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## **Vietnam War** Operations

Coming into this project, I had a pre-conceived notion of what I wanted to see. I wanted the quirky codenames to be displyed in patterns that engage the viewer, at least to come closer and read the language of our past. However, the story behind this was not a priority until I read further into the subjects. Of course, these subjects are heavy in their implications regarding their effect on history, but choosing the datasets and timeframes offered new insights, and missed opportunities. First of all, Little Boy and Fat Man are listed as "tests" in the spreadsheet of nuclear experimentation and fall outside of my chosen dataset. These are tests that killed 326,000 people in Hiroshima and Nagasaki, Japan. The casualties of nuclear testing in Japan equal about 1/10 of the approximately 3,000,000 casualties in Vietnam. The numbers are staggering, especially since all of the death caused by nuclear testing was caused by two tests, right at the start of the dataset. This has led to a rethinking of my approach to data by choosing ranges that tell the right story and are comparable to a peripheral dataset of concern. For now, please see the correlation between a slight peak in nuclear tests and Vietnam War operations between 1966 and 1969. If anything, the 1966 increase in operations might have caused a demand to test nuclear weapons in 1968 as potential tools of combat. The real story however, is that two tests - not shown in the data - could equal one

tenth of the deaths in Vietnam.