# Assignment #7

*Sanittawan Nikki Tan*

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Note: Total number of files submitted with this assignment is 10, including this writeup. I put my name at the beginning of every `.py` file.

**Part 1**

Files submitted for problem 1 are:

- `smallest_factor.py` (This file shows that the function failed edge cases that I came up with)
- `test_smallest_factor.py` (This file includes all the tests for edge cases)
- `improved_smallest_factor.py` (This file is an improved version of the function which passes all the test cases in `test_improved_smallest_factor.py` which includes all the same test cases as in `test_smallest_factor.py`)
- `test_improved_smallest_factor.py` (This file includes all the test cases used for `improved_smallest_factor.py` which are the same as `test_smallest_factor.py`. The difference between this file and the `test_smallest_factor.py` is that this file has 100 percent coverage.)

Files submitted for problem 2 are:

- For the smallest_factor part, please refer to files submitted for problem 1. All the test files have 100 percent coverage as the problem required.
- `month.py` (This file includes the month_length function)
- `test_month.py` (This file includes test cases for month.py which has 100 percent coverage)

Files submitted for problem 3 are:

- `operate.py` (This file includes the operate function)
- `test_operate.py` (This file includes test cases for month.py which has 100 percent coverage)

Summary of coverage

Please refer to the Test Coverage Report (figure 2) in Part 2. All the tests have 100 percent coverage.

```
Sanittawans-MacBook-Pro:Assignment_7 sanittawan$ py.test
============================= test session starts ==============================
platform darwin -- Python 3.7.0, pytest-4.0.0, py-1.7.0, pluggy-0.8.0
rootdir: /Users/sanittawan/Documents/Nikki/UChicago/Classes/Autumn_2018/Perspect
ive Analysis/Assignment_7, inifile:
plugins: cov-2.6.0
collected 267 items

test_r.py ............................................................. [ 23%]
........................................................................ [ 50%]
........................................................................ [ 77%]
.....................................                                    [ 91%]
test_specs.py .                                                          [ 91%]
month/test_month.py .....                                                [ 93%]
operate/test_operate.py .                                                [ 94%]
smallest_factor/test_improved_smallest_factor.py ........                [ 97%]
smallest_factor/test_smallest_factor.py ..FFFF..                         [100%]
```

Figure 1: get r.py test results

```
---------- coverage: platform darwin, python 3.7.0-final-0 -----------
Name                                                Stmts   Miss  Cover
-----------------------------------------------------------------------
get_r.py                                                3      0   100%
month/month.py                                         10      0   100%
month/test_month.py                                    11      0   100%
operate/operate.py                                     14      0   100%
operate/test_operate.py                                16      0   100%
smallest_factor/improved_smallest_factor.py             9      0   100%
smallest_factor/smallest_factor.py                      5      0   100%
smallest_factor/test_improved_smallest_factor.py       17      0   100%
smallest_factor/test_smallest_factor.py                17      0   100%
specs.py                                                2      0   100%
test_r.py                                              29      0   100%
test_specs.py                                           5      0   100%
```

Figure 2: Test Coverage Report

**Part 2**

Please refer to the submitted `get_r.py` file for my function. The function that I wrote passes all the tests in `test_r.py` as shown in figure 1. The proof of test coverage is shown in figure 2.

**Part 3**

In Common Sense and Sociological Explanations, Duncan Watts (2014) discussed why sociological explanations are prone to scientific invalidity and proposed several solutions to move beyond theories which were founded on "common sense" to more scientifically valid and testable, though less satisfying, theories. He cited rational choice theory as one of the examples where common sense permeates sociological theorizing. According to Watts (2014, 319), sociologists and political scientists adopted the rational choice theory in the late 1960s. Despite its powerful explanation and its parsimonious nature, the rational choice theory was heavily criticized by social scientists. Firstly, some viewed that rational choice theory makes impractical and possibly empirically invalid assumptions about actors' preferences. In other words, humans are not always rational and calculative, seeking to maximize utility at all times. In response to these criticisms, proponents of rational choice have altered or relaxed their rigid assumptions in some cases and shifted to empathetic explanation or, as Watts put it, "emphasis on understandability and sense-making." This shift in rational choice theory leads to Watts' second criticism about the theory that it distances itself from being a scientifically testable explanation based on generalizable causal mechanisms to a theory that is based on common sense which is not necessarily scientifically valid.

Watts argued that the main pitfall of basing theoretical explanations on common sense is that it misleads academics to believe that explanations that are valid in everyday situations are valid universally as well. As a result, a theory can be perceived as true rather than false and more valid than it actually is (327). The problem and complication, as Watts saw, stem from the fact that social scientists are humans and it is difficult, or nearly impossible, not to construct a theory without imagining oneself in the same situation as a mental exercise (325-326). In fact, this technique is prevalent among many disciplines of the social sciences. In addition, Watts argued that because of this mental exercise, social scientists are more prone to not distinguishing making predictions and making inferences about an actor. As a result, some explanations that seem to make sense in everyday life are used as a causal explanation of some observed outcomes; however, there is no guarantee that such sensible or understandable explanations can actually explain the causes of an outcome, let alone predicting it.

After having laid out the flaws of commonsense theories of action, Watts proposed three main solutions for sociologists in order to make sure that an explanation or a theory can pinpoint causal effects and mechanisms. The first solution is to use experimental designs which are invented to isolate causal effects through a randomization process. Experiments can be done in various forms and settings such as field experiments, lab experiments, or even natural/ quasi-experiments. Although some question the external validity of field experiments, these research designs are still regarded as a gold standard for understanding causal effects. Another alternative to experiments is statistical inferences by conducting studies based on large-scale nonexperimental/ observational data coupled with a counterfactual model of causal inference. Nevertheless, this approach does not increase validity as the number of observation grows. The final solution is tested explanations' ability to predict, especially with out-of-sample testing. Although some sociologists disregard the significance of predictability, Watts believed that testing a theory's ability to predict with hold-out data will increase its scientific validity. The tradeoff, however, is that sociological explanations may lose understandability which could be less satisfying compared with intuitive, sense-making explanations.

**Addendum**

Although Watts pointed out the limitations of theoretical models that make rigid assumptions, strong causal claims, and offer powerful, yet empirically and realistically questionable, explanation, these models can be useful as they could be as a starting point or a stepping stone for rigorous causal studies which could validate or falsify such theories, thus benefiting causal inference and prediction. To illustrate, it is sensible to be convinced that political ads should have some effects on the audience that are exposed to them. In fact, campaigns tend to believe that in order to persuade voters, they should air as many political ads as possible, especially in battleground states. This is considered commonsense since we tend to believe that things that are omnipresent could steer people's behaviors towards a direction. In this case, voters who have seen many political ads of a candidate could be persuaded to vote for that candidate. If a candidate were to win an election and that candidate happens to invest a lot of campaign money in televised ads, we may conclude that that candidate wins an election because of his political advertisement and, even further, generalize that if candidates want to win an election, they should invest in airing political ads. One may go as far as constructing a model with political ads as one of the predictors contributing to a candidate's success. However, as we learn from Watts, we must be skeptical of such conclusion because there is no scientific testing of such a relationship between political ads and being a successful candidate. In fact, various political scientists embarked on testing such theoretical models using causal inference techniques such as field experiments: for example, Gerber, Gimpel, Green, and Shaw (2011) found in their research that political ads have effects on voting preferences though the effects are short-lived. However, it is difficult to persuade voters to change their minds and political ads are only useful for priming rather than educating voters. As we may see, theoretical models serve as a useful starting point to further studies of causal effects and prediction. Another benefit of theoretical models is that it is a simplified version of the reality. By making assumptions, academics are certain that a model would work and offer a reasonable explanation if the assumptions are met. In this light, theoretical models act as a good "box" in a sense that they also allow us to think "outside the box" more clearly as we are aware of the limitations of the box.

Gerber, Alan S., James G. Gimpel, Donald P. Green, and Daron R. Shaw. 2011. How Large and Long-lasting are the Persuasive Effects of Televised Campaign Ads? Results from a Randomized Field Experiment. American Political Science Review 105(1):135-150.