In [70]:
```
import pandas as pd
import numpy as np
import datetime
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.preprocessing import MinMaxScaler

from scipy.stats import pearsonr
from scipy.stats import spearmanr

from sklearn.feature_selection import SelectKBest, SelectPercentile
from sklearn.feature_selection import chi2, f_classif, mutual_info_cla
ssif
from sklearn.feature_selection import f_regression, mutual_info_regres
sion
from sklearn.feature_selection import RFE

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestRegressor, RandomForestClassi
fier
from sklearn.metrics import r2_score, mean_squared_error, mean_absolut
e_error
from sklearn.metrics import accuracy_score, precision_score, recall_sc
ore

import joblib

import data_utilities as du
import model_utilities as mu
```

Project Motivation

The year 2020 was defined by the novel coronavirus, COVID19, pandemic. Countries around the world instituted various policies to protect their citizens and minimize contagion. It would be useful to know which of those policies most impacted outcomes measured in cases or deaths, or if they impacted them at all. It would also be useful to know if uncontrollable factors like percent of population living in cities, population density, or the median age of the population had as much or more of an impact than active government interventions.

I would like to 1) understand the relationships between specific policies and outcomes, and 2) determine if there is any predictive capability of policies to outcome.

Oxford University publishes a dataset of government policy interventions with COVID19 cases and deaths daily per country. I added demographic data per country representing the uncontrollable factors. To gain an understanding of policy to outcome relationships, I will evaluate statistical correlations. To determine if there are predictive capabilities, I will use model feature selection and model training feature importances.

Based on the way that the novel coronavirus and its variants flow through a population and the attributes of people most impacted, you might start with these ideas:

- The stronger the actions taken by governments, the lower the contagion rate, as measured by confirmed cases, and the lower the casualty rate, as measured by deaths. There should be some identifiable, measurable correlations between policies and outcomes.
- The strongest correlations might be inverse relationships between policies that restrict physical proximity such as school closings or limited private gatherings, thus minimizing ability to spread the disease, and outcomes.
- Uncontrollable factors like the percentage of population living closely together in urban environments or the median age of the population could have as much or more impact than active interventions.

In [2]:
```
filestring1 = 'DSND_covid19_policy_tracker.csv'
filestring2 = 'worldmeter_info2020.csv'
merge_field = 'country_name'
covid = pd.read_csv(filestring1)
demos = pd.read_csv(filestring2)
covid = pd.merge(covid, demos, how='inner', on=merge_field)
covid = covid.drop(columns=['Unnamed: 0'], axis=1)
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/IP
ython/core/interactiveshell.py:3051: DtypeWarning: Columns (2,3) hav
e mixed types.Specify dtype option on import or set low_memory=False
.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:
```
covid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 104877 entries, 0 to 104876
Data columns (total 57 columns):
 #   Column                                  Non-Null Count   Dtype
---  ------                                  --------------   -----
 0   country_name                            104877 non-null  objec
t
 1   alpha_3_code                            104877 non-null  objec
t
 2   region_name                             37152 non-null   objec
t
 3   region_code                             37152 non-null   objec
t
 4   date                                    104877 non-null  objec
t
 5   school_closing                          102029 non-null  float
64
 6   school_closing_flag                     78892 non-null   float
64
 7   school_closing_notes                    4593 non-null    objec
t
 8   workplace_closing                       102023 non-null  float
64
 9   workplace_closing_flag                  72813 non-null   float
64
 10  workplace_closing_notes                 4803 non-null    objec
t
 11  cancel_public_events                    102058 non-null  float
64
 12  cancel_public_events_flag               78570 non-null   float
64
 13  cancel_public_events_notes              3937 non-null    objec
t
```

```
 14  restrictions_on_gatherings                102010 non-null  float
64
 15  restrictions_on_gatherings_flag           73630 non-null   float
64
 16  restrictions_on_gatherings_notes          4193 non-null    objec
t
 17  close_public_transit                      102042 non-null  float
64
 18  close_public_transit_flag                 43864 non-null   float
64
 19  close_public_transit_notes                3033 non-null    objec
t
 20  stay_at_home_requirements                 102025 non-null  float
64
 21  stay_at_home_requirements_flag            63611 non-null   float
64
 22  stay_at_home_requirements_notes           3696 non-null    objec
t
 23  restrictions_on_internal_movement         102052 non-null  float
64
 24  restrictions_on_internal_movement_flag    60355 non-null   float
64
 25  restrictions_on_internal_movement_notes  3604 non-null    objec
t
 26  international_travel_controls             101446 non-null  float
64
 27  international_travel_controls_notes       4886 non-null    objec
t
 28  income_support                            99774 non-null   float
64
 29  income_support_flag                       55712 non-null   float
64
 30  income_support_notes                      2499 non-null    objec
t
 31  debt_contract_relief                      99382 non-null   float
64
 32  debt_contract_relief_notes                2428 non-null    objec
t
 33  fiscal_measures                           79036 non-null   float
64
 34  fiscal_measures_notes                     1882 non-null    objec
t
 35  international_support                     79235 non-null   float
64
 36  international_support_notes               887 non-null     objec
t
 37  public_information_campaigns              101812 non-null  float
64
 38  public_information_campaigns_flag         90302 non-null   float
64
```

```
 39  public_information_campaigns_notes      2864 non-null    objec
t
 40  testing_policy                         101807 non-null  float
64
 41  testing_policy_notes                   3442 non-null    objec
t
 42  contact_tracing                        101699 non-null  float
64
 43  contact_tracing_notes                  2752 non-null    objec
t
 44  emergency_healthcare_investment        79519 non-null   float
64
 45  emergency_healthcare_investment_notes  1299 non-null    objec
t
 46  vaccine_investment                     79684 non-null   float
64
 47  vaccine_investment_notes               922 non-null     objec
t
 48  misc_wildcard                          0 non-null       float
64
 49  misc_wildcard_notes                    1155 non-null    objec
t
 50  confirmed_cases                        95059 non-null   float
64
 51  deaths                                 94948 non-null   float
64
 52  stringency_index                       102668 non-null  float
64
 53  density                                104877 non-null  float
64
 54  median_age                             104877 non-null  float
64
 55  population                             104877 non-null  float
64
 56  urban_perc                             104877 non-null  float
64
dtypes: float64(34), object(23)
memory usage: 46.4+ MB
```

Document preprocessing data transformations

In [4]:
```
covid['country_name'].value_counts()
```

Out[4]:
```
United States           20511
Brazil                  10836
Canada                   5418
United Kingdom           1935
Ethiopia                  387
                        ...
United Arab Emirates      387
Sudan                     387
Zimbabwe                  387
Eritrea                   387
Faeroe Islands            387
Name: country_name, Length: 175, dtype: int64
```

Some countries, eg. the United States and Brazil, include regions in their tracking, vastly multiplying their datapoints. In comparison, China is tracked in total, with one datapoint per day. Add a 'geo' column to increase analytic flexibility.

In [5]:
```
# Cleaning and filling
# drop all rows missing the target labels
covid = covid.dropna(subset=['deaths','confirmed_cases'], axis=0)
# drop all rows where target labels are zero
covid = covid.loc[(covid['confirmed_cases'] > 0.0) & (covid['deaths']
> 0.0)]
# drop all rows missing summary indicator
covid = covid.loc[covid['stringency_index'].notnull()]
# ensure date field is datetime to manipulate more easily
covid['date'] = pd.to_datetime(covid['date'])
# make regional data consistent: if NA, cumulative for the country
covid['region_name'] = covid['region_name'].fillna('Total')
# create a combined field to break up larger countries into regions
covid['geo'] = covid['country_name'] + covid['region_name']
# drop unused identifying columns
covid = covid.drop(['alpha_3_code','region_code'], axis=1)
# drop uncategorized policy columns
covid = covid.drop(['misc_wildcard','misc_wildcard_notes'], axis=1)
# prepare for change calcs
covid.sort_values(['geo', 'date'], ascending=True,
                      inplace=True, na_position='last')
# subset the free text columns and drop them from main df
cols_notes = ['school_closing_notes','workplace_closing_notes',
             'cancel_public_events_notes','restrictions_on_gatherings_
notes',
             'stay_at_home_requirements_notes', 'restrictions_on_inter
nal_movement_notes',
             'international_travel_controls_notes','income_support_not
es',
             'debt_contract_relief_notes', 'fiscal_measures_notes',
             'international_support_notes', 'public_information_campai
gns_notes',
             'testing_policy_notes', 'contact_tracing_notes',
             'emergency_healthcare_investment_notes', 'vaccine_investm
ent_notes']
covid_notes = covid[list(covid[cols_notes])]
covid = covid.drop(cols_notes, axis=1)
```

In [6]:
```
# normalize the raw statistics by population
covid['case_perc_pop'] = (covid['confirmed_cases'] / covid['population
'])
covid['death_perc_pop'] = (covid['deaths'] / covid['population'])
```

In [7]:
```
# get the changes in target data over time
covid['case_perc_change'] = np.round(covid['confirmed_cases'].pct_chan
ge(), decimals=2)
covid['death_perc_change'] = np.round(covid['deaths'].pct_change(), de
cimals=2)
# remove calculation infinites
covid = covid.drop(covid.index[list(np.where(np.isfinite(covid['case_p
erc_change']) == False))])
covid = covid.drop(covid.index[list(np.where(np.isfinite(covid['death_
perc_change']) == False))])
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexes/base.py:4114: FutureWarning: Using a non-tuple seq
uence for multidimensional indexing is deprecated; use `arr[tuple(se
q)]` instead of `arr[seq]`. In the future this will be interpreted a
s an array index, `arr[np.array(seq)]`, which will result either in
an error or a different result.
  result = getitem(key)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexes/base.py:4114: FutureWarning: Using a non-tuple seq
uence for multidimensional indexing is deprecated; use `arr[tuple(se
q)]` instead of `arr[seq]`. In the future this will be interpreted a
s an array index, `arr[np.array(seq)]`, which will result either in
an error or a different result.
  result = getitem(key)
```

In [8]:
```
# get whether outcomes are increasing (0) or decreasing (1)
covid['case_direction'] = covid['case_perc_change'].apply(lambda x: 0
if x <= 0 else 1)
covid['death_direction'] = covid['death_perc_change'].apply(lambda x:
0 if x <= 0 else 1)
```

At this point, the outcomes to be analyzed are available in four formats:

- original: absolute and cumulative, columns confirmed_cases and deaths
- relative to population: columns case_perc_pop, death_perc_pop
- change over time: columns case_perc_change, death_perc_change
- direction over time: columns case_direction, death_direction

In [9]:
```
cols_outcomes = ['confirmed_cases', 'deaths','case_perc_pop', 'death_p
erc_pop',
                'case_perc_change','death_perc_change','case_direction'
,'death_direction']
```

In [10]:
```
# The true desired outcome is decreasing cases, a negative percent cha
nge
# How much of the dataset represents that case?
num_best_outcomes = len(covid.loc[covid['case_perc_change'] < 0])
print('Best outcomes: ', num_best_outcomes, num_best_outcomes/len(covi
d))
num_good_outcomes = len(covid.loc[covid['case_perc_change'] <= 0])
print('Good outcomes: ', num_good_outcomes, num_good_outcomes/len(covi
d))
```

```
Best outcomes:  324 0.0044276812069531
Good outcomes:  24426 0.33379796654640864
```

In [11]:
```
# the binary case direction has values 0 for stable or decreasing case
s, 1 for increasing cases
covid['case_direction'].value_counts()
```

Out[11]:
```
1    48750
0    24426
Name: case_direction, dtype: int64
```

In [12]:
```
# enhance the summary metric, the stringency_index
# get the change in stringency_index
covid['stringency_change'] = np.round(covid['stringency_index'].pct_ch
ange(), decimals=2)
# remove calculation infinites
covid = covid.drop(covid.index[list(np.where(np.isfinite(covid['string
ency_change']) == False))])
# get the stringency direction, are governments tightening (1) or loos
ening/keeping (0) policy?
covid['stringency_direction'] = covid['stringency_change'].apply(lambd
a x: 0 if x <= 0 else 1)
# at this point, the summary metric is available in three formats
cols_stringency = ['stringency_index','stringency_change','stringency_
direction']
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexes/base.py:4114: FutureWarning: Using a non-tuple seq
uence for multidimensional indexing is deprecated; use `arr[tuple(se
q)]` instead of `arr[seq]`. In the future this will be interpreted a
s an array index, `arr[np.array(seq)]`, which will result either in
an error or a different result.
  result = getitem(key)
```

In [13]:
```
# do quick cleaning step to prevent calculation errors
if covid.isnull().sum().sum() > 0:
    covid = covid.fillna(value=0)
```

In [14]:
```
# How much does the summary metric, stringency index, vary?
covid['stringency_index'].value_counts()
```

Out[14]:
```
64.81    1709
60.19    1407
84.26    1382
65.74    1314
62.96    1284
         ...
21.76       1
98.15       1
26.39       1
18.06       1
88.43       1
Name: stringency_index, Length: 175, dtype: int64
```

In [15]:
```
# We can see that the stringency index varies significantly among coun
tries,
# but how often does the stringency index change once set by that gove
rnment?
len(covid.loc[covid['stringency_change'] != 0])/len(covid)
```

Out[15]:
```
0.058131270331592905
```

In [ ]:
```

```

In [16]:
```
# monetary values are different scale from binary or ordinal rankings
cols_financial_amts = ['income_support', 'debt_contract_relief',
                       'fiscal_measures', 'international_support',
                       'emergency_healthcare_investment', 'vaccine_invest
ment']
```

In [17]:
```
scaler = MinMaxScaler()
for col in cols_financial_amts:
    # scale the financial amounts to range [0..1]
    sc_colname = 'scaled_'+col
    covid[sc_colname] = scaler.fit_transform(covid[[col]])
    # get the binary for whether policy was active (>0 allocated) or n
ot
    bi_colname = col+'_flag'
    covid[bi_colname] = covid[col].apply(lambda x: 0 if x <= 0 else 1)
```

In [19]:
```
# scale the demographic data
cols_demos = ['population', 'urban_perc', 'density', 'median_age']
for col in cols_demos:
    # scale the diverse units to range [0..1]
    scd_colname = 'scaled_'+col
    covid[scd_colname] = scaler.fit_transform(covid[[col]])
```

In [20]:
```
covid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73162 entries, 39278 to 103331
Data columns (total 61 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   country_name                           73162 non-null  object
 1   region_name                            73162 non-null  object
 2   date                                   73162 non-null  datetim
e64[ns]
 3   school_closing                         73162 non-null  float64
 4   school_closing_flag                    73162 non-null  float64
 5   workplace_closing                      73162 non-null  float64
 6   workplace_closing_flag                 73162 non-null  float64
 7   cancel_public_events                   73162 non-null  float64
 8   cancel_public_events_flag              73162 non-null  float64
 9   restrictions_on_gatherings             73162 non-null  float64
 10  restrictions_on_gatherings_flag        73162 non-null  float64
 11  close_public_transit                   73162 non-null  float64
 12  close_public_transit_flag              73162 non-null  float64
 13  close_public_transit_notes             73162 non-null  object
 14  stay_at_home_requirements              73162 non-null  float64
 15  stay_at_home_requirements_flag         73162 non-null  float64
 16  restrictions_on_internal_movement      73162 non-null  float64
 17  restrictions_on_internal_movement_flag 73162 non-null  float64
 18  international_travel_controls          73162 non-null  float64
 19  income_support                         73162 non-null  float64
 20  income_support_flag                    73162 non-null  int64
 21  debt_contract_relief                   73162 non-null  float64
 22  fiscal_measures                        73162 non-null  float64
 23  international_support                  73162 non-null  float64
 24  public_information_campaigns           73162 non-null  float64
 25  public_information_campaigns_flag      73162 non-null  float64
 26  testing_policy                         73162 non-null  float64
 27  contact_tracing                        73162 non-null  float64
 28  emergency_healthcare_investment        73162 non-null  float64
 29  vaccine_investment                     73162 non-null  float64
 30  confirmed_cases                        73162 non-null  float64
 31  deaths                                 73162 non-null  float64
 32  stringency_index                       73162 non-null  float64
 33  density                                73162 non-null  float64
```

```
 34  median_age                              73162 non-null  float64
 35  population                              73162 non-null  float64
 36  urban_perc                              73162 non-null  float64
 37  geo                                     73162 non-null  object
 38  case_perc_pop                           73162 non-null  float64
 39  death_perc_pop                          73162 non-null  float64
 40  case_perc_change                        73162 non-null  float64
 41  death_perc_change                       73162 non-null  float64
 42  case_direction                          73162 non-null  int64
 43  death_direction                         73162 non-null  int64
 44  stringency_change                       73162 non-null  float64
 45  stringency_direction                    73162 non-null  int64
 46  scaled_income_support                   73162 non-null  float64
 47  scaled_debt_contract_relief             73162 non-null  float64
 48  debt_contract_relief_flag               73162 non-null  int64
 49  scaled_fiscal_measures                  73162 non-null  float64
 50  fiscal_measures_flag                    73162 non-null  int64
 51  scaled_international_support            73162 non-null  float64
 52  international_support_flag              73162 non-null  int64
 53  scaled_emergency_healthcare_investment  73162 non-null  float64
 54  emergency_healthcare_investment_flag    73162 non-null  int64
 55  scaled_vaccine_investment               73162 non-null  float64
 56  vaccine_investment_flag                 73162 non-null  int64
 57  scaled_population                       73162 non-null  float64
 58  scaled_urban_perc                       73162 non-null  float64
 59  scaled_density                          73162 non-null  float64
 60  scaled_median_age                       73162 non-null  float64
dtypes: datetime64[ns](1), float64(47), int64(9), object(4)
memory usage: 34.6+ MB
```

Correlation analysis one: Policies active or not

For the first test of correlation, let's look at the dataset flags for which policies were active, and compare them with whether cases were going up or down, using scipy.stats for Pearsons and Spearmans. Correlation is the degree to which any two data points are related. For statistical analysis, the [Pearson correlation coefficent (https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html)](https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html) is the degree to which they are linearly related and is represented by a float between -1.0 and 1.0. The relationship is linear only when a change in one feature is associated with a proportional change in the other. A negative coefficient indicates an inverse relationship and a zero would be no relationship at all. The Pandas corr function uses Pearson's calculation for correlation between numeric columns. (Note: I wrote my own function using scipy.stats for a slightly cleaner output.) If you want a broader perspective, you can use scipy for [Spearman's correlation (https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.spearmanr.html)](https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.spearmanr.html). The difference is that Spearman does not assume a constant, proportional rate of change, simply that there is a directional change. Spearman captures monotonic relationships as well as linear relationships. Spearman is generally considered best for ranked data.

In [21]:
```
cols_binary = ['geo','country_name', 'region_name','date',
        'case_direction','death_direction',
        'stringency_direction',
       'school_closing_flag', 'workplace_closing_flag',
       'cancel_public_events_flag',
       'restrictions_on_gatherings_flag',
       'close_public_transit_flag',
       'stay_at_home_requirements_flag',
       'restrictions_on_internal_movement_flag',
       'international_travel_controls',
       'income_support_flag',
       'public_information_campaigns_flag',
       'testing_policy',
       'contact_tracing',
       'debt_contract_relief_flag',
       'fiscal_measures_flag',
       'international_support_flag',
       'emergency_healthcare_investment_flag',
       'vaccine_investment_flag']
covid_binary = covid[list(covid[cols_binary])]
covid_binary.shape
```

Out[21]:
```
(73162, 24)
```

In [22]:
```
# get pearsons coefficient on binary policies and directional change i
n cases
cols_to_check = cols_binary[6:]
binary_corr = du.get_pearsons_corr(covid_binary, cols_to_check, 'case_
direction')
impt_binaries = binary_corr.loc[(abs(binary_corr['corr']) > 0.10)]
impt_binaries.head()
```

Out[22]:

	feature	corr
6	stay_at_home_requirements_flag	0.113356
7	restrictions_on_internal_movement_flag	0.148206
8	international_travel_controls	0.153325

In [23]:
```
# try spearmans to get directional relationships
spearman_corr = du.get_spearmans_corr(covid_binary, cols_to_check, 'ca
se_direction')
impt_sc_bin = spearman_corr.loc[(abs(spearman_corr['corr']) > 0.10)]
impt_sc_bin.head()
```

Out[23]:

	feature	corr
6	stay_at_home_requirements_flag	0.113356
7	restrictions_on_internal_movement_flag	0.148206
8	international_travel_controls	0.154078

In [24]:
```
cols_ordinal = ['geo','country_name', 'region_name','date',
                'case_perc_change','death_perc_change',
                'case_direction','death_direction',
                'stringency_index',
                'school_closing', 'workplace_closing',
                'cancel_public_events', 'restrictions_on_gatherings',
                'close_public_transit', 'stay_at_home_requirements',
                'restrictions_on_internal_movement',
                'international_travel_controls',
                'public_information_campaigns','testing_policy',
                'contact_tracing',
                'scaled_income_support', 'scaled_debt_contract_relief'
,
               'scaled_fiscal_measures','scaled_international_support'
,
               'scaled_emergency_healthcare_investment',
               'scaled_vaccine_investment',
                'scaled_population','scaled_density',
                'scaled_urban_perc','scaled_median_age'
               ]
```

In [25]:
```
covid_ordinal = covid[list(covid[cols_ordinal])]
covid_ordinal.shape
```

Out[25]: (73162, 30)

In [26]:
```
ords_to_check = cols_ordinal[8:]
pc_ordinal_corr = du.get_pearsons_corr(covid_ordinal, ords_to_check, '
case_direction')
impt_ordinals = pc_ordinal_corr.loc[(abs(pc_ordinal_corr['corr']) > 0.
10)]
impt_ordinals.head()
```

Out[26]:

	feature	corr
0	stringency_index	0.255634
1	school_closing	0.233636
2	workplace_closing	0.218994
3	cancel_public_events	0.176953
4	restrictions_on_gatherings	0.139392

In [27]:
```
# try spearmans to get directional relationships
sc_ordinal_corr = du.get_spearmans_corr(covid_ordinal, ords_to_check,
'case_direction')
impt_sc_ord = sc_ordinal_corr.loc[(abs(sc_ordinal_corr['corr']) > 0.10
)]
impt_sc_ord.head()
```

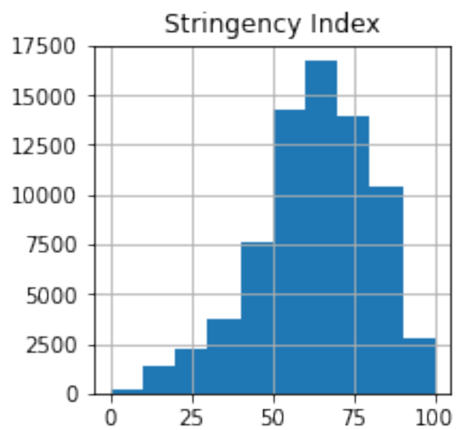
Out[27]:

	feature	corr
0	stringency_index	0.240886
1	school_closing	0.230886
2	workplace_closing	0.203726
3	cancel_public_events	0.160724
4	restrictions_on_gatherings	0.162954

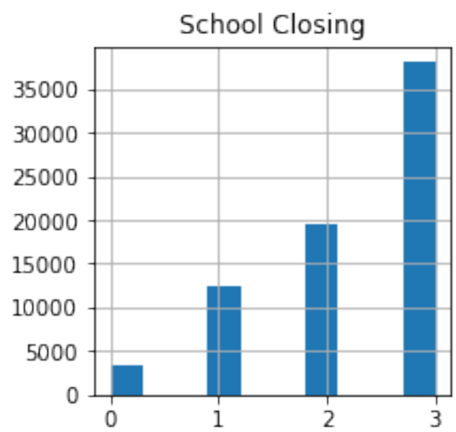
Build data visualizations to demonstrate data explorations

Let's visualize some of the features showing correlations.

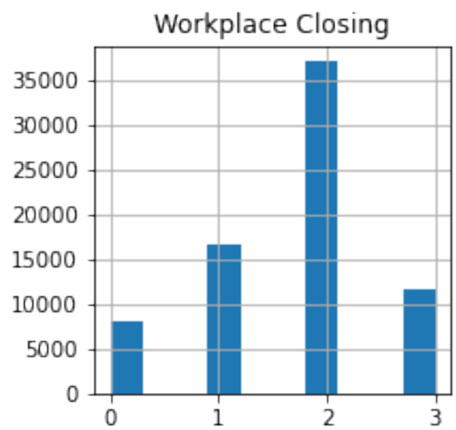
In [28]:
```
#covid['stringency_index'].hist()
fig, ax = plt.subplots(figsize=(3,3))
covid.hist('stringency_index', ax=ax)
ax.set_title('Stringency Index')
fig.savefig('stringency_index_hist_3x3.png', bbox_inches='tight')
plt.show()
```



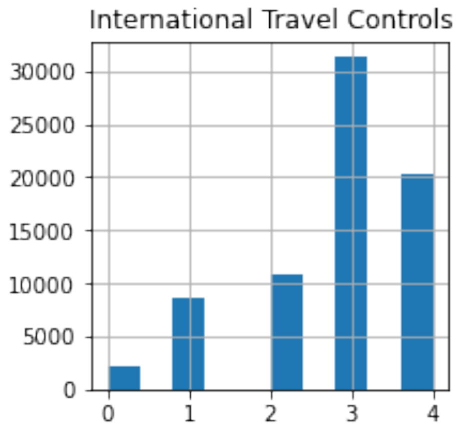
In [29]:
```
# covid['school_closing'].hist()
fig, ax = plt.subplots(figsize=(3,3))
covid.hist('school_closing', ax=ax)
ax.set_title('School Closing')
fig.savefig('school_closing_hist_3x3.png', bbox_inches='tight')
plt.show()
```



In [30]:
```
# covid['workplace_closing'].hist()
fig, ax = plt.subplots(figsize=(3,3))
covid.hist('workplace_closing', ax=ax)
ax.set_title('Workplace Closing')
fig.savefig('workplace_closing_hist_3x3.png', bbox_inches='tight')
plt.show()
```

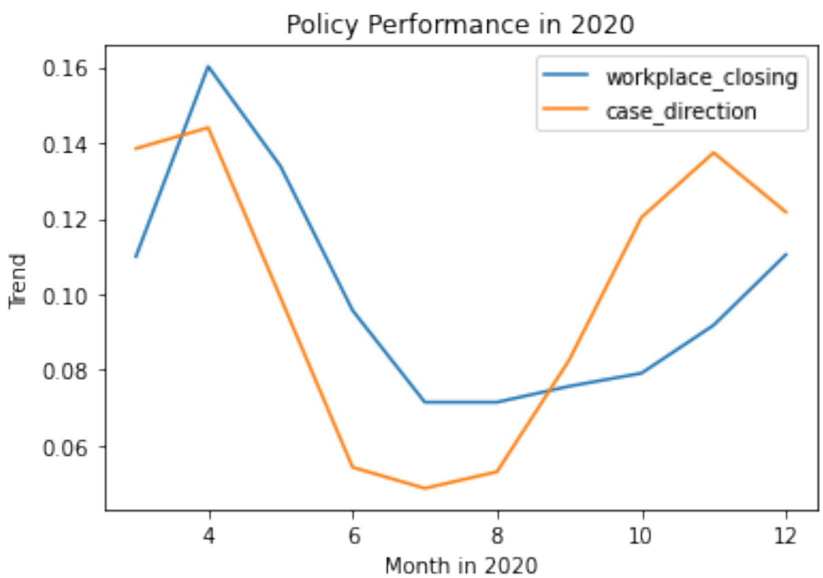


In [31]:
```
# covid['international_travel_controls'].hist()
fig, ax = plt.subplots(figsize=(3,3))
covid.hist('international_travel_controls', ax=ax)
ax.set_title('International Travel Controls')
fig.savefig('international_travel_contols_hist_3x3.png', bbox_inches='
tight')
plt.show()
```



In [32]:
```
du.compare_policy_outcomes(covid, 'Canada', 'workplace_closing', 'case
_direction')
```

```
/Users/lquera/Dropbox/DSND/DSND_Project_Capstone/Quera_capstone_subm
ission/data_utilities.py:365: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  comp_df['date'] = pd.to_datetime(comp_df['date'])
```




```
<Figure size 432x288 with 0 Axes>
```

In [33]:
```
cols_demos = ['geo','country_name', 'region_name','date',
                'case_perc_pop','death_perc_pop',
                'urban_perc', 'median_age','density'
               ]
```

In [34]:
```
covid_demos = covid[list(covid[cols_demos])]
covid_demos.shape
```

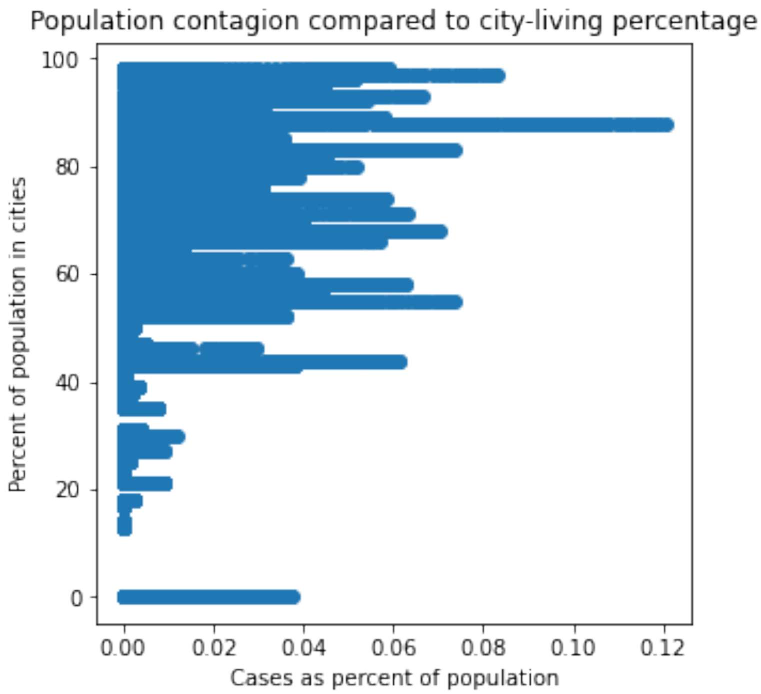
Out[34]:
```
(73162, 9)
```

In [35]:
```
# just to validate the use of scatter plot rather than scipy corrs
demos_to_check = cols_demos[6:]
pc_demos_corr = du.get_pearsons_corr(covid_demos, demos_to_check, 'cas
e_perc_pop')
impt_demos = pc_demos_corr.loc[(abs(pc_demos_corr['corr']) > 0.10)]
impt_demos.head()
```

Out[35]:

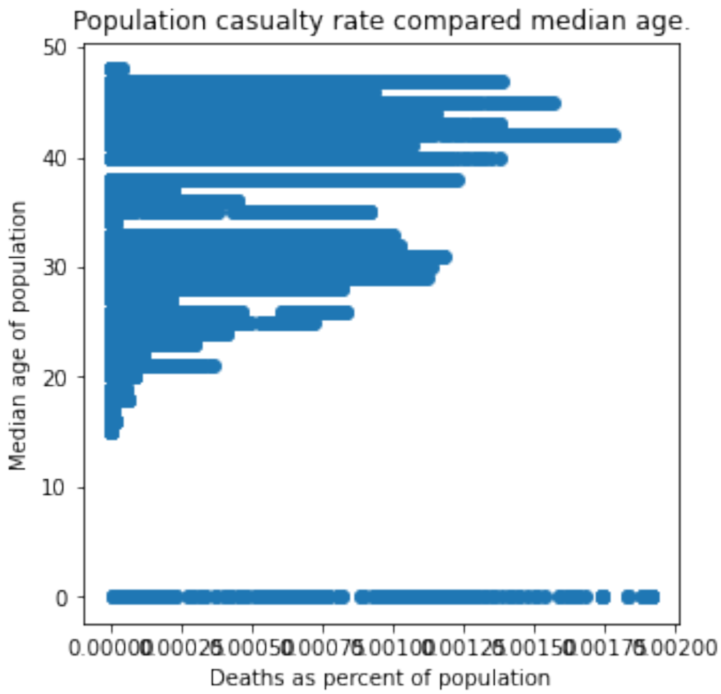
feature	corr

In [36]:
```
#pd.plotting.scatter_matrix(covid_demos[['case_perc_pop','urban_perc']
], figsize=(15,15))

plt.scatter(covid_demos['case_perc_pop'], covid_demos['urban_perc'])
plt.xlabel('Cases as percent of population')
plt.ylabel('Percent of population in cities')
plt.title('Population contagion compared to city-living percentage')
fig = plt.gcf()
fig.set_size_inches(5,5)
plt.savefig('case_perc_pop_and_urban_perc_5x5.png')
plt.show()
```



In [37]:

```
plt.scatter(covid_demos['death_perc_pop'], covid_demos['median_age'])
plt.xlabel('Deaths as percent of population')
plt.ylabel('Median age of population')
plt.title('Population casualty rate compared median age.')
fig = plt.gcf()
fig.set_size_inches(5,5)
plt.savefig('death_perc_pop_and_median_age_5x5.png')
plt.show()
```



Modeling for feature understanding

Another approach to understanding policies and outcomes, is to use models to identify which features improve predictive capability. Let's look at feature selection and feature importance.

Feature selection is the process of testing the relationships between each training feature and the target feature and selecting the ones with the strongest relationship. It shows the impact of the variable on the model success metric and the higher it is, the more valuable the feature's predictive capability. Negative feature importance means that the feature increases the loss and either the model is underfitting or the model would benefit from removing the feature.

SelectKBest is a univariate method that uses statistical means to evaluate the relationships and keeps the K highest-scoring features. RFE (Recursive Feature Elimination) fits a model on all features and then recursively eliminates the one with the lowest importance score until it gets to the K highest scoring features.

You can use feature selection in your model training process and then access the feature*importance* attribute to visualize which features impacted the model most. I chose Random Forests (an ensemble of bagged Decision Trees) because the random splits create better tree diversity with less overfitting than simple Decision Trees. The feature importances are weighted averages of how much the feature reduces impurities across all trees in the forest.

First, let’s look at using SelectKBest feature selection for a RandomForestRegressor optimized for the Mean Absolute Error.

A note on metrics: MAE, mean absolute error, is best suited to the task at hand because my goal is interpretability, teasing out the underlying relationships of policies and outcomes. MAE is considered superior for interpretability because it simply describes average errors and is not as impacted by test sample size. The downside is the significantly larger computation time. (“When the random forest regressor optimizes for MSE it optimizes for the L2-norm and a mean-based impurity metric. But when the regressor uses the MAE criterion it optimizes for the L1-norm which amounts to calculating the median.”[https://stackoverflow.com/questions/57243267/why-is-training-a-random-forest-regressor-with-mae-criterion-so-slow-compared-to (https://stackoverflow.com/questions/57243267/why-is-training-a-random-forest-regressor-with-mae-criterion-so-slow-compared-to)])

In [42]:
```
# Define training data parameters
model_data = covid
train_cols = cols_ordinal[8:]
target = 'case_perc_change'
# Feature Selection
n_features = 12
selection = 'stat'
problem_type = 'regression'
scoring = 'f_regression'
# Data Splitting
test_size = 0.30
random_state = 17
# RandomForest
n_estimators = 100
criterion = 'mae'
```

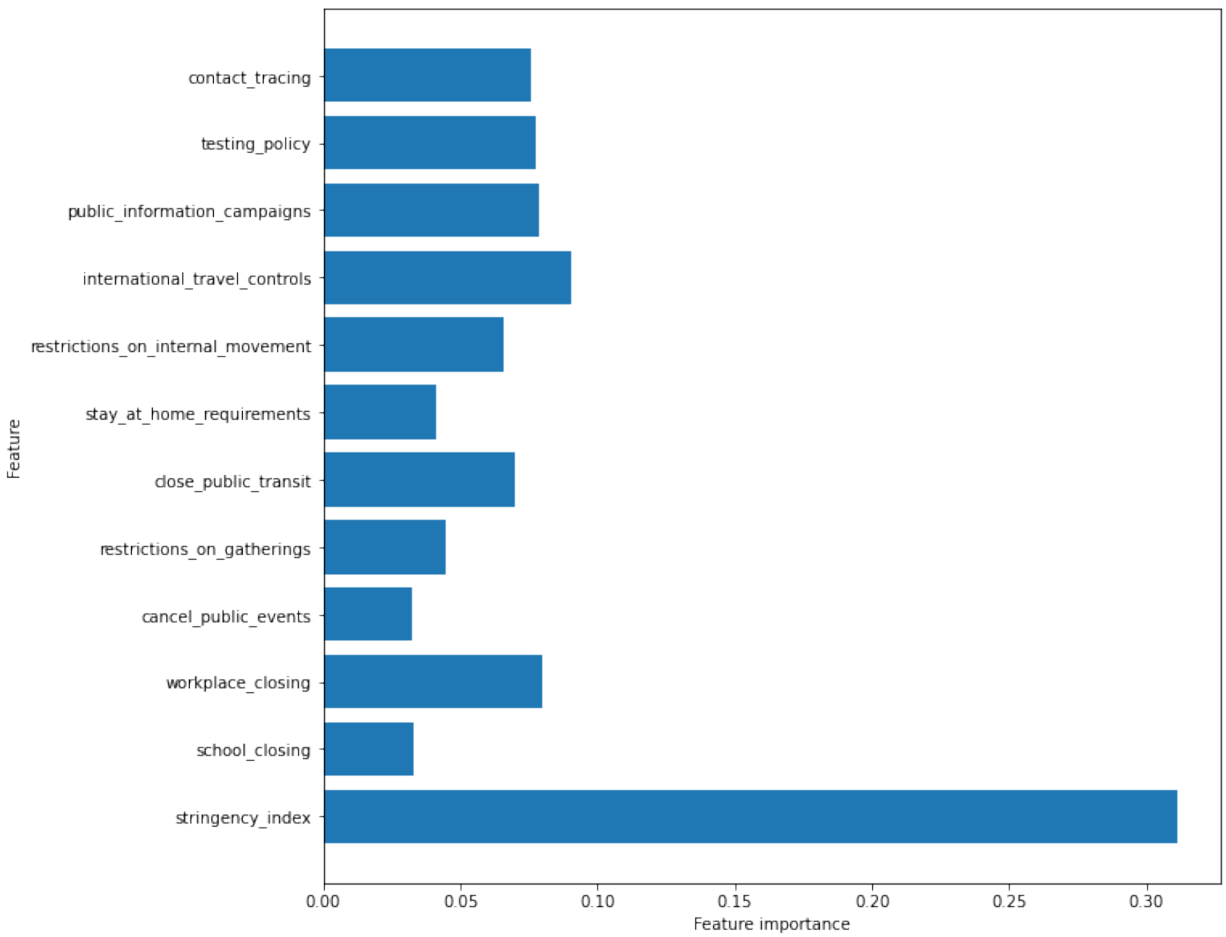
In [43]:
```
X_train, X_test, y_train, y_test, stat_features_used = mu.get_train_te
st_data(
            model_data, train_cols, target,
            problem_type=problem_type,
            scoring=scoring,
            n_features=n_features,
            selection=selection,
            test_size=test_size)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(51213, 12) (51213,) (21949, 12) (21949,)

/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
```

In [44]:
```
rfstat = RandomForestRegressor(n_estimators=n_estimators,
                               criterion=criterion,
                               random_state=random_state,
                               n_jobs=-1)
rfstat, rfstat_results = mu.train_and_score_model(rfstat, X_train, y_t
rain, X_test, y_test, problem_type,
                                                   'RandomForestRegressor')
```

```
RandomForestRegressor
R2 train: 0.257, test: -0.000
MSE train: 0.008, test: 0.015
MAE train: 0.020, test: 0.022
```

In [45]:
```
mu.visualize_feature_importance(rfstat, X_train, stat_features_used, '
RF_reg_stat_ordinals_10x10.png', selection, 'tree')
```



In [ ]:
```
len(covid.loc[abs(covid['case_perc_change']) < 0.04])/len(covid)
```

In [47]:
```
rfstat_cross_vals = cross_val_score(rfstat, X_train, y_train, cv=3)
rfstat_cross_vals
```

Out[47]:
```
array([-0.02653215,  0.00137319,  0.02343883])
```

Does Recursive Feature Elimination return different features?

Next, let’s look at using Recursive Feature Elimination feature selection for a RandomForestRegressor optimized for the Mean Absolute Error

In [49]:
```
# Define training data parameters
model_data = covid
train_cols = cols_ordinal[8:]
target = 'case_perc_change'
# Feature Selection
n_features = 12
selection = 'RFE'
problem_type = 'regression'
scoring = 'f_regression'
# Data Splitting
test_size = 0.30
random_state = 17
# RandomForest
n_estimators = 30
criterion = 'mae'
```

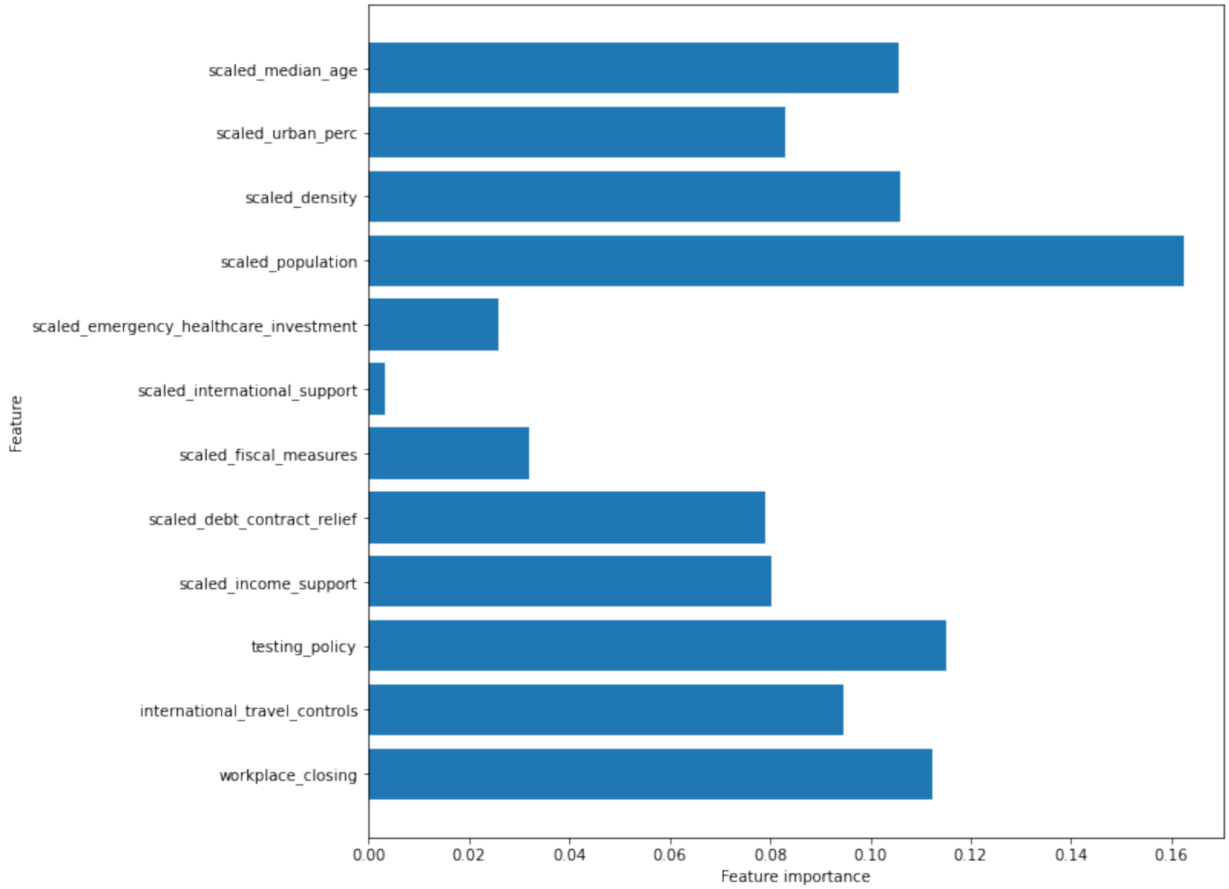
In [50]:
```
X_train, X_test, y_train, y_test, rfe_features_used = mu.get_train_tes
t_data(
            model_data, train_cols, target,
            problem_type=problem_type,
            scoring=scoring,
            n_features=n_features,
            selection=selection,
            test_size=test_size)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)

[11  2  1  5  6  8  7  9  1 10  1  4  1  1  1  1  1  3  1  1  1  1]
(51213, 12) (51213,) (21949, 12) (21949,)
```

In [51]:
```
rfrfe = RandomForestRegressor(n_estimators=n_estimators,
                           criterion=criterion,
                           random_state=random_state,
                           n_jobs=-1)
rfrfe, rfrfe_results = mu.train_and_score_model(rfrfe, X_train, y_trai
n, X_test, y_test, problem_type,
                                          'RandomForestRegressor')
```

```
RandomForestRegressor
R2 train: 0.179, test: 0.014
MSE train: 0.009, test: 0.015
MAE train: 0.021, test: 0.022
```

In [53]:
```
mu.visualize_feature_importance(rfrfe, X_train, rfe_features_used, 'RF_reg_RFE_ordinals_10x10.png', selection, 'tree')
```



Reframe as binary classification problem

Lastly, since we calculated the directional change of the outcomes, we can reformulate the problem to a binary classification - cases up or cases down. Let's see if that makes anything clearer using SelectKBest feature selection for a RandomForestClassifier optimized for information gain, ie. entropy.

In [54]:
```
# Define training data parameters
model_data = covid
train_cols = cols_ordinal[8:]
target = 'case_direction'
# Feature Selection
n_features = 12
selection = 'stat'
problem_type = 'classification'
scoring = 'mutual_info_classif'
# Data Splitting
test_size = 0.30
random_state = 17
# RandomForest
n_estimators = 500
criterion = 'entropy'
```

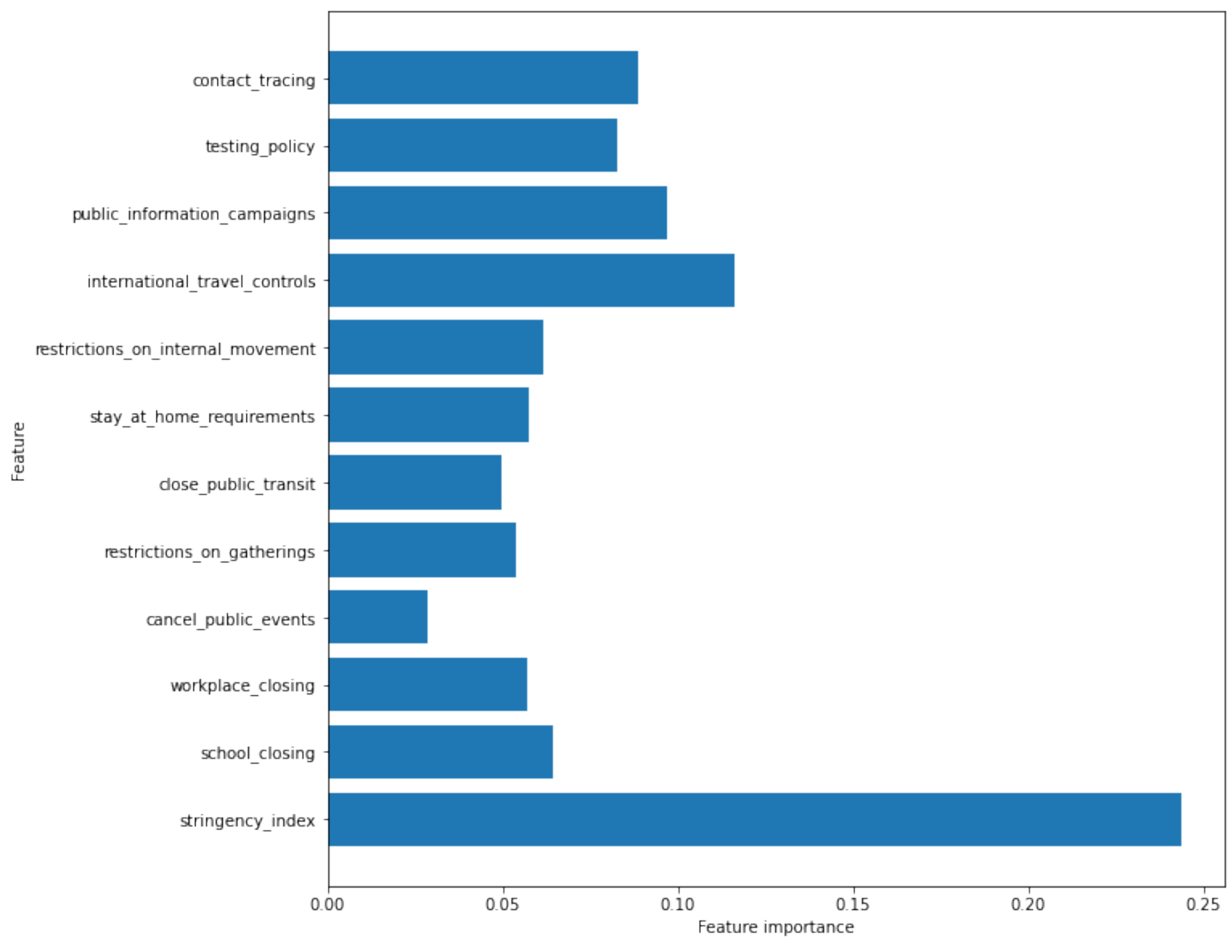
In [55]:
```
X_train, X_test, y_train, y_test, rfc_features_used = mu.get_train_tes
t_data(
            model_data, train_cols, target,
            problem_type=problem_type,
            scoring=scoring,
            n_features=n_features,
            selection=selection,
            test_size=test_size)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)

(51213, 12) (51213,) (21949, 12) (21949,)
```

In [56]:
```
rfc = RandomForestClassifier(n_estimators=n_estimators,
                             criterion=criterion,
                             random_state=random_state,
                             n_jobs=-1)
rfc, rfc_results = mu.train_and_score_model(rfc, X_train, y_train, X_t
est, y_test, problem_type,
                                            'RandomForestClassifier')
```

```
RandomForestClassifier
Accuracy train: 0.859, test: 0.838
Precision train: 0.880, test: 0.862
Recall train: 0.913, test: 0.899
```

In [57]:
```
mu.visualize_feature_importance(rfc, X_train, rfc_features_used,
                                'RFC_stat_ordinals_10x10.png', selecti
on, 'tree')
```



In [58]:
```
rfc_cross_vals = cross_val_score(rfc, X_train, y_train, cv=3, scoring=
'precision')
rfc_cross_vals
```

Out[58]:
```
array([0.87018861, 0.86453474, 0.8662678 ])
```

In [59]:
```
# Define training data parameters
model_data = covid
train_cols = cols_ordinal[8:]
target = 'case_direction'
# Feature Selection
n_features = 12
selection = 'RFE'
problem_type = 'classification'
scoring = 'mutual_info_classif'
# Data Splitting
test_size = 0.30
random_state = 17
# RandomForest
n_estimators = 500
criterion = 'entropy'
```

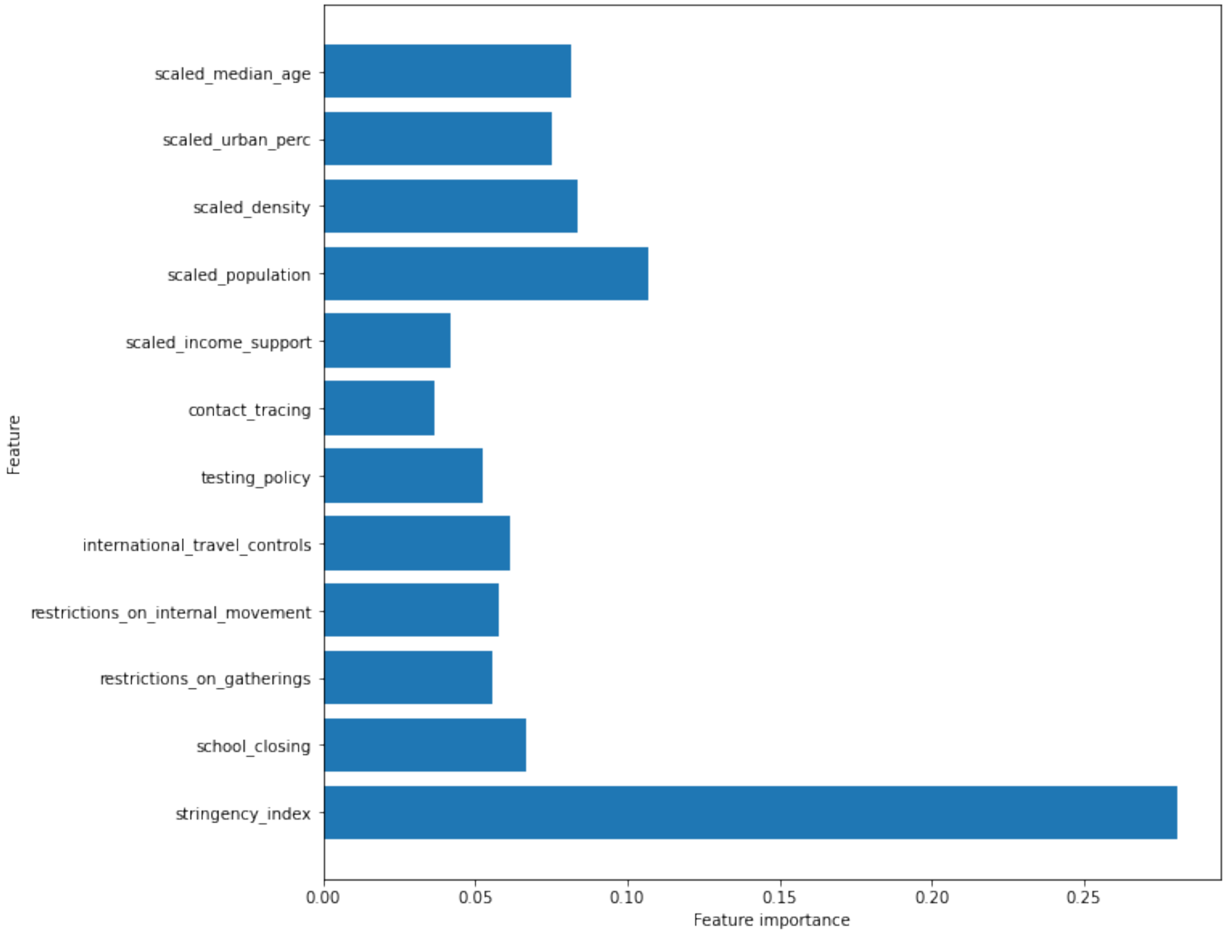
In [60]:
```
X_train, X_test, y_train, y_test, rfcrfe_features_used = mu.get_train_
test_data(
            model_data, train_cols, target,
            problem_type=problem_type,
            scoring=scoring,
            n_features=n_features,
            selection=selection,
            test_size=test_size)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)

[ 1  1  3  6  1  4  2  1  1  9  1  1  1  5  7 10  8 11  1  1  1  1]
(51213, 12) (51213,) (21949, 12) (21949,)
```

In [61]:
```
rfcrfe = RandomForestClassifier(n_estimators=n_estimators,
                               criterion=criterion,
                               random_state=random_state,
                               n_jobs=-1)
rfcrfe, rfcrfe_results = mu.train_and_score_model(rfcrfe, X_train, y_t
rain, X_test, y_test, problem_type,
                                                 'RandomForestClassifier')
```

```
RandomForestClassifier
Accuracy train: 0.865, test: 0.841
Precision train: 0.885, test: 0.865
Recall train: 0.917, test: 0.901
```

In [62]:
```
mu.visualize_feature_importance(rfcrfe, X_train, rfcrfe_features_used,
                                'RFC_RFE_ordinals_10x10.png', selectio
n, 'tree')
```



In [63]:
```
rfcrfe_cross_vals = cross_val_score(rfcrfe, X_train, y_train, cv=3, sc
oring='precision')
rfcrfe_cross_vals
```

Out[63]:
```
array([0.87447375, 0.86886366, 0.87052062])
```

In [64]:
```
# Define training data parameters
model_data = covid
train_cols = cols_binary[6:]
target = 'case_direction'
# Feature Selection
n_features = 12
selection = 'stat'
problem_type = 'classification'
scoring = 'mutual_info_classif'
# Data Splitting
test_size = 0.30
random_state = 17
# RandomForest
n_estimators = 500
criterion = 'entropy'
```

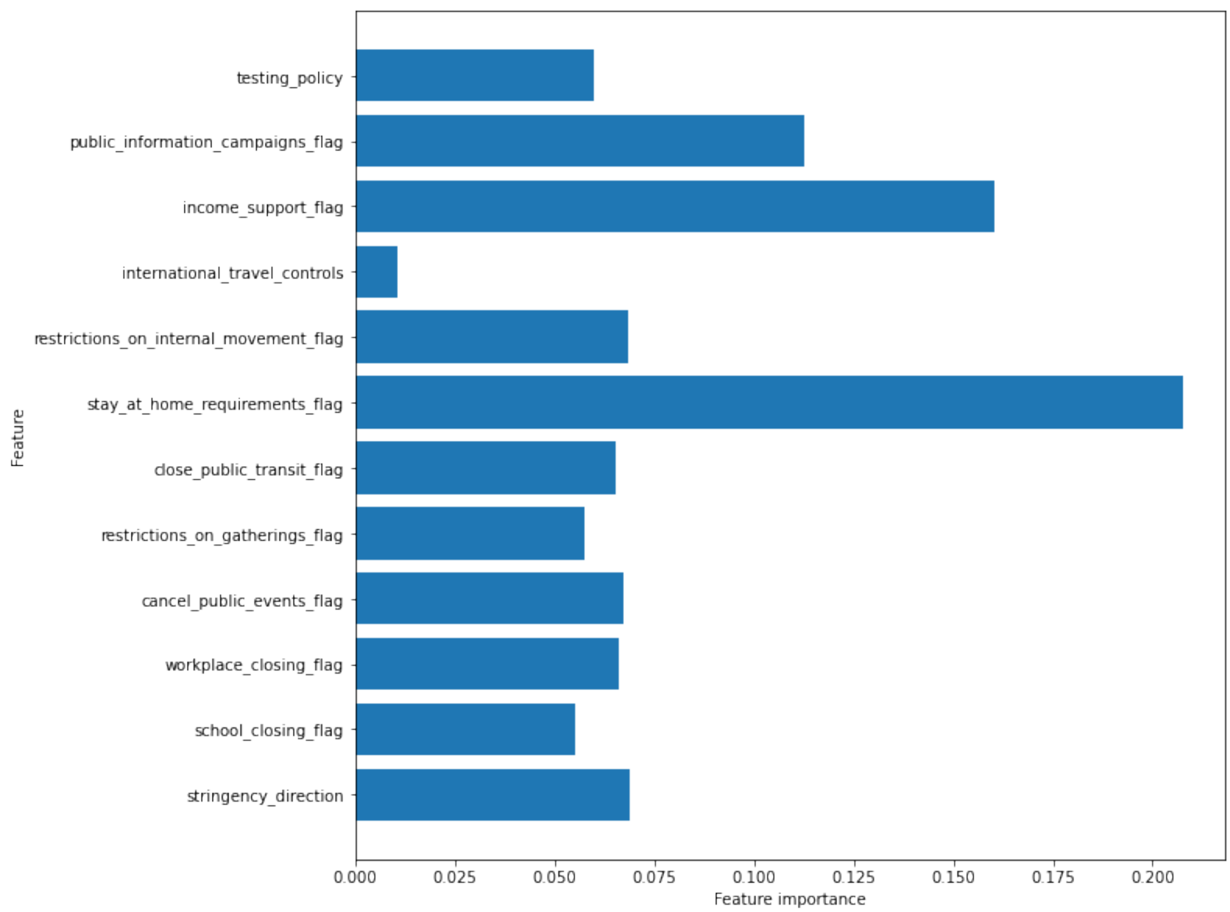
In [65]:
```
X_train, X_test, y_train, y_test, rfcb_features_used = mu.get_train_te
st_data(
            model_data, train_cols, target,
            problem_type=problem_type,
            scoring=scoring,
            n_features=n_features,
            selection=selection,
            test_size=test_size)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)
/Users/lquera/opt/anaconda3/envs/DSND/lib/python3.6/site-packages/pa
ndas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  iloc._setitem_with_indexer(indexer, value)

(51213, 12) (51213,) (21949, 12) (21949,)
```

In [66]:
```
rfcb = RandomForestClassifier(n_estimators=n_estimators,
                              criterion=criterion,
                              random_state=random_state,
                              n_jobs=-1)
rfcb, rfcb_results = mu.train_and_score_model(rfcb, X_train, y_train,
X_test, y_test, problem_type,
                                    'RandomForestClassifier')
```

```
RandomForestClassifier
Accuracy train: 0.773, test: 0.760
Precision train: 0.797, test: 0.786
Recall train: 0.886, test: 0.878
```

In [67]:
```
mu.visualize_feature_importance(rfcb, X_train, rfcb_features_used,
                               'RFC_stat_binary_10x10.png', selection
, 'tree')
```



In [68]:
```
rfcb_cross_vals = cross_val_score(rfcb, X_train, y_train, cv=3, scorin
g='precision')
rfcb_cross_vals
```

Out[68]:
```
array([0.79431479, 0.78907914, 0.79597608])
```

In [71]:
```
joblib.dump(rfc, 'RFC_stat_ord.joblib')
```

Out[71]:
```
['RFC_stat_ord.joblib']
```

Model evaluation and validation

Classification is much better suited to our problem and dataset. The goal is not to predict a precise number on a continuum, but to understand what impacts the desirable outcome, stable/negative case direction. This aligns nicely with binary classification and you can see that alignment in the results. The regression metric MAE was large, signifying an inability to reliably predict the outcome. The classification metric, Precision, was high, signifying a good ability to predict the desirable outcome. Precision was also very stable in cross-validation.

Conclusions

Now that we've analyzed the data and run it through some models, what do we know about our original hypotheses?

- The correlations between policies and outcomes are much weaker than hoped for.
- The strongest of the admittedly weak correlations are indeed the proximity-impacting policies such as stay at home requirements, school closings, workplace closing, restrictions on travel, etc. This aligns with a logical understanding of how the disease spreads.
- Government capabilities are indeed bounded by uncontrollable factors like urban percentages and median age. This aligns with known data, that is, that proximity is a key factor in contagion and older citizens will die at higher rates than younger ones.

While the data did support the initial logic, the correlation coefficients are too small to enable strong recommendations for any specific policy. This is disappointing but perhaps as more data accumulates, better correlations will emerge and we will be more prepared for the next aerosol/droplet contagious disease.

Technical Lessons Learned

I started with an idea: data on government policies and disease outcomes might help identify which policies are most impactful. I gathered data from multiple sources, did the necessary cleaning and transformations, and used statistical analysis to identify correlations. Then I used feature selection and Random Forest models to identify predictive features. Lastly, I evaluated the original hypotheses against the accumulated data.

1) Why did some techniques work better? Classification worked much better than regression for this problem/dataset. The binary nature of desirable outcome and primary goal of interpretability aligned well with classification.

2) What was the most difficult part? The two most difficult parts were 1) determining which data transformations would be most useful, and 2) determining which input variations, ie. binary flags vs ordinal policy intensities, would align best with which outcome variations, ie. changes in amounts vs changes in direction. I tried to use as much logic as possible but there was a lot of trial and error involved.

3) What is one thing that could be improved? To improve the process, you could do more class and input balancing. For example, the inputs were weighted towards countries that tracked regions, such as the United States and Brazil. You could try taking only the totals for those countries and dropping the regions as potentially noise. (I kept them in to maximize number of datapoints available but more is not necessarily always better.) And for the classification model, the outcomes were unfortunately imbalanced towards increases in cases rather than the desired decreases. You could experiment with giving up half of the datapoints in that class but my concern was making the dataset too small.

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