Smart People Behaving Foolishly: Lessons from a Career in Scientific Research

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Most management decisions involve politics, so they are often based more on fear and ego than principle. The biggest fear is "looking bad."

Introduction

The focus of this article is on things I wish someone had told me when I was a young person embarking on a career in scientific research. My specialty is statistical signal processing for applications in acoustics, electromagnetics, and particle physics. This includes underwater acoustics, ultrasonic nondestructive testing, bioacoustics, and speech processing. However, although most of the ideas in this article are relevant to science and engineering, they are also relevant to life in general. The lessons I have learned have been valuable to me, but it would have been wonderful if I had not had to learn them via the "school of hard knocks." By sharing lessons here, my hope is that at least a few people might be saved the trouble of learning them the hard way.

As humans, we are all susceptible to some level of poor judgment at one time or another. Murphy's Law is alive and well in scientific and engineering systems. Over my career, I have served in various positions, including electronics technician, staff scientist, principal investigator, technology leader, program leader, and director of research. At every level, I have made my share of foolish mistakes and I have observed countless brilliant colleagues behaving in ways that are decidedly not brilliant. I call this "smart people behaving foolishly."

Aside from sociopathic ethical breaches, I believe the cause of smart people behaving foolishly is the general frailty of human nature, especially the ego. We become overwhelmed by excessive demands, and we make too many decisions based on fear rather than principle. We live in a society obsessed with finding fault and assigning blame, yet everybody wants to avoid "looking bad." In addition, schools simply cannot teach us all the practical lessons that we will need in our careers.

In this article, I take a playful look at the practical "technical folklore" that is necessary for real-world laboratory work but is rarely found in textbooks or journals. I emphasize the assumptions, limitations, and trade-offs associated with various signal-processing algorithms and provide "rules of thumb" for use in the laboratory.

My goal is to explore the effects of human nature on projects in Science, Technology, Engineering, and Mathematics (STEM) and demonstrate the concepts with "horror stories" from actual real-world projects. In doing so, I use quotes from others as well as my own "Clark's Laws" to have some fun with the nasty problems that keep many of us up at night.

H. L. Mencken (1880-1956)

Explanations exist; they have existed for all time; there is always a well-known solution to every human problem - neat, plausible, and wrong (Mencken, 1982).

Human Nature/Ego Issues

The dark and absurd side of human nature, including the human ego, is the source of most career problems. This is why the cartoon "Dilbert" (Adams, 1989) is popular. Technical problems are often easier to solve than problems with human beings.

Clark's Law of Career Egos

Most career problems are caused by someone's ego. Make sure it is not yours. Do a "self-ego-ectomy" and focus on the highest good (Clark, 2014, 2016).

Fred Followill,

Lawrence Livermore National Laboratory Geophysicist (Retired)

Nobody believes a theorist - save another theorist. Everybody believes an experimentalist - save another experimentalist (Followill, 1980).

Ego problems often rear their ugly heads when new ideas are published or otherwise presented to the technical community at large.

Arthur Schopenhauer (1788-1860)

All truth passes through three stages: First, it is ridiculed, Second, it is violently opposed, and Third, it is accepted as self-evident.

Howard Aiken,

American Computer Engineer and Mathematician (1900-1973)

Don't worry about people stealing your ideas. If your ideas are any good, you'll have to ram them down peoples' throats (Weiss, 1988).

The human tendency to underestimate the difficulty and scope of projects routinely plays havoc with scientific enterprises.

Fundamental Principle of Projects

Time, Quality, Cost (or Faster, Better, Cheaper): We cannot maximize all three of these conditions simultaneously. Once any two are chosen, the third is automatically determined ("pick two") (Clayton, 2014).

Meskimen's Law of Time

There is never enough time to do it right, but there is always enough time to do it over again (Hoover, 2007).

Clark's Law of Project Time

Estimate the actual, realistic time required to finish a project as follows: Make your most generous estimate, assuming Murphy's Law is in full effect. (2) Multiply by pi (Clark, 2014, 2016).

The fundamental principle of projects (sometimes known as the time-cost-quality triangle) expresses the practical constraints on projects, and it is routinely violated in projects of all kinds. Because there is no free lunch, every project has its trade-offs. However, it is easy to believe and proclaim to our sponsors that we are faster, better, and cheaper than our competitors. As Dirty Harry (Warner Bros., 1973) says, "A man's gotta' know his limitations."

When I was a young scientist, I saw a "joke" poster about the "Six Phases of a Project" posted on the bulletin board of one of my senior colleagues (see **Figure 1**). As my career progressed, I realized that this was not a joke but a deadly serious admonition.

After years of watching countless projects and people being crushed in the gears of the six phases, I learned my lesson. When someone asks me to work on a project, I first assess the current phase of the project. If it is in Phase III or higher, I do my best to avoid working on the project. I have seen many innocent people blamed for project shortcomings to protect someone else (usually a manager) from looking bad.

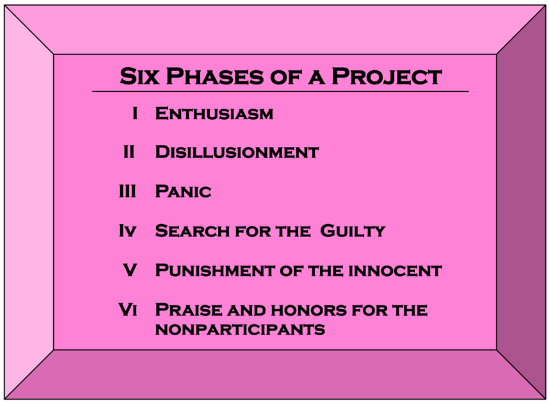

Figure 1. The six phases of a project are real, and they apply especially well to large projects. This "joke" should be taken very seriously. Human nature is to blame others for one's own shortcomings, and innocent people are often used as "fall guys." Derived from a poster by Decision Technology Corporation, Kensington, MD, 1976.

Horror Story About Faster, Better, Cheaper

During the 1990s, a popular slogan in various federal agencies was faster, better, cheaper. A manager instructed me to use that phrase when talking with our sponsors. I refused and explained that it is foolish to violate the Fundamental Principle of Projects. I got a "talking to" about my attitude, and I "took a beating" for it. I was told, "That's how you have to talk to sponsors now."

Another agency, the National Aeronautics and Space Administration, launched the $125 million Mars Climate Orbiter Spacecraft that crashed into Mars (National Aeronautics and Space Administration, 1999). The project team forgot to get mixed units of distance (English and metric) to jibe in their software. Lockheed used English units, and the Jet Propulsion Laboratory used metric units. It is no wonder that the spacecraft crashed. The project deliverables may have been faster and cheaper, but they were clearly not better. Smart people behaving foolishly.

Common Signal-Processing "Gotchas"

Signal Sampling

Errors in sampling continuous signals to create discrete time signals are very common. I have seen far too many projects that used aliased signals because the people acquiring the data did not pay enough attention to the physics of the problem and did not understand the Nyquist sampling theorem (McGillem and Cooper, 1974). In a nutshell, if the sampling period (in seconds) is denoted by T, then the sampling frequency is $f_s = 1/T$ (in hertz), and f_s must be greater than or equal to twice the bandwidth (B) of the analog signal to preserve the information in the signal or $f_s \geq 2B$.

Horror Story About Signal Sampling

I was asked to estimate the system response of a shock-hardened recorder that measured accelerometer signals. The data-acquisition team showed me accelerometer measurements from a centrifuge, but the signals made no sense to me. I asked how they chose the sampling rate on their digitizer. The answer was that they adjusted the sampling period knob until the time domain plots "looked good."

I got a spectrum analyzer oscilloscope, measured the bandwidth of the analog signals, and calculated the maximum sampling period they could use. It turned out that their measurements were undersampled and aliased by a factor of more than 100. Once I adjusted the digitizer's sampling period properly, the data made good sense and my later processing results were able to solve an important engineering problem. The real horror of this story is that they had been digitizing their signals improperly for many years. Smart people behaving foolishly.

Abuses of Fourier Spectra

I have witnessed countless miscalculations, misinterpretations, misuses, and abuses of the discrete Fourier transforms (DFTs) of signals.

Horror Story About Fourier Magnitude

Some scientists proposed a $2 million project to study some subtle "bumps and wiggles" in the magnitude of the DFT of a measured signal from an experiment. They believed that they knew the physics that caused the wiggles and wanted to test their hypotheses. I was asked to review the project proposal. I commented that the wiggles looked to me a lot like Gibbs phenomena (McGillem and Cooper, 1974). When the DFT of a temporally truncated signal (or one with a jump discontinuity) is computed, the DFT contains artifacts in the form of spectral wiggles, often called "leakage."

When I computed the DFT using a tapered window on their data, the bumps and wiggles went away. I was never asked to review another of their proposals. Smart people behaving foolishly.

Data Chasing

Generally, the goal of signal processing is to allow us to interpret the meaning of the signals and use the signals to solve problems.

Richard Hamming,
Professor of Electrical Engineering, Naval Postgraduate School, Monterey, CA (1915-1998)

The business of computing is insight, not numbers (Hamming, 1973).

George E. P. Box,
Professor of Statistics, University of Wisconsin (1919-2013)

Essentially, all models are wrong, but some are useful. Remember that all models are wrong. The practical question is how wrong do they have to be to not be useful (Draper, 1987).

It is tempting to use the latest cool fad algorithm that is making its way through the literature. However, many times people do this while putting insufficient priority on the fundamental physics and signal processing of the problem.

"Data chasing" is a term coined by my friend, colleague, and mentor Dr. James V. Candy of the Lawrence Livermore National Laboratory (LLNL). Data chasing is what one does when (1) one knows little or nothing about the physical processes that created the data being processed (no models or prior knowledge), (2) one has no access to controlled experiments in which the signal-processing "answer" is known, and/or (3) one applies various filters, DFTs, and ad hoc signal-processing algorithms to the data, yet one cannot explain the meaning of the results.

Data chasing and the use of ad hoc algorithms can have very serious consequences, including the following. (1) One does not understand the meaning of the processing results. The results are often inconclusive and/or not useful. (2) Results are often not repeatable by other researchers. (3) If the algorithms work, one does not know why they worked. If the algorithms do not work, one does not know why they did not work. (4) One does not know what to do to make things better, yet by this time, one has probably exhausted one's time and money for the project. (5) The results are usually not extensible. Model-based signal processing can often mitigate these shortcomings of data chasing (Candy, 2006).

Data chasing leads to enormous waste and stress. Countless times, people have come to me near the end of a project with a project review scheduled in a few days or weeks. They typically ask me, "What signal-processing magic can you do to save the project?" Usually, the measurements are inadequate for processing.

First, I tell them that I'll apply my special *"SESP (sow's ear-to-silk purse) Algorithm."* After we chuckle, I tell them that the experiment is flawed, the data are inadequate, this is a Phase III or IV project, and they really should have included me in the experiment planning at the beginning of the project. I tell them that I do not work on Phase III projects. Of course, that gets me nowhere, and I end up "busting my chops" during nights and weekends in a vain attempt to put a last-minute Band-Aid on a gaping wound. Finally, when the project cannot be saved, I get blamed.

Clark's Law of Heroic Efforts

If you "bust your chops" in an heroic effort, you will usually be repaid with compound ingratitude (Clark, 2016).

When a manager asks you to do something beyond the call of duty to save him/her from looking bad or to do something absurd or wrong in some way, he/she usually says something like, "I'll remember this at raise time." Don't believe it. My colleagues and I have many horror stories to the contrary. Later, the manager usually says something like, "I never said that!" Also, the ingratitude is not simple. It is exponential (compound ingratitude).

Horror Story About an Heroic Effort

Nikola Tesla came to the United States in 1884 from Croatia and was hired by Thomas Edison. After about a year, Edison was impressed by Tesla's abilities and offered to give him a $50,000 bonus if he could create an improved design for Edison's direct current (DC) dynamos. After months of work, Tesla delivered the desired solution and requested his bonus. Edison replied, "Tesla, you don't understand our American humor." Tesla resigned soon after and went on to create a vast legacy of important inventions (History.com Staff, 2009).

The ways to avoid data chasing (aside from avoiding Phase III projects) include the following. (1) Study, really study, the physics/science of the problem and use all possible prior knowledge. (2) Build and validate models of the physical process and the measurement system that produce the measured signals. Do simulation studies. Use first-principles models, nonparametric models, or parametric models that give your insight into the measurements. (3) Involve a statistical signal-processing specialist in the very beginning parts of the project, including basic system design and especially experiment design. The performance of signal-processing algorithms is only as good as the quality of the input data. Of course, there is rarely enough funding to do all of this important work.

Clark's Law of Garbage In, Garbage Out

Signal processing algorithms are garbage-in, garbage-out devices (Clark, 2014, 2016).

Clark's Law of Measurement Quality

The best "signal processing" is a good experiment with good measurements (Clark, 2014, 2016).

Clark's Law of Signal Preprocessing

You'll spend about 80% to 90% of your project effort acquiring, modeling, and preparing your data for your main signal processing algorithm (if you do it right) (Clark, 2014, 2016).

Important Algorithm Assumptions Are Often Overlooked

Every signal processing algorithm is derived under a set of assumptions. If these assumptions are not met by the real-world system under analysis, something must be done to bring the algorithms in line with physical reality. Nonetheless, people often pay little attention to the algorithm assumptions when processing signals.

System Linearity

Linear systems obey the superposition principle (McGillem and Cooper, 1974). Consider a system with system response $h(t)$. Let t denote the continuous time variable and a and b denote real constants. For a system to be linear, if input $x_1(t)$ produces output $y_1(t)$ and input $x_2(t)$ produces output $y_2(t)$, then input $ax_1(t)+bx_2(t)$ must produce $ay_1(t)+by_2(t)$. Thus, the scaling and additive properties must hold. If they do not, then the system is nonlinear.

In practical systems, one can often construct experiments to test system linearity using this definition. However, in my experience, almost nobody bothers to conduct such an experiment. People tend to assume that their system is linear whether it is or not. Then they apply signal-processing algorithms that assume system linearity, obtain bad results, and wonder what went wrong. Smart people behaving foolishly.

Note that in a linear system, zero input must yield zero output. This is often overlooked in practice. For example, consider a system with the following system model. Let $y(t)=4x(t)+5$. If we look at this equation strictly in a mathematical sense, we see that it is a linear equation. However, viewing it as a system model, we see that if the input is zero, then the output is 5. The system, by definition, is not linear. In the real world, the constant 5 implies the existence of an energy source of some kind, so the system is active, not passive. Such a system is known as "incrementally linear" (McGillem and Cooper, 1974). If one is working with an incrementally linear system and using algorithms that assume system linearity, then it is important to preprocess the signals to remove any biases (means) or trends.

Linearity Horror Story About Computing the Autocorrelation of a Signal with Bias

Dr. James V. Candy of the LLNL contributed this story. Early in his career, he computed the autocorrelation of a signal measured at the output of an apparently linear system and obtained results that made no sense. After some time, he realized that the measured signal contained a bias (a nonzero mean). Clearly, the system was actually incrementally linear. When he removed the mean of the signal before computing the autocorrelation, the result made sense and was useful. Note that the autocovariance includes mean removal as part of the calculation (Papoulis and Pillai, 2002).

System Time Invariance

Most signal-processing algorithms assume that the system is linear and time invariant. A system is time invariant if a temporal shift of t_0 seconds in the input signal causes a temporal shift of t_0 seconds in the output signal. Thus, a linear system input $x(t - t_0)$ will produce output $y(t - t_0)$. Note that a time-invariant system has a constant gain, but a time-varying system has a time-varying gain. This means that a time-varying system is also nonlinear over time. If a system is time varying, then the measured signals are generally nonstationary. In this case, adaptive algorithms are appropriate (Candy, 2006).

Observability

In signal processing, we are often concerned with estimating models of systems. Observability is a measure of how well the internal states of a system can be inferred from knowledge of its external outputs (Kailath, 1980). Generally, the measurements must be at least as numerous as the internal states. All too often, scientists and engineers do not take this into account when designing systems and experiments. I have seen it many times.

Horror Story About Observability

I was invited to work on a multiyear project that was nearing completion. The goal was to use a cubic array of six accelerometers to replace gyroscopes in a space vehicle. Six accelerometers were used because the system kinematics could be modeled as a sixth-order nonlinear ordinary differential equation (ODE). Later, the team realized that ODE solvers do not work well with noisy measurements, so I was asked to build a recursive estimator for the linear and angular velocities of the vehicle. A two-axis magnetometer was available but could only measure two angular velocities. I showed that the system was not observable because not enough measurements were available to estimate the six system states. All I could do was build an extended Kalman filter and use simulations to show what could have been done if enough measurements had been available.

Gaussianity

Measured signals are modeled as stochastic processes with particular probability density functions (Papoulis and Pillai, 2002). Many (if not most) signal processing algorithms are derived assuming that the stochastic processes are Gaussian distributed, mostly because the Gaussian assumption makes algorithm derivation mathematically tractable. In real-world applications, however, we often measure non-Gaussian distributed signals that must be processed.

In my experience, very few people ever test their signals for Gaussianity. Most people go ahead and apply algorithms derived for Gaussian signals without giving the data distribution any consideration. Later, they wonder why the signal-processing algorithms produced poor results. I advocate that the data should be tested for Gaussianity at the beginning of the project (Crawley, 2012; Clark, 2014).

Stationarity

Many signal-processing algorithms are derived assuming that the signals are statistically wide-sense stationary (Papoulis and Pillai, 2002). Many problems are caused when people apply these algorithms to nonstationary signals. A real stochastic process $x(t)$ is called wide-sense stationary if its mean (expected value) is constant, $E\{x(t)\}= \eta$, and its autocorrelation $R(\tau)=E\{x(t)x(t+\tau)\}$ depends only on the time shift $\tau = t_1 - t_2$. Clearly, transient signals (e.g., broadband pulses) are not stationary, yet we routinely process transient signals using algorithms derived for stationary signals because these algorithms are tractable. However, we must understand that the processing results may be surprising and/or not useful (Candy et al., 1986).

Inverse Problems

Two of the most common inverse problems in signal processing are the system identification and deconvolution problems, as depicted in **Figure 2**.

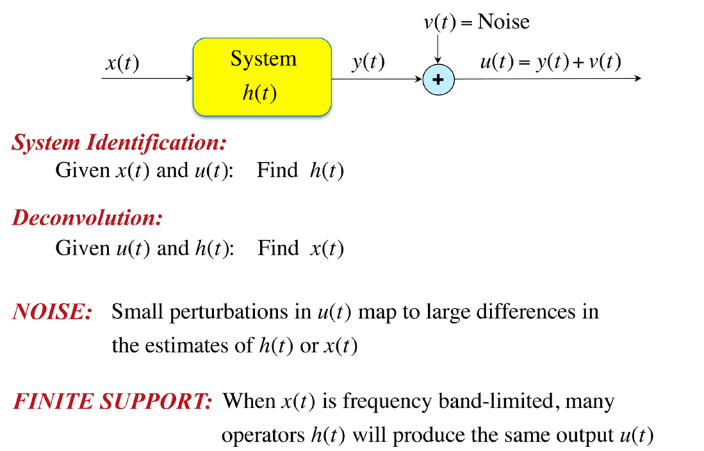

Figure 2. *Many practical inverse problems have this form. In system identification, given measurements of the input x(t) and the output u(t), we wish to estimate the system function h(t). In deconvolution, given measurements of the system function h(t) and the output u(t), we wish to estimate the input x(t) .*

In the absence of noise, if the signal functions are invertible, inverse problems are often easy to solve. However, in real-world problems with noisy measurements and functions that are often not invertible, inverse problems are very difficult (Candy et al., 1986). Most often in practice, the problem is “ill posed” and/or “ill conditioned.”

In a well-posed problem, a solution exists, the solution is unique, and the solution’s behavior changes continuously with the initial conditions. Ill-posed problems are highly sensitive to changes in the output data, so there may exist an infinite number of possible solutions (the solution is not unique). In addition, we discretize the data for solution on a computer, so the solutions can suffer from numerical instability when solved with finite precision. Even if the problem is well posed, it may be ill conditioned, meaning that a small error in the initial data can result in much larger errors in the final solutions (see **Figure 3**).

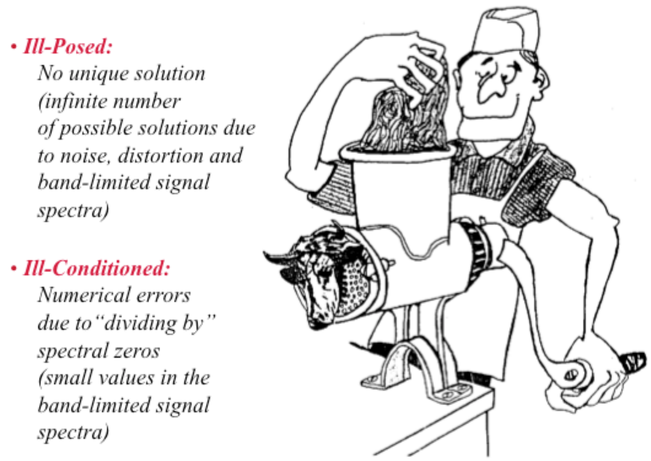

Figure 3. *Inverse problems are very difficult because they are often ill posed and/or ill conditioned. Imagine inserting hamburger into a meat grinder, turning the grinder backward, and expecting to obtain a cow at the output.*

I have seen a frightening number of projects in which people have not recognized the ill-posed and ill-conditioned nature of the inverse problems they were studying. Many of the project results have been useless or worse. Typically, people like to divide the DFTs of the signals. This is a very bad idea (Candy et al., 1986). The approach to dealing with ill-posed and ill-conditioned problems is generally called "regularization." This involves defining an associated well-posed problem, the solution of which is well behaved and offers a reasonable approximation to the solution of the ill-posed problem (Candy et al., 1986).

Statistical Detection/Classification/Target Recognition Issues

The technical area in which I have witnessed the largest number and most serious cases of algorithm abuse is in detection/classification/target recognition problems. Many groups of people embark on such problems without having studied detection/classification theory (Van Trees, 1968; Duda et al., 2001). The hubris is startling and the results are disastrous. Nonetheless, the problem is ubiquitous.

Poor Experiment Design

When using a supervised classifier, the training and testing data sets must be separate and representative of each other. Most of all, the classifier must not be tested using the same data set on which it was trained (Duda et al., 2001; Narins and Clark, 2016). Another important point is that the classification experiment must include the measurement of both target detections and false alarms. Amazingly, I have seen countless costly projects in which only the detections were measured, with no regard to false alarms. This ensures that classification performance cannot be measured properly, as described next.

Erroneous Methods of Measuring System Performance

The most egregious and most common error is that of using the quantity probability of detection P_D as the performance index for a classifier. Bayesian hypothesis testing theory tells us that both P_D and probability of false alarm P_{FA} (or their complements) are required to specify detection performance (Van Trees, 1968). The user must make the trade-off between the two by choosing a decision threshold based on a receiver operating characteristic (ROC) curve. Nonetheless, I have witnessed countless people who computed only the P_D and reported the results as if they were meaningful (e.g., in PhD theses, project reports, and program reviews). Smart people behaving foolishly.

If one wants a single scalar classification performance index, one should use the probability of correct classification or P_{CC} or its complement, the probability of error $P_{Error} = 1 – P_{CC}$. Under some simplifying assumptions, $P_{CC} = ½ [P_D + (1 – P_{FA})]$. In addition, one should always compute a statistical confidence interval about P_{CC} (Duda et al., 2001; Narins and Clark, 2016).

Proposals

Proposals are all about trust. When writing proposals, you should do your best to understand the point of view of the sponsor/manager. This means knowing what is important to the organization and its sponsors, including its mission and priorities. The sponsor must trust that you have in mind her/his best interests and trust that you will deliver. I have witnessed countless people living diminished careers because they never learned to give enough thought to the priorities of their sponsors rather than their own. Smart people behaving foolishly.

Clark's Law of Knowing What Is Important

The most important ability one can have is the ability to know what is important (Clark, 2016).

Clark's Law of Management Decisions

Most management decisions involve politics, so they are often based more on fear and ego than principle. The biggest fear is looking bad (Clark, 2016).

Managers/sponsors have limited budgets, many mouths to feed, and political forces acting on them from many directions. They live in a world that loves to assign blame for any kind of shortcoming. They do not want to look bad by funding a weak project or a weak principal investigator, getting "crosswise" with their bosses' priorities, or making a foolish move. Try to understand these pressures on your sponsor and do everything you can to earn the sponsor's trust.

Clark's Law of Project Funding

Project funding has little or nothing to do with how much is actually required to do the work (Clark, 2014, 2016).

The funding amount you receive is usually much less than that which you proposed. In this case, it is critically important to negotiate a new, more attainable set of project deliverables. Otherwise, *you* will look bad. Remember faster, better, cheaper.

Clark's Proposal Strategy

Make your proposal so compelling that management will "look bad" if they do not support it (Clark, 2016).

Consider the following characteristics of a proposal and the associated probabilities of receiving funding. (1) Your ideas are exceptionally innovative. This is necessary but usually not sufficient to get funding. (2) The first characteristic is true and your technical ideas are very important to the mission of the organization. This is necessary but often not sufficient to get funding. (3) Both the first and second characteristics are true, and the proposal is so compelling that management will look bad if they do not support it. This is often sufficient to get management support, but there are no guarantees.

General Project and Career Issues

I have reviewed many journal papers, participated in many program reviews, and attended many sales pitches that conveniently avoided the downsides and trade-offs involved with technical ideas/products. This is wasteful and wrong. Everybody knows there is no free lunch, and trade-offs are ubiquitous. Your credibility will only grow if you acknowledge this and level with everyone. Tell the entire story.

Clark's Principle of Intellectual Honesty

Tell the full truth about your ideas - the advantages, disadvantages, and trade-offs because a half-truth masquerading as the whole truth is an untruth (Clark, 2016).

Clark's Law of Integrity

Once you've lost your integrity, you've lost everything (Clark, 2014).

Clark's Law of Mental Health

Mental health is having options (Clark, 2016).

A good way to mitigate career stress is to spend a serious amount of effort making sure your life is balanced and you always have the option to get another job. This includes protecting your health and the health of your family, working with integrity, staying on the cutting edge of technology, not accepting dead-end jobs, publishing in the literature, going to conferences, and nurturing a network of colleagues around the world who know and trust you.

Conclusions

Don't let fear drive your agenda. Rather, focus on your principles and your health. Have the courage to live by your convictions. If you make a mistake, apologize sincerely and do your best to avoid making the same mistake again. Always level with your sponsors, management, and journal paper readers about the limitations and trade-offs associated with your research. Tell them even if they don't want to hear it. Tell them even if it might cost you funding. It will cement your credibility because the full truth is so rare. You'll be able to sleep at night. This is a matter of integrity and ethics. Once you've lost your integrity, you've lost everything. In the short run, you might take a beating, but in the long run, it will be good for your career and life because the laws of nature eventually punish hubris.

If at all possible, avoid data chasing. Sometimes management may demand compliance with unreasonable technical ideas or promises. Tell them that you are being asked to do data chasing with little or no chance of a good result. I wish you the best of fortune in your future endeavors. If you like, please send me your horror stories!

Biosketch

Grace Clark is currently a statistical signal-processing consultant at Grace Clark Signal Sciences, Livermore, CA. In 2013, she retired from the Lawrence Livermore National Laboratory. She served as thesis advisor for 10 graduate students at the Naval Postgraduate School, Monterey, CA, and the University of California, Davis. She has a BS and MS from the Purdue University Electrical Engineering Honors Program, a PhD in electrical and computer engineering from the University of California, Santa Barbara, and more than 235 publications. She is a Fellow of the IEEE and a member of the Acoustical Society of America Technical Committee on Signal Processing in Acoustics, the Society of Exploration Geophysicists, Eta Kappa Nu, and Sigma Xi.

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