50.925652         0.667193   -0.094585    0.810457
1560        51.800068         0.732971   -0.065283    0.723612
1561        52.674484         0.752826   -0.066005    0.751208

      positive_affect  negative_affect  government_confidence  gini_index
0            0.517637         0.258195               0.612072         NaN
1            0.583926         0.237092               0.611545    0.441906
2            0.618265         0.275324               0.299357    0.327318
3            0.611387         0.267175               0.307386    0.336764
4            0.710385         0.267919               0.435440    0.344540
…               …               …                      …          …
1557         0.711885         0.182288               0.527755    0.555439
1558         0.725214         0.239111               0.566209    0.601080
1559         0.715079         0.178861               0.590012    0.655137
1560         0.737636         0.208555               0.699344    0.596690
1561         0.806428         0.224051               0.682647    0.581484

[1535 rows x 13 columns]
```

Edit this cell to answer the following question:

7. What variables were dropped from the original data set? Would you drop any additional variables from this data set and why?

The deleted variables are:

- Democratic Quality
- Delivery Quality
- Standard deviation of ladder by country-year
- Standard deviation/Mean of ladder by country-year
- GINI index (World Bank estimate)
- GINI index (World Bank estimate), average 2000-15

The standard deviations are derived variables, democratic and delivery quality had a lot of null values (>10%) and were poorly defined, and the World Bank GINI index estimates had a lot of null values.

Government confidence might also be considered to be dropped as it also has a high proportion (>10%) of null values.

8. How would you impute the gini_index variable? Explain why. (You do not have to write code to do this unless you need to do so for your model. In this case, include an imputation function and call it from the data cleaning function)

To impute the `gini_index` variable, one could take the World Bank estimates (the average if required) if the `gini_index` is NaN. As shown below, this removed all but 36 of the NaN values. comparing the statics on the field before and after, the mean, STD, and percentiles did not

drastically change, so this method may be valid.

[10]:
```
print(f"#NA after impute: {happiness_clean["gini_index"].isna().sum()}")
print("\n\nBEFORE:")
print(happiness_orig["gini of household income reported in Gallup, by␣
  ↪wp5-year"].describe())
print("\n\nAFTER:")
print(happiness_clean["gini_index"].describe())
```

```
#NA after impute: 36


BEFORE:
count    1205.000000
mean        0.445204
std         0.105410
min         0.223470
25%         0.368531
50%         0.425395
75%         0.508579
max         0.961435
Name: gini of household income reported in Gallup, by wp5-year, dtype: float64


AFTER:
count    1499.000000
mean        0.433817
std         0.103580
min         0.223470
25%         0.357906
50%         0.417843
75%         0.494689
max         0.961435
Name: gini_index, dtype: float64
```

Now we will visualize the relationships between variables.

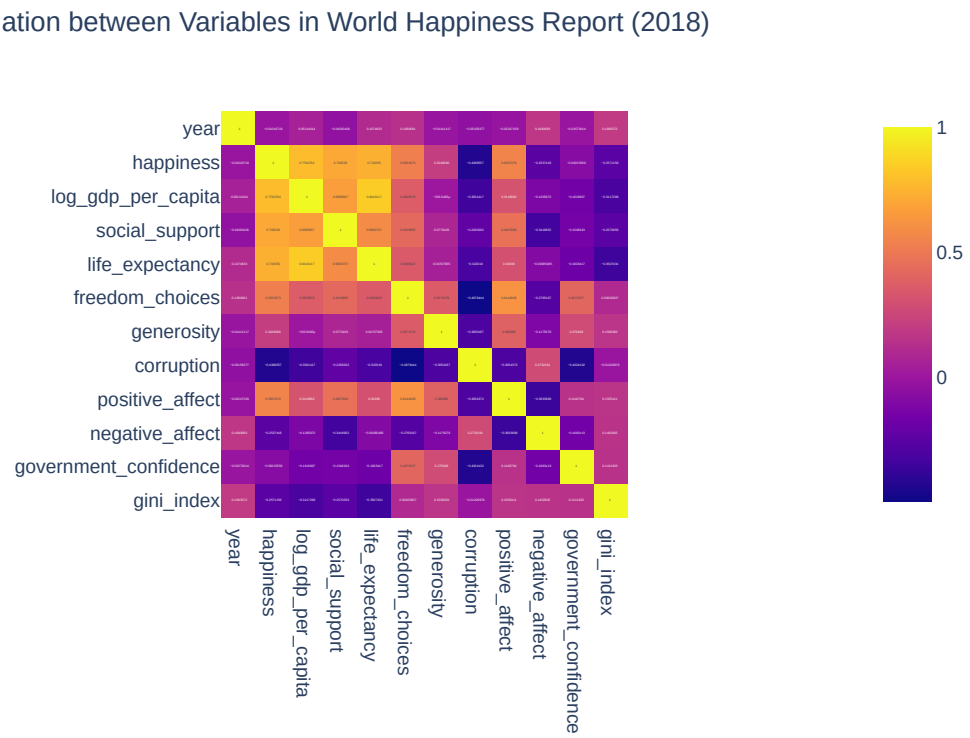
3 Plot Guidelines

For all plots and visualizations for this assignment please include

- Captions: Descriptive captions summarizing the plot's insights.
- Legends: Clear legends identifying each element in the plot.
- Axis Labels: Informative labels for both the x and y axes, including units if applicable.
- Style: appropriate colors, font sizes, and plot layouts for better readability and presentation.

It is important that your visualizations are easy-to-understand plots.

[11]:
```
# Since we are predicting happiness, we need to figure out what variable to use
# as a predictor.
# 1. Calculate the correlation between the happiness variable
#   and your set of remaining potential predictor variables
px.imshow(
    happiness_clean.select_dtypes(include="number").corr(),
    text_auto=True,
    title="Correlation between Variables in World Happiness Report (2018)"
)
# 2. Visualize the correlations between the dependent variable
```



9. From this investigation, what variable do you choose as your predictor and why?

The variables with highest correlation to happiness are GDP per capita, social support, life expectancy, freedom, and positive affect, all with magnitude greater than 0.5.

The most highly correlated variable is GDP, so I will choose that as my predictor. Life expectancy, freedom, and positive affect may all be confounded with GDP, so it might be a bad idea to choose these. Social support is also a good choice and may be less confounded with GDP, though that is an informal guess.

Separate data into training and validation sets

During this stage it is important that we choose data sets for training predictive models and

validating predictive models.

[12]:
```
# (You do not need to worry about a test set right now)
# Explain your decision to separate the data this way.
# You will reuse these data subsets in the following DSLC stage.

# you can use sklearn.train_test_split
def partition(df: pd.DataFrame, proportion: float = 0.6, random_state=None) ->␣
 ↪pd.DataFrame:
    shuffled = df.sample(frac=1, random_state=random_state)
    partition1_size = int(proportion * len(shuffled))
    return (shuffled[:partition1_size], shuffled[partition1_size:])

(happiness_train, happiness_test_val) = partition(happiness_clean, 0.6,␣
 ↪random_state=99999)
happiness_train
```

[12]:

	country	year	happiness	log_gdp_per_capita	\
516	Greece	2013	4.720251	10.075173	
390	Dominican Republic	2016	5.238698	9.553850	
200	Burkina Faso	2008	3.846439	7.239715	
566	Hong Kong S.A.R. of China	2010	5.642835	10.781198	
254	Chad	2007	4.141327	7.462495	
…	…	…	…	…	
978	Netherlands	2010	7.501876	10.726009	
1503	Uzbekistan	2015	5.972364	8.648263	
84	Azerbaijan	2015	5.146775	9.723096	
426	El Salvador	2016	6.139825	8.985946	
330	Costa Rica	2015	6.854004	9.610069	

	social_support	life_expectancy	freedom_choices	generosity	\
516	0.686650	71.250137	0.425967	-0.277970	
390	0.894753	63.335289	0.872712	-0.085081	
200	0.726651	47.875610	0.612064	-0.089791	
566	0.857314	74.827393	0.890418	0.314442	
254	0.478951	42.016632	0.294612	-0.020856	
…	…	…	…	…	
978	0.956537	70.739174	0.921448	0.337370	
1503	0.968225	62.896912	0.979937	0.370149	
84	0.785703	62.864544	0.764289	-0.221827	
426	0.793660	64.094536	0.799847	-0.193339	
330	0.878273	69.531830	0.906926	-0.060608	

	corruption	positive_affect	negative_affect	government_confidence	\
516	0.941310	0.689162	0.482183	0.143609	
390	0.737183	0.759946	0.278095	0.549425	
200	0.887124	0.523474	0.303892	0.462705	

```
566     0.255775          0.710370          0.183106                0.634737
254     0.873610          0.613522          0.245208                0.228145
…            …                 …                 …                       …
978     0.398592          0.853234          0.206079                0.636186
1503    0.470917          0.839981          0.103494                0.973944
84      0.615553          0.606569          0.206114                0.788487
426     0.797312          0.761256          0.345736                0.251705
330     0.761419          0.849710          0.286440                0.261169

      gini_index
516     0.319988
390     0.484080
200     0.394667
566     0.435544
254     0.415500
…          …
978     0.464675
1503    0.356073
84      0.287745
426     0.457765
330     0.477598

[921 rows x 13 columns]
```

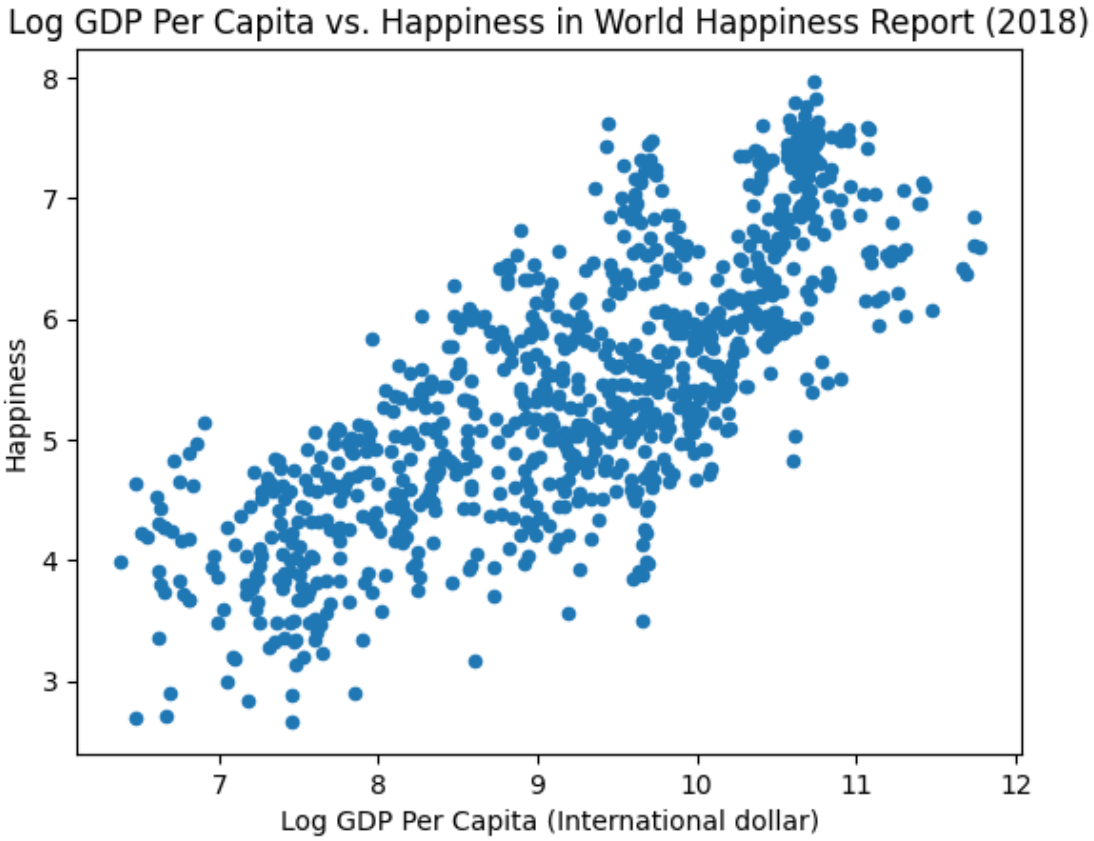
A random sample seemed to be adequate to partition the data.

4 [DSLC stage 4]: Predictive analysis

In this section we will examine the relationship between happiness as the response variable and your predictor variable. First we will visualize the relationship between happiness and the predictor variable.

[13]:
```
# 1. Create data frames that only contain columns for
# country, year, happiness, and your predictor variable
predictor = "log_gdp_per_capita"
predictor_label = "Log GDP Per Capita (International dollar)"
columns = ["country", "year", "happiness", predictor]
happiness_train_filtered = happiness_train[columns]
happiness_val_filtered = happiness_train[columns]

# 2. Create a scatterplot of happiness vs your predictor variable
happiness_train_filtered.plot.scatter(
    x=predictor, y="happiness",
    xlabel=predictor_label, ylabel="Happiness",
    title="Log GDP Per Capita vs. Happiness in World Happiness Report (2018)",
)
```

[13]:
```
<Axes: title={'center': 'Log GDP Per Capita vs. Happiness in World Happiness
Report (2018)'}, xlabel='Log GDP Per Capita (International dollar)',
ylabel='Happiness'>
```



5 Modeling the relationship

Using your training data set

Train the LAD (L1 loss) and LS (L2 loss) linear fits for predicting happiness based on your chosen predictor variable of your choosing.

Once you have completed this, edit this cell here to report the formulas for your fitted models.

LAD: y=0.73209501 X + -1.3832882612278787s LS: y=0.74976482 X + -1.4894560279254465

For the LAD model you will use LADRegression from sklego.linear_model. Examples are available in the L04 notebook and API documentation

[14]:
```
# 1. Train LAD model on your training Set
from sklego.linear_model import LADRegression
```

```
X_train = happiness_train_filtered[predictor].to_numpy().reshape(-1, 1)
y_train = happiness_train_filtered["happiness"].to_numpy()
X_val = happiness_val_filtered[predictor].to_numpy().reshape(-1, 1)
y_val = happiness_val_filtered["happiness"].to_numpy()

lad_reg = LADRegression()
lin_reg = LinearRegression()

# 2. Get the parameters of your model to write formula

# 3. Train LS model on your training Set
lad_reg.fit(X_train, y_train)

# 4. Get the parameters of your model to write formula
lad_m = lad_reg.coef_
lad_b = lad_reg.intercept_
print(f"LAD: y={lad_m}X + {lad_b}")
```

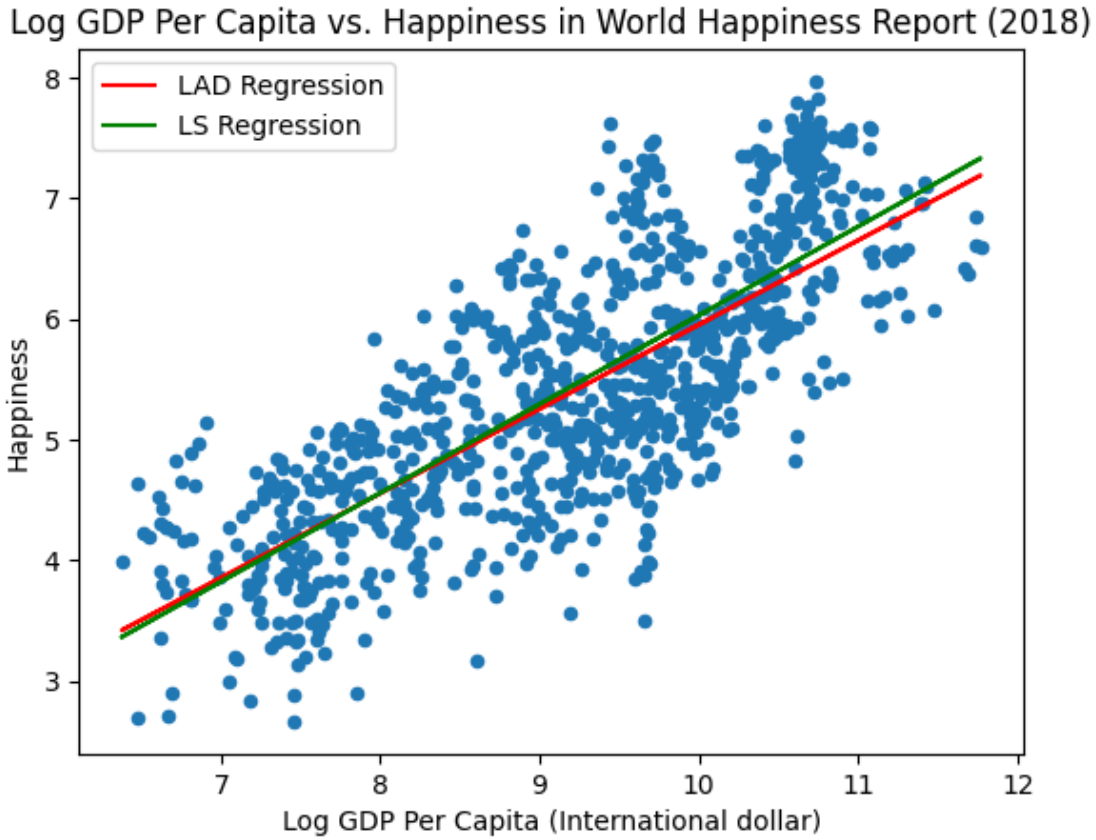
```
LAD: y=[0.69954264]X + -1.0436701364130059
```

For the LS model you will use LinearRegression from sklearn.linear_model. Examples are available in the L04 notebook and API documentation

[15]:
```
# 3. Train LS model on your training Set
lin_reg.fit(X_train, y_train)

# 4. Get the parameters of your model to write formula
lin_m = lin_reg.coef_
lin_b = lin_reg.intercept_
print(f"LS: y={lin_m}X + {lin_b}")

# 5. Create a scatterplot of happiness vs your predictor variable
#    with a line for each model

happiness_train_filtered.plot.scatter(
    x=predictor, y="happiness",
    xlabel=predictor_label, ylabel="Happiness",
    title="Log GDP Per Capita vs. Happiness in World Happiness Report (2018)",
)
lad_y = lad_m * happiness_train_filtered[predictor] + lad_b
lin_y = lin_m * happiness_train_filtered[predictor] + lin_b
plt.plot(happiness_train_filtered[predictor], lad_y, color="red", label="LAD␣
 ↪Regression")
plt.plot(happiness_train_filtered[predictor], lin_y, color="green", label="LS␣
 ↪Regression")

plt.legend()
```

```
LS: y=[0.73629989]X + -1.333753801778899
```

[15]: <matplotlib.legend.Legend at 0x71450211df40>



Now we'd like to evaluate how each model has done.

Using your validation data set

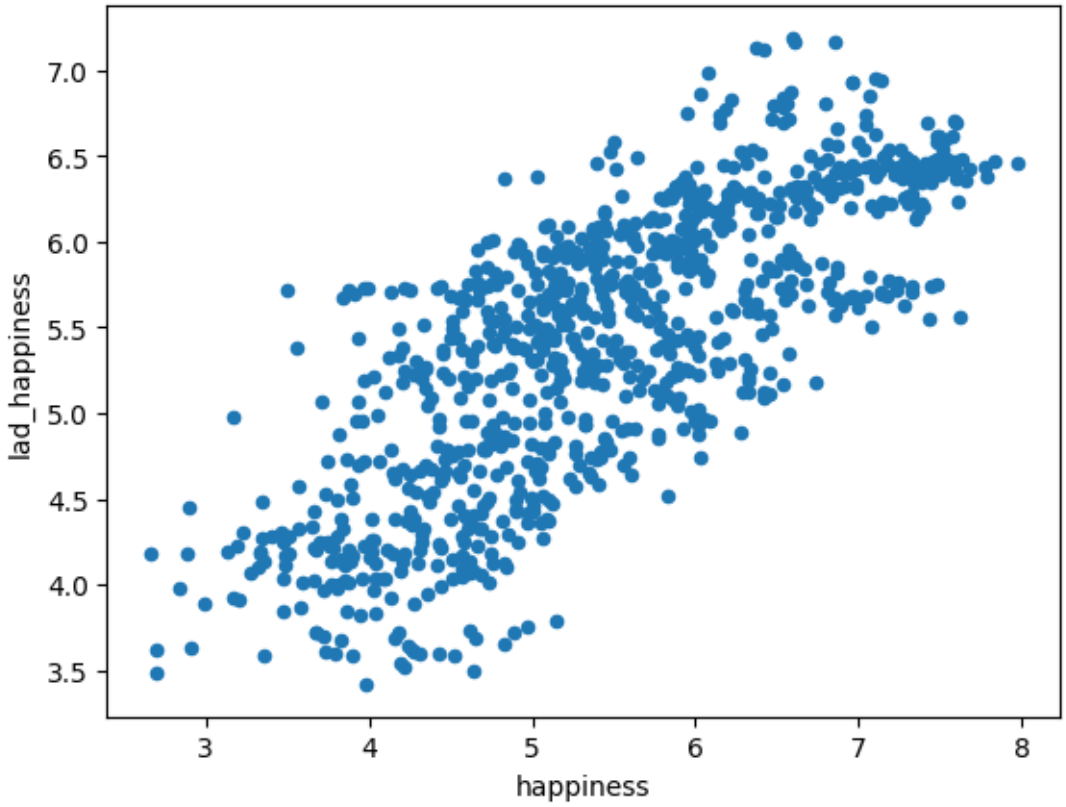
Compute the rMSE, MAE, MAD, correlation and R^2 evaluations for each algorithm.

[16]:
```
# Create a  3 column dataframe that for each point in your validation set
# contains the actual observed happiness score, the happiness score predicted
# from LAD, and the happiness score predicted from LS
predictions = pd.DataFrame({
    "happiness": y_val,
    "lad_happiness": lad_reg.predict(X_val),
    "ls_happiness": lin_reg.predict(X_val),
})
```

[17]:
```
# Create a scatterplot of the observed happiness score vs
# the happiness score predicted from LAD
# What would a perfect prediction look like?
#       A perfect predictino would look like a straight line
```

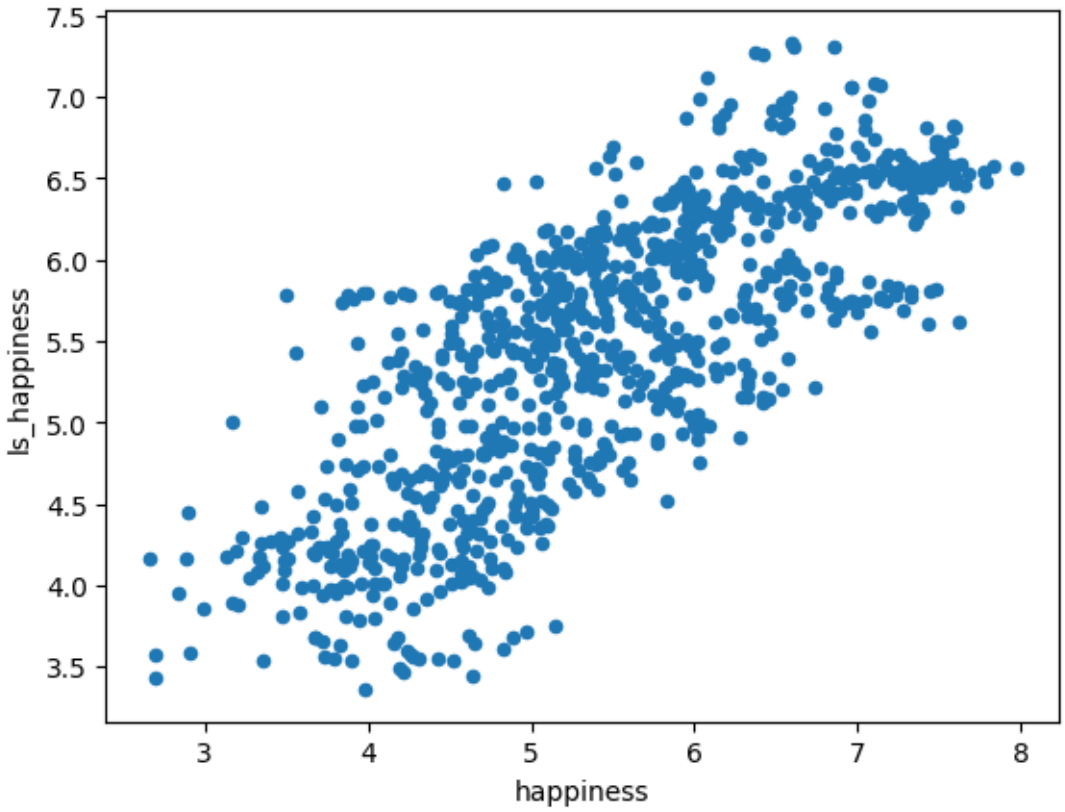
```
predictions.plot.scatter(x="happiness", y="lad_happiness")
```

[17]: <Axes: xlabel='happiness', ylabel='lad_happiness'>



[18]:
```
# Create a scatterplot of the observed happiness score vs
# the happiness score predicted from LS
# What would a perfect prediction look like?
#           A straight line
predictions.plot.scatter(x="happiness", y="ls_happiness")
```

[18]: <Axes: xlabel='happiness', ylabel='ls_happiness'>



[19]:
```
# Write code in this cell to calculate and print
# the rMSE, MAE, MAD, correlation, and R2 of
# the true price with the LS and LAD predictions
def print_stats(real: pd.Series, pred: pd.Series):
    print("RMSE: ", mean_squared_error(real, pred)**0.5)
    print("MAE: ", mean_absolute_error(real, pred))
    print("MAD: ", (pred - real).abs().mean())
    print("Correlation: ", real.corr(pred))
    print("R2: ", r2_score(real, pred))

print("LAD")
print_stats(predictions["happiness"], predictions["lad_happiness"])
print()
print("LS")
print_stats(predictions["happiness"], predictions["ls_happiness"])
```

```
LAD
RMSE:  0.713868629854809
MAE:  0.5859002753981548
MAD:  0.5859002753981548
Correlation:  0.7778832435688353
```

```
R2:  0.6016712520024537

LS
RMSE:  0.7107874514606999
MAE:  0.5880119028196019
MAD:  0.5880119028196019
Correlation:  0.777883243568835
R2:  0.6051023406251717
```

Evaluating the models

Based on the scatterplots and evaluation metrics that you have calculated, what model is better for the relationship between happiness and your predictor variable? Please explain why with supporting evidence from your plots and calculations.

Both models performed about the same. LS had slightly higher R2 score, but this was dependent on the sample (as well as all other error metrics);

Citation:

This problem set is adapted from Ch. 9 exercise 22 from the following upcoming book:

Yu, B., & Barter, R. L. (2024). Veridical data science: The practice of responsible data analysis and decision making. The MIT Press.