The Crisis Sensitivity Simulator

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ABSTRACT

The purpose of the Crisis Sensitivity Simulator (CSS) is to perform scenario analysis on country performance by shocking individual factor behavior for a country, and visually interpret the country behavior within each shocked factor scenario.

To perform this analysis, the input provided is the minimum and maximum value of each factor, and recent factor behavior. These values can be calculated or can be provided by domain experts. The CSS then uses these parameters to simulate the expected country behavior. This is done by first generating values that represent expected behavior of the individual factors for each country using a 4-parameter beta distribution, and then aggregating the values together to obtain country behavior in that simulation. This process is performed multiple times to create an expected behavior distribution which will be used to compare the shocked behavior. To generate the shocked behavior, we modify the input parameters one factor at a time. Then, we perform the same steps of simulating behavior of individual factors and aggregating the factor behavior together to obtain country behavior, and repeating this process multiple times to generate the shocked behavior distribution. These distributions are then output to the dashboard for the user to ingest in an easily accessible, interactive manner.

The process flow below gives a high-level overview of how the CSS functions. The screenshot after the process flow is an of the visualization component that help users interpret and verify results.

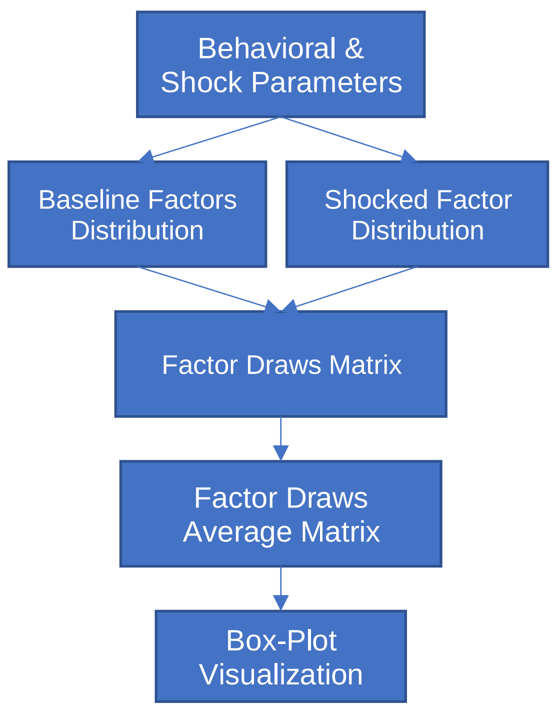

Figure 1: Crisis Sensitivity Simulator Process Flow

Figure 1: Visualization Component of Crisis Sensitivity Simulator

INTRODUCTION

Fund for Peace (FFP) is a US-based non-profit educational and research institution that aims to prevent violent conflict and promote sustainable security worldwide. They came to SAS as part of a Data for Good initiative in 2021, motivated by unexpected outcomes in the COVID-19 pandemic, where some countries faired poorer than expected, while others were not as affected as expected. FFP was looking for help analyzing their data to help discover how sensitive each country around the world was to various crises. Their overall aim was to help better prepare various organizations, and countries themselves, to deal with future crises around the globe, and better understand which countries may be more heavily affected by crises in different sectors.

FFP provided SAS with two sets of data – the Fragile States Index (FSI), looking at the amount of pressure countries were under in different sectors (economic, political, social, cohesion, with 3 factors under each pillar), as well as the State Resilience Index (SRI), which examines the capacity each country has for managing these pressures in each sector. Please see the following website for more information on these indices and their development.

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This situation would be a perfect candidate for scenario analysis - a common practice in the financial industry to plan and prepare for unlikely but impactful. While the data provided by FFP was rich in qualitative observation and domain expertise, it was limited in terms of quantity traditionally needed for scenario analysis. For most countries, there were 15 observations in the FSI data – one per year since 2005, and one observation per country (2021) for the SRI data. events - but the data was simply unavailable to perform a traditional scenario analysis exercise. This led us to developing the Crisis Sensitivity Simulator as described below.

Economic Foundation

The Simulator is based on an economic model. This model is simple to understand, yet allows for substantial flexibility to represent behavior. While not based on original research, it aligns well with observation and basic economic theory.

To understand the dynamics, begin by defining *pressure*. Pressure is an umbrella term for stresses faced by a given country. It is assumed to be highly variable in the short-term. This is borne out by observation where stresses, such as natural disasters or economic shocks, arise in a matter of weeks, if not days. Accordingly, pressure can be considered the driving force in the model as it evolves from an initial shock in a linear or potentially non-linear fashion.

Capacity is the resources able to be brought to bear in response to stress. In contrast to pressure, capacity is considered relatively static over the short term. Again, this assumption accords with observation. Resources such as infrastructure, governance, and societal support mechanisms are not readily improved and often require years of consistent attention.

Pressure and capacity do more than evolve independently. Together, they determine the response of a country to an exogenous stressor. Periods of extreme pressure (relative to capacity) act to degrade capacity. Conversely, in more benign periods when capacity exceeds pressure sufficiently, capacity can be “repaired” or expanded. As a practical example, consider the recent experience with healthcare systems. As COVID overwhelmed hospital facilities and staffs, their ability to treat patients weakened. Between waves of infection, these were able to recover and their ability rebounded.

TECHNICAL

Baseline and Stressed Distributions

For the Crisis Sensitivity Simulator, we initially considered utilizing the PERT distribution to describe each factor’s behavior. The PERT has an interesting history, being developed to describe the uncertainty in tasks during the development of the Polaris missile by CE Clark in 1962. This scenario is similar to the one facing FFP, as both entail data that are sparse from either not having been collected or not existing. The PERT distribution is defined by three parameters: the minimum, the maximum, and the most likely. From these three pieces of information, a distribution can be constructed and analyzed.

Unfortunately, the PERT suffers from a few failings. First, it lacks a simple closed form for either Cumulative Distribution Function (CDF) or its percentiles. This complicates both the ease of calculation and the ability to shift the distribution. Second, the definition of the most likely parameter is subjective, with no clear computational method.

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Luckily, the PERT distribution is closely related to a more amenable distribution: the 4-parameter beta. The 4-parameter beta is a scaled and shifted version of the 2-parameter beta. This provides an easy way to adjust the distribution as noted in the process above.

Now that we have selected the 4-parameter beta distribution to represent factor behavior in the Crisis Sensitivity Simulator, we will define the mathematics that demonstrates how this is used. Let S be a random variable representative of overall system behavior whose behavior is driven by a series of n factors, Y_i, that each have minimum value a_i and maximum value b_i. Let

$$X_i \sim \mathrm{B}(p,q), \text{ and}$$
$$Y_i = (b_i - a_i) * X_i + a_i. \text{ Then,}$$
$$Y_i \sim \mathrm{B}(p,q,a_i,b_i),$$

and an observation of the overall system behavior can be defined as

$$S = \frac{\sum_{i=1}^{n} Y_i}{n}.$$

The overall distribution of S can be determined empirically.

To understand how the distribution of S may change when a given factor is shocked, the distribution of said factor must be updated. This is done by modifying the minimum or maximum parameter values. Let

$$Y_j' \sim \mathrm{B}(p,q,a_j,\max(b_j, \quad h_j * (1 + \frac{r_j}{100}))$$

where

Y_j' represent the factor whose distribution will be shocked,
h_j is the recently observed value of the factor and
r_j is a percentage shock to the maximum parameter for factor Y_j'.

Note that the factor's distribution will not experience a shock if the shock applied to the most recent observed value of that factor does not result in a value greater than the historical/estimated maximum of that value. This makes intuitive sense, as this means a shock applied at this current state of the factor does not lead to behavior outside what was previously expected as part of the baseline behavior of this factor.

Once these parameters have been updated for Y_j', an observation of the overall system behavior can now be defined as

$$S = \frac{\sum_{i=1}^{n} Y_i, i \neq j + Y_j'}{n}$$

and the distribution can again be determined empirically through running many simulations.

Simulation Methodology

Now that the mathematics have been defined, the algorithm that utilizes the mathematics will be discussed. An

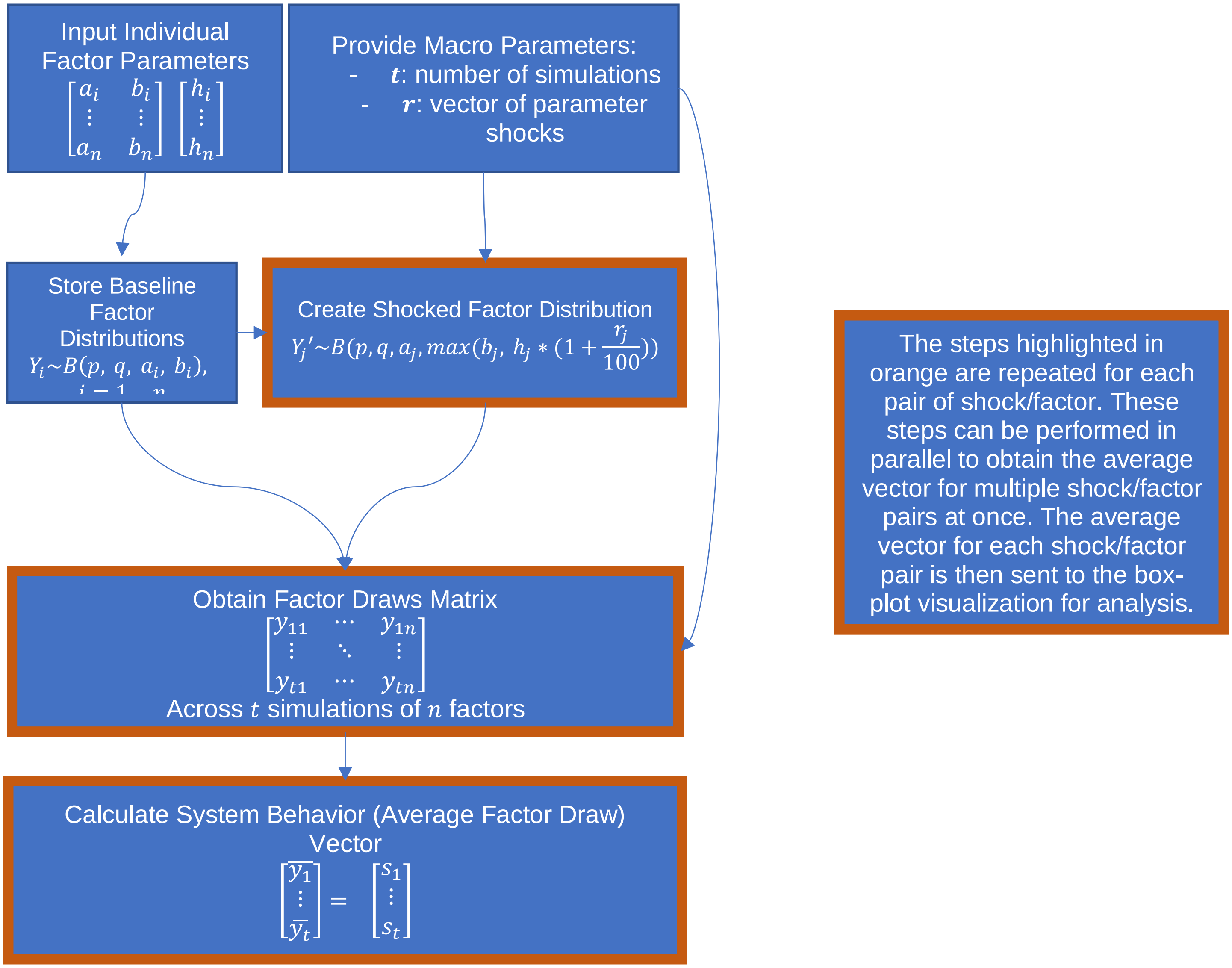

Figure 3: Detailed Crisis Sensitivity Simulator Process Flow

overall diagram is shown below.

The first step that must be taken in this situation is to read in the distribution parameters for each factor, namely the minimum and maximum values. These can either be derived from historical data, or directly provided by experts. If these parameters are to be derived from historical data, at least three observations must be provided. Additionally, in the historical data case, it is recommended for the estimated parameters to be reviewed by a domain expert to ensure the calculated results are as expected, and if appropriate, these values can be modified.

The minimum and maximum parameters are used to generate the alpha and beta parameters. This set of four parameters defines the baseline distributions for each factor, i.e. their expected behavior under typical circumstances. A factor draws matrix will be generated where all factors exhibit baseline behavior for comparison purposes. The matrix dimensions will be number of draws done from each factor distribution (i.e. number of simulations) by the number of factors. To obtain the baseline system behavior from the matrix, the row-wise average will be taken. In other words, the behavior of the system can be considered as the average behavior over all the factors within the system. This leaves us with a vector with length equal to the number of simulations performed.

Once the baseline system behavior has been calculated, the shocked behavior will then be generated. For each factor/shock value pair, the following process will occur: First, a shocked distribution will be generated by modifying the maximum parameter of the baseline distribution of said factor using the desired shock value (as explained in the mathematics section above). Then, the factor draws matrix is generated using the baseline behavior for all factors, except the shocked factor, whose values in the factor draws matrix will come from the shocked distribution. Finally, as in the baseline scenario, the row-wise average of the matrix will be taken to generate the vector of system behavior in each factor-shocked scenario.

The system behavior vectors for baseline behavior, as well as shocked behavior for each shock/factor pair is then output to the box-plot visualization for further investigation. This allows the user to inspect the effect shocking each factor at a given level had on the overall system behavior, and compare this behavior to both the baseline behavior, as well as the behavior in other shock scenarios. The box-plots provide the user with a variety of summary statistics to describe the range of possible outcomes in each shocked scenario. They are also very intuitive to interpret – if the box-plot for the baseline scenario looks visually different from the box plot for a shocked scenario, then it is clear that the system is sensitive to changes in that particular factor's behavior.

These results can then be passed along to a domain expert to verify that the output for the shocked scenarios are aligned with expected system behavior. Once these results have been verified by the experts, they may utilize them to make more informed decisions.

ACKNOWLEDGEMENTS

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