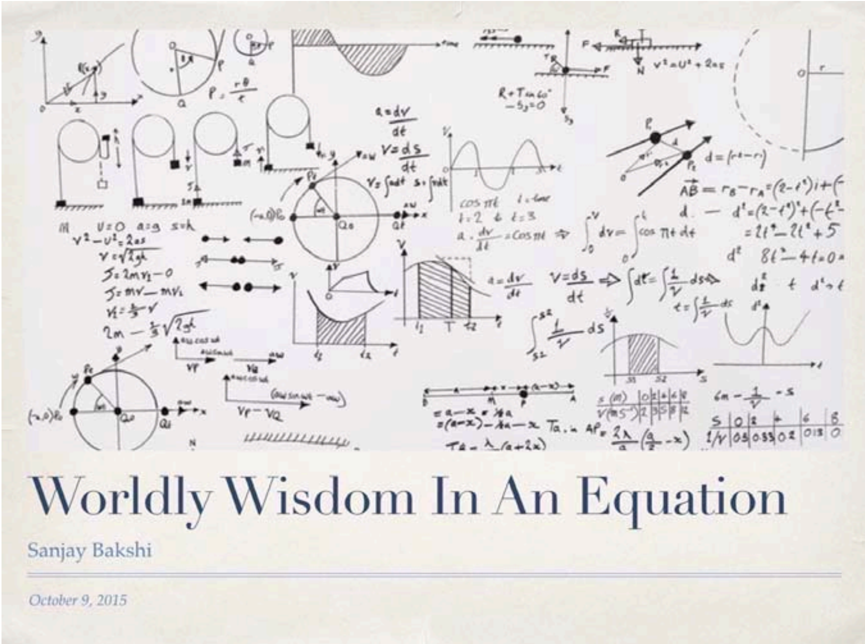


I want to talk to you today about a lesson that you studied in school and have, perhaps, forgotten by now. The lesson is comprised in a 255-year old mathematical equation which, it turns out, contains a lot of worldly wisdom. Indeed, I will try to show you that it has vast practical implications for us as investors.

However, before I do that, let me tell you a fascinating story of a Martian told by Riccardo Rebonato in his excellent book called *Plight of the Fortune Tellers.*[1]

The Story of a Martian and a Coin

A Martian has just landed on earth, a planet he has never visited before. In particular, he has never seen a coin, let alone flipped one. The Martian has landed next to you.

Not knowing how to strike up polite conversation, you take a coin out of your pocket. This is any old regular coin. You toss the coin four times. Both you and your Martian friend record the outcomes of the four coin tosses. All four tosses happen to yield heads.

What do *you* conclude about the fairness of the coin? What is the *Martian* likely to conclude?

Let's start with you.

If you're at all like me, you would view the occurrence of four consecutive heads as only very mildly odd. Would you draw any strong conclusions about the biasedness of the coin from this outcome? Personally, I would not. I may have a small niggling doubt that might prompt me to toss the coin a few more times just to check. But, if I were forced to bet on the next outcome on the basis of the available evidence, I would be likely to require odds of fifty-fifty for heads or tails.

Things look very different to our Martian friend. He has never seen a coin. He does not even know that coins are for buying goods. For all he knows, and judging from his four observations, they could just as well be devices that earthlings have invented to produce heads after a toss. He cannot be sure of this, of course, but in his mind the possibility that heads are much more likely than tails is very real. If forced to bet on the outcome of the fifth coin toss, he will not accept fifty-fifty odds. For him heads is much more likely than tails.

You and your Martian friend have observed the same experiment, yet you reach very different conclusions. How can that be?

The answer to that profound question lies in the fact that we almost never approach anything without having some *prior beliefs* — a key phrase which I will refer to several times during this talk.

Logically:

1. New evidence *should* modify our *prior beliefs* and transforms them into our *posterior beliefs* — another key phrase you should keep in mind for this talk.
2. The stronger the prior belief, the more difficult it will be to change it. If we really and truly have no prior beliefs about the situation at hand, as was the case with the Martian, then and only then will we be totally guided by the evidence.

A lifetime's experience with coins has created in you and me a very strong prior belief about probability of landing heads on a coin toss. The rather weak evidence from four consecutive tosses will only mildly shake our prior belief.

Matters look very different from the point of view of our Martian friend. He has never seen coins in his life, and therefore he is very open-minded about the situation. He has no *preconceived notions* about the fairness of the coin and can only form his views based on evidence.

In Defence of Preconceived Notions

Preconceived notions. That term, normally has a negative connotation but for our purposes that shouldn't be the case.

Is having preconceived notions a bad idea?

Clearly, the above example shows that having pre-conceived notions — the correct ones of course — gives you an advantage over the Martian.

So, the first key point to remember is pre-conceived notions are not necessarily a bad thing. Indeed, they are required for understanding the world.

Take the example of Sherlock Holmes. Peter Bevelin's brilliant book[2] on the thought process of Sherlock Holmes provides vital clues about preconceived notions.

But, *before* you have any such notion — your prior belief, or initial hypothesis, writes Bevelin — you need to have some data.

> What are the facts? Holmes first gathered enough evidence - both positive and negative - that was relevant to his problem

He quotes Holmes:

> I should like a few more facts before I get so far as a theory. (Holmes; The Valley of Fear)
>
> The temptation to form premature theories upon insufficient data is the bane of our profession. (Holmes; The Valley of Fear)

Once you have some data, usually comprising of something unusual, you form a theory — but only a provisional one. Bevelin writes:

> We can't observe or collect facts without some kind of view — what to look for, how to look and how to interpret what we see… Without an idea of how reality works, a purpose, provisional idea of what is important and what to look for, our observation or collection of facts is of little use.

He quotes Claude Bernad:

> A hypothesis is...the obligatory starting point of all experimental reasoning. Without it no investigation would be possible, and one would learn nothing: one could only pile up barren observations. To experiment without a preconceived idea is to wonder aimlessly. (Claude Bernard)

And Sherlock Holmes:

> "You have a theory?" "Yes, a provisional one." (Holmes; The Yellow Face)
>
> "One forms provisional theories and waits for time or fuller knowledge to explore them." (Holmes; The Sussex Vampire)

> "Let us take that as a working hypothesis and see what it leads us to." (Holmes; Silver Blaze)
>
> "Well, we can adopt it as a working hypothesis and then see how far our difficulties disappear." (Holmes; The Valley of Fear)

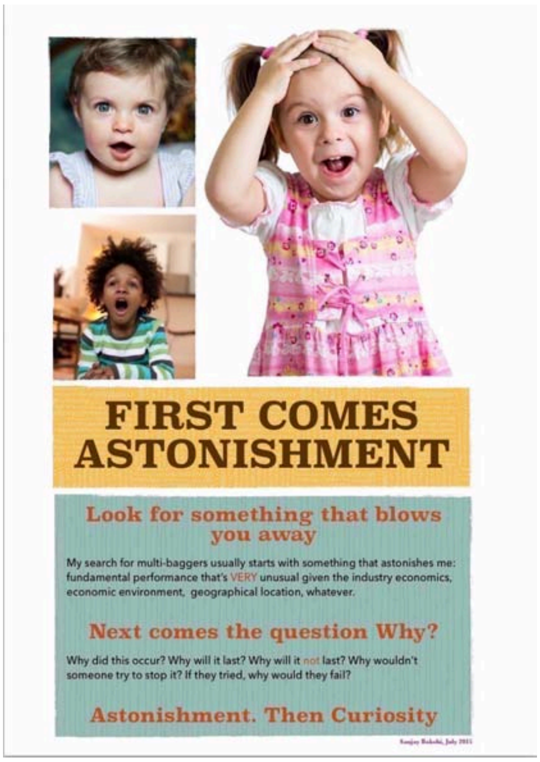
And Louis Pasteur:

> "Nothing can be done without preconceived ideas; only there must be the wisdom not to accept their deductions beyond what experiments confirm."

Charlie Munger expressed similar thoughts when someone asked him about how he goes about reading annual reports of various businesses.

> You have to have some idea of why you're looking for the information. Don't read annual reports the way Francis Bacon said you do science—which, by the way, is not the way that you do science—where you just collect endless (amounts of) data and then only later do you try to make sense of it. You have to start with some ideas about reality. And they you have to look to see whether what you're seeing fits in with that basic thought structure. Frequently, you'll look at a business having fabulous results. And the question is, "How long can this continue?" Well, there's only one way I know of to do that. And that's to think about why the results are occurring now – and then to figure out the forces that could cause those results to stop occurring.[3]

Some time ago, I made this for my students.



Notice the sequence. First, there has to be *some* data that arouses your curiosity. Once you look at it, you form a preconceived notion — a hypothesis which is your *prior belief*. You then look for ways to confirm or disconfirm that belief. This could cause your hypothesis to be strengthened, weakened or even abandoned. You must have an open mind about this. That, of course, is the correct way to understand the world — the way prescribed by the mathematical formula I am going to now tell you about.

Conditional Probability (or Bayes' Rule)

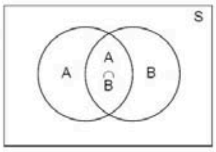
When I was in school, they taught us "conditional probability" which measures the probability of an event, given that another event has occurred.

It wasn't fun to do this. Here's what a typical problem looked like (from a CBSE Class XII textbook.)

CONDITIONAL PROBABILITY

The probability of occurrence of an event B when it is known that some event A has occurred is called a condition probability and is denoted by P(B/A). The symbol P(B/A) is usually read "the probability that B occurs given that A occurs" or "simply probability of B, given A".

Consider two events 'A' and 'B' of sample-space S. When it is known that event 'A' has occurred, it means that sample space would reduce to the sample points representing event A. Now for P(B/A) we must look for the sample points representing the simultaneous occurrence of A and B i.e. sample points in $A \cap B$.



$$\Rightarrow P(B/A) = \frac{n(A \cap B)}{n(A)} = \frac{\frac{n(A \cap B)}{n(S)}}{\frac{n(A)}{n(S)}} = \frac{P(A \cap B)}{P(A)}$$

Thus $P(B/A) = \frac{P(A \cap B)}{P(A)}$, where $0 < P(A) \leq 1$

Similarly, $P(A/B) = \frac{P(A \cap B)}{P(B)}, 0 < P(B) \leq 1$

Hence, $P(A \cap B) = \begin{cases} P(A) \cdot P(B/A), & P(A) > 0 \\ P(B) \cdot P(A/B), & P(B) > 0 \end{cases}$

Consider the event 'B' of getting a '4' when a fair die is tossed. Now suppose that it is known that toss of die resulted in a number greater than 3 (say event A). And we have to obtain P(B/A)
i.e. the probability of getting a '4' given that a number greater than 3 has occurred. Clearly

$A = \{4, 5, 6\}$, $B = \{4\} \Rightarrow P(B/A) = \frac{1}{3}$

also $P(A \cap B) = \frac{1}{6}$ and $P(A) = \frac{3}{6} = \frac{1}{2} \Rightarrow P(B/A) = \frac{P(A \cap B)}{P(A)} = \frac{1/6}{1/2} = \frac{1}{3}$

When it was over, I was so glad that it was over.

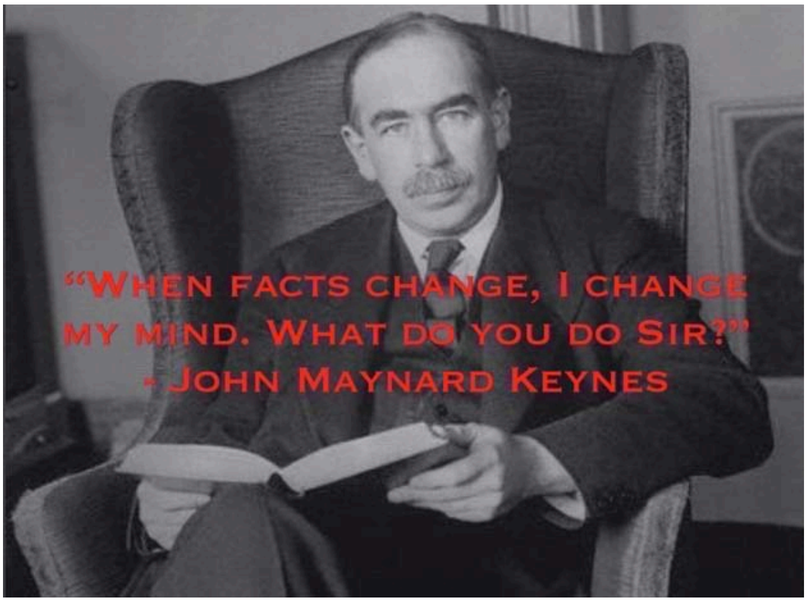
A couple of decades later, I discovered Charlie Munger and the power of multi-disciplinary thinking. I remember musing over his words:

> *Worldly wisdom is quite academic when you get right down to it.*

and

> *If you don't get this elementary, but mildly unnatural, mathematics of elementary probability into your repertoire, then you go through a long life like a one-legged man in an ass-kicking contest. You're giving a huge advantage to everybody else.*[4]

Well, obviously I didn't want to be a one-legged man in an ass-kicking contest. And so, as part of my education, I sought better lessons in the subject. I already had great teachers like Munger and Buffett but I also found others like Daniel Kahneman, Nate Silver, Philip Tetlock and Peter Bevelin. These folks, put together, forced me to re-look at Bayes' rule and try to understand its power. They also provided wonderful examples of how the rule's underlying logic is used by some of the world's best thinkers to help them change their mind in the light of new evidence which, by the way, is just what Keynes would want us to do.



"Changing minds in light of new evidence."

Does that phrase ring a bell? It should. After all, one of the key problems faced by investors is to know how to respond to new information. It turns out that Bayes' rule provides a beautiful framework for doing just that.

The problem is that form of Bayes' rule I just described, as taught to us at school, is somewhat complicated. But it can be reduced to a *much* simpler form. Daniel Kahneman did that in his book, *Thinking Fast and Slow.*

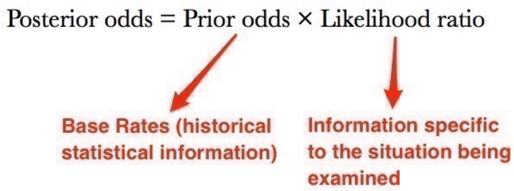
> The simplest form of Bayes's rule is in odds form:
>
> Posterior odds = Prior odds × Likelihood ratio
>
> where the posterior odds are the odds (the ratio of probabilities) for two competing hypotheses.

According to the equation, one's prior beliefs (prior odds) are subject to modification with the help of likelihood ratio. The higher that ratio, the higher should be the change in one's view of the world.

While one's prior beliefs can come from many sources, one excellent source is *base rates* which represent historical statistical information. In the Martian example, the base rate was

50:50 (our belief based on decades of experience that most coins are unbiased).

The likelihood ratio represents new information about a *specific* case which changes the odds. The higher the likelihood ratio, the higher the posterior odds.



Recall that for *you*, the fact that all four coin flips produced four heads was only mildly odd. Mathematically, for you the likelihood ratio was 1 and you saw no reason to increase it just on the basis of four coin flips. But what if you got the same result over a hundred coin flips? Under those circumstances, should you not change your mind in light of this new information? Of course you should.

The key lesson here is a powerful one: Sometimes, information specific to the situation is so powerful that it should force you to change your mind. I will show you how this works in the world of investing in a while. For now, just park that lesson for now.

Now, let's invert the situation. Is it possible for people to completely ignore the base rate because they have been seduced by the powerful narrative of the specific situation being examined? In other words, do people focus on the likelihood ratio without any regard to prior odds or base rates? Do they behave like the Martian? Well, the answer is yes.

Let me illustrate this with the help of an example created by Julia Galef, President and co-founder of the Center for Applied Rationality.

> Imagine that you're walking across the campus of some large American University and you meet a guy called Tom. You chat with him for a few minutes and you notice the Tom is shy. He's not really making eye contact very often, he sounds as if he's mumbling.
>
> Is Tom more likely to be in a Math PhD program or in the business school? (Let's assume it has to be one or the other.)

What do you think? Doesn't the description of shyness goes much better with a math Phd student than a business school student?

Most people who are asked this question guess that Tom is a Math Phd student. They forget to ask how many Math Phd's are there relative to business school students (the base rate). Even if the base rate has been provided (for example, there are 10 times as many business school students as math students) many people still guess that Tom is a math Phd student.

Posterior odds = Prior odds × Likelihood ratio

Base Rates (historical statistical information)

Information specific to the situation being examined

Like the Martian, they focus on the likelihood ratio and not the base rate. They are identical, in a sense, to those who speculate in a hot IPO, oblivious to the "average historical experience" in IPO's.

Bayes Rule Goes Visual

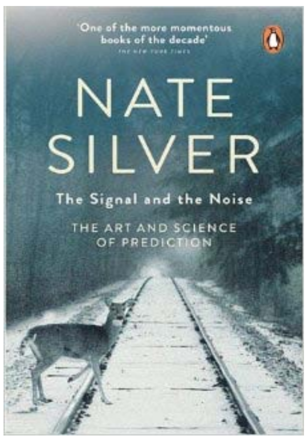
Let's take a look at a video by Galef who describes this problem and Bayes rule in a wonderful, visual manner. Watch this video[5] titled *A Visual Guide to Bayesian Thinking* by Julia Galef (from the beginning till 3:36):

https://youtu.be/BrK7X_XlGB8

Now that you've hopefully understood how Bayes rule works, let's derive some counter-intuitive conclusions from it. The first counter-intuitive conclusion is that sometimes pretty incriminating evidence about someone's alleged guilt does not necessarily translate into a high probability of guilt. Obviously, this is very important for us in the investment context. The second counter-intuitive conclusion is that Bayes rule allows for a rapid change of low prior odds to high posterior odds.

The best examples I have seen on these counter-intuitive applications of Bayes' rule were created by Nate Silver — a Bayesian super-forecaster with a wonderful track record, who has also written an excellent book[6] which I recommend to all of you.

How Bayes Rule Can Save (or End) a Marriage



Here is a modified version of Silver's example.

Suppose you are married woman who comes home from a business trip to discover a strange pair of woman's underwear in your dresser drawer. You will probably ask yourself: what is the probability that your husband is cheating on you? The condition is that you have found the underwear; the hypothesis you are interested in evaluating is the probability that you are being cheated on.

Bayes's theorem, believe it or not, can give you an answer to this sort of question—provided that you know (or are willing to estimate) three quantities:

First, you need an estimate of prior odds. What is the probability you would have assigned to him cheating on you *before* you found the underwear? What is the base rate? You decide to rely on empirical statistics and find that about 4 percent of married partners cheat on their spouses in any given year, so we'll set that as our prior.

Second, you need to estimate the probability of the underwear's appearing as a condition of the hypothesis being true—that is, you are being cheated upon. If he's cheating on you, it's certainly easy enough to imagine how the underwear got there. Then again, even (and perhaps especially) if he is cheating on you, you might expect him to be more careful. Let's say that the probability of the underwear appearing, assuming he is indeed cheating on you, is 50 percent.

Finally, you need to estimate the probability of the underwear's appearing conditional on the hypothesis being false. If he isn't cheating, are there some innocent explanations for how they got there? Sure, although not all of them are pleasant. They could be *his* underwear (you just discovered he is kinky) . It could be that his luggage got mixed up. It could be that a platonic female friend of his, whom you trust, stayed over one night. The underwear could be a gift to you that he forgot to wrap up. None of these theories is inherently untenable, although some verge on dog-ate-my-homework excuses. Collectively you put their probability at 5 percent.

If we've estimated these values, Bayes's theorem can then be applied to establish a posterior possibility. This is the number that we're interested in: how likely is it that we're being cheated on, given that we've found the underwear? The calculation (and the simple algebraic expression that yields it) is in figure 8-3.

FIGURE 8-3: BAYES'S THEOREM—UNDERWEAR EXAMPLE

PRIOR PROBABILITY		
Initial estimate of how likely it is that he is cheating on you.	x	4%
A NEW EVENT OCCURS: MYSTERIOUS UNDERWEAR ARE FOUND		
Probability of underwear appearing conditional on his cheating on you.	y	50%
Probability of underwear appearing if he is *not* cheating on you.	z	5%
POSTERIOR PROBABILITY		
Revised estimate of how likely it is that he is cheating on you, given that you've found the underwear.	$\frac{xy}{xy + z(1-x)}$	29%

	Cheating	Not Cheating
Prior odds ratio	4	96
Likelihood ratio	50	5
Posterior odds ratio	200	480
Posterior odds ratio	1	2.4
Posterior probability of cheating, given that underwear has been found	29%	

As it turns out, this probability is still fairly low: just 29 percent. If you are a bayesian wife, you should give your husband the benefit of the doubt. Imagine that you do this but give a warning to your husband. You tell him not to ever buy woman's underwear for himself or to buy underwear for you as a gift or allow any platonic female friend to spend a night at the house with him while she is away. That will leave just one plausible excuse from our earlier list of plausible excuses - mixed up luggage. So now, in future the probability of underwear appearing if he is *not* cheating on you drops to, say 1%.

Now imagine that after a few months, the same thing happens again. The idea behind Bayes's rule, however, is not that we update our probability estimates just once. Instead, we do so continuously as new evidence presents itself to us. Thus, the posterior probability of a cheating, given that the underwear was found the first time, becomes the prior possibility before it was found again

	Cheating	Not Cheating
Prior odds ratio	29	71
Likelihood ratio	50	1
Posterior odds ratio	1450	71
Posterior odds ratio	1	0.05
Posterior probability of cheating, given that underwear has been found	95%	

I guess this could result in the end of this marriage.

Thinking Like a Bayesian is a Way of Life

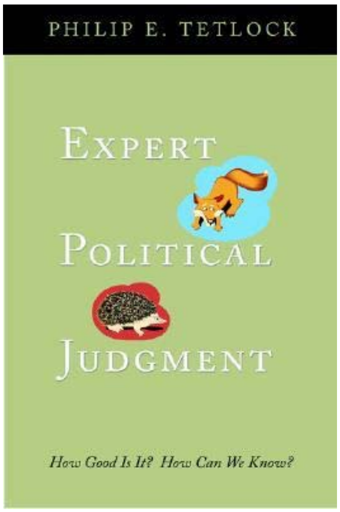
In a Bayesian view of the world, writes Riccardo Rebonato,

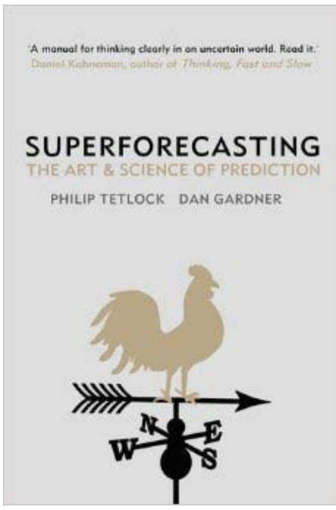
> So, the first role of models is to tell us which past information is relevant. Models seen as mental structures, however, are not static; rather, they interact with new evidence in a very dynamic and subtle way. How evidence should be incorporated into our new beliefs is the bread and butter of Bayesian statistical analysis. Faced with new evidence about the "world out there," Bayesians say, rational beings will update their probabilistic assessment about future events in a well-defined and optimal manner: according to Bayes's rule"
>
> We always start from some prior belief about the problem at hand. We then acquire new evidence. If we are Bayesians, we neither accept in full this new piece of information, nor do we stick to our prior belief as if nothing had happened. Instead, we modify our initial views to a degree commensurate with the weight and reliability both of the evidence and of our prior belief.[7]

It's obvious that inculcating the habit of thinking like a Bayesian is an admirable quality. Indeed, thinking like a Bayesian is a way of life. If you learn it and practice it, it will change you in many ways. It changed Julia Galef as she explains in this video[8]:

> After you've been steeped in Bayes' rule for a little while, it starts to produce some fundamental changes to your thinking. For example, you become much more aware that your beliefs are grayscale. They're not black and white and that you have levels of confidence in your beliefs about how the world works that are less than 100 percent but greater than zero percent and even more importantly as you go through the world and encounter new ideas and new evidence, that level of confidence fluctuates, as you encounter evidence for and against your beliefs.
>
> Also, I think that many people, certainly including myself have this default way of approaching the world in which we have our pre existing beliefs. We go through the world and we pretty much stick to our beliefs unless we encounter evidence that's so overwhelmingly inconsistent with our beliefs about the world that forces us to change our minds and adopt a new theory of how the world works. And sometimes, even then we we don't do it.
>
> So, the implicit question that people ask themselves, as they go through the world is this: When I see new evidence, can this be explained with my theory? And, if the answer is yes, then we stop there. But after you've got some familiarity with Bayes' rule, what you start doing is instead of stopping after asking yourself can this evidence be explained with my own pet theory, you also ask well would it be explained better with some other theory or maybe is some other theory is this actually evidence for my theory?

If Galef is right, and I believe she is, then how does one steep oneself in Bayesian thinking? Would it require the ability to do math in the head and think in terms of complex formulae? Happily, the answer is no.





Philip Tetlock, a political science writer, who is also a Professor at U Penn has spent most of his career in debunking "experts" who have little predictive abilities. But his thorough and extensive research also revealed superforecasters who have built exceptional track records. It turns out that while all of them rely on the Bayesian belief-updating equation, they don't always do formal number crunching. He writes:

> Do forecasters really have to understand, memorise, and use an algebraic formula? I have good news: No, they don't. The superforecasters are a numerate bunch: many know about Bayes' theorem and could deploy it if they felt it was worth the trouble. But they rarely crunch the numbers so explicitly. What matters far more to the superforecasters than Bayes' theorem is Bayes' core insight of gradually getting closer to the truth by constantly updating in proportion to the weight of the evidence.[9]

Six Core Insights From Bayesian Thinking for Investors

Here are six core Bayesian insights which, in my view, are quite important for us to internalise, as investors.

1. Mind Your Language

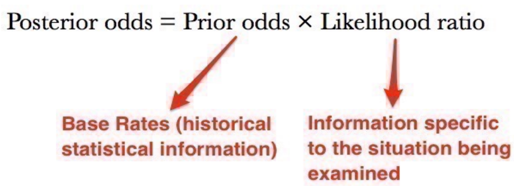
Bayesians are careful about the language they use when they think in terms of probabilities. Tetlock writes:

> Strive to distinguish as many degrees of doubt as the problem permits but no more. Few things are either certain or impossible. And "maybe" isn't all that informative. So your uncertainty dial needs more than three settings. Nuance matters. The more degrees of uncertainty you can distinguish, the better a forecaster you are likely to be. As in poker, you have an advantage if you are better than your competitors at separating 60/40 bets from 40/60—or 55/45 from 45/55. Translating vague-verbiage hunches into numeric probabilities feels unnatural at first but it can be done. It just requires patience and practice.[10]

My favorite guide for using Bayesian language is a CIA publication called *Words of Estimative Probabilities* which offers a framework[11] which I find quite useful.

100% Certainty		
The General Area of Possibility		
93%	give or take about 6%	Almost certain
75%	give or take about 12%	Probable
50%	give or take about 10%	Chances about even
30%	give or take about 10%	Probably not
7%	give or take about 5%	Almost certainly not
0% Impossibility		

2. Never Ignore Base Rates



Earlier, we saw how people are insensitive to base rates when they encounter some vivid description of a specific case. Base rates are boring piece of statistics. Stories, on the other hand, are seductive.

In his book, *What Works on Wall Street, James* O'Shaughnessy writes:

> Human nature makes it virtually impossible to forgo the specific information of an individual case (likelihood ratio) in favor of the results of a great number of cases (prior odds or base rates). We're interested in this stock and this company, not with this class of stocks or this class of companies. Large numbers mean nothing to us. As Stalin chillingly said: "One death is a tragedy, a million, a statistic." When making an investment, we almost always do so stock-by-stock, rarely thinking about an overall strategy. If a story about one stock is compelling enough, we're willing to ignore what the base rate tells us about an entire class of stocks.[12]

Before paying very high P/E multiple for a business, it would make sense to study the averaged-out experience of buying such stocks in the past. Similarly, before committing money to IPO's it will make sense to research the averaged-out experience of investing in an IPO. Before investing in a highly leveraged business, or a business where management has a track record of poor capital allocation, or mis-governance, it will make sense to find out average long-term outcomes of making investments in such situations.

Base rates should be used as useful anchors to check one's enthusiasm for a *specific* story about a business. In his book, Kahneman gives an example which we can use in the context of business and investing.

You meet a man called Tom and based on his looks and the way he talks and behaves and so you come to the conclusion that he is a computer scientist. But how likely is it that your hypothesis is correct?

If Tom is in an environment where only 3% of people are computer scientist and therefore 97% of people are not computer scientists, the *prior odds* correspond to a base rate of 3% are (.03/. 97 = .031). Then, even if the *likelihood ratio* is 4 (the description is 4 times as likely if Tom W is a computer scientist than if he is not), the *posterior odds* are 4 × . 031 = 12.4. From these odds you can compute that the posterior probability of Tom W being a computer scientist is now 11% (because 12.4/112. 4 = .11).[13]

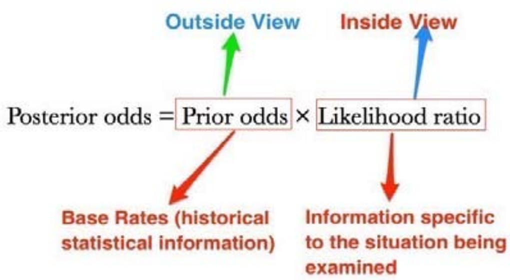
Bayesian analysis shows your intuitive feelings of being *almost certain* that Tom is a computer scientist are incorrect. There's an 89% chance that he is *not* a computer scientist. So you must learn to overcome your intuitions. Bayes rule forces you to reflect on aggregate statistics. It forces you to ask, where am I? Why am I here?

When Warren Buffett usually avoids investing in turnaround situations, it's because he relies on base rates. According to him, "turnarounds seldom turn." When he usually avoids investing in high-technology businesses and justifies that by writing that "severe change and exceptional returns usually don't mix," he is relying on base rates.

When I ask you to be "beware of story stocks" my advice applies to seductive stories of businesses which have little or no fundamental value. That's because the track record (base rate) of speculating in such businesses is not good.

An excellent way to think about base rates to think in terms of the language used by Kahneman, which Tetlock also loves. He writes:

> Daniel Kahneman has a much more evocative visual term for [base rates]. He calls it the "outside view"—in contrast to the "inside view," which is the specifics of the particular case... It's natural to be drawn to the inside view. It's usually concrete and filled with engaging detail we can use to craft a story about what's going on. The outside view is typically abstract, bare, and doesn't lend itself so readily to storytelling. So even smart, accomplished people routinely fail to consider the outside view.

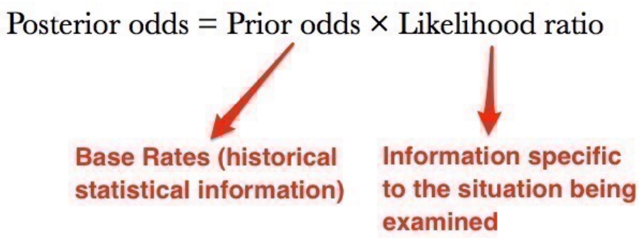


> Superforecasters don't make that mistake. If Bill Flack were asked whether, in the next twelve months, there would be an armed clash between China and Vietnam over some border dispute, he wouldn't immediately delve into the particulars of that border dispute and the current state of China-Vietnam relations. He would instead look at how often there have been armed clashes in the past. "Say we get

> hostile conduct between China and Vietnam every five years," Bill says. "I'll use a five-year recurrence model to predict the future." In any given year, then, the outside view would suggest to Bill there is a 20% chance of a clash. Having established that, Bill would look at the situation today and adjust that number up or down.[14]

3. Don't Ignore The Power of a Good Story

Of course that doesn't mean that there aren't good stories out there. The word "story" has a negative connotation in the world of value investing but I think that's a prejudice. Not all stories are bad stories to be avoided. At least that's what Bayes rule tells us. Take a look at the equation again.



For investors investigating a specific opportunity, a genuinely good story improves the likelihood ratio which then translates into higher posterior odds.

When Buffett made an investment in Nebraska Furniture Mart, or GEICO he recognized that they operated in a very competitive business (having low prior odds of success based on base rates). Yet he made the investment.Why? Because there were offsetting forces which are reflected in the likelihood ratio. Indeed, if you look at many of Berkshire Hathaway's investments, you'll find several of them in deeply competitive industries with poor average returns on capital including the insurance industry where BRK makes most of its money. So, while the prior odds of being in such industries is poor, it has not deterred Buffett from making highly profitable investments in such industries.

The key reason is not that he discards the poor prior odds. In fact he candidly highlights them in his letters. The key reason is that he looks for specific factors in those businesses which make them above-average and will keep them that way for a long time.

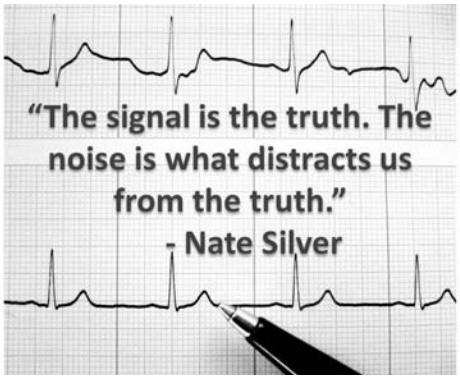
For public market investors who make concentrated bets, I think this is a very important point. That's because they are bottoms-up investors in *specific* businesses and not investing in *strategies*. A Graham-and-Dodd style investor wants to invest in statistical bargains. For him, base rates are terribly important, and specific stock stories are not so important. For an investor who wants to follow Philip Fisher or Charlie Munger, however, learning as much as possible about the specific business is critically important. To be sure, such an investor must never lose sight of the underlying base rate. But he should also be able to identify *diamonds in the rough.* In a sense, such an investor must follow Kahneman's advice:

> The essential keys to disciplined Bayesian reasoning can be simply summarized:[15]
> - Anchor your judgment of the probability of an outcome on a plausible base rate.

- Question the diagnosticity of your evidence.

When it comes to narratives, it's important to recognize that underneath every great compounding machine, there is a compelling story which makes it *different* from the rest of the crowd. Usually, that story is about an extraordinary individual or a group of such individuals who have demonstrated capabilities of creating value even in those businesses where it's hard to create a lot of value. Charlie Munger likes to call such individuals *intelligent fanatics*.

4. Know The Difference Between Noise and Signal



Silver is right. If we want to become good Bayesian forecasters, we have find ways to increase our signal/noise ratio.

> There isn't any more truth in the world than there was before the Internet or the printing press. Most of the data is just noise, as most of the universe is filled with empty space.[16]

If we have to increase the signal/voice ratio, we have to first cut out the cacophony of the noise. One way to do that is to avoid most news. My friend Ian Cassel, who runs the MicroCap Club in the US writes:

Nassim Taleb writes:

> The more frequently you look at data, the more noise you are disproportionally likely to get (rather than the valuable part called the signal); hence the higher the noise to signal ratio. And there is a confusion, that is not psychological at all, but inherent in the data itself. Say you look at information on a yearly basis… Assume further that for what you are observing, at the yearly frequency the ratio of signal to noise is about one to one (say half noise, half signal) —it means that about half of changes are real improvements or degradations, the other half comes from randomness. This ratio is what you get from yearly observations. But if you look at the very same data on a daily basis, the composition would change to 95% noise, 5% signal. And if you observe data on an hourly basis, as people immersed in the news and markets price variations do, the split becomes 99.5% noise to .5% signal. That is two hundred times more noise than signal —which is why anyone who listens to news (except when very, very significant events take place) is one step below sucker.

And, Tetlock writes:

> Belief updating is to good forecasting as brushing and flossing are to good dental hygiene. It can be boring, occasionally uncomfortable, but it pays off in the long term… Skilful updating requires teasing subtle signals from noisy news flows—all the while resisting the lure of wishful thinking. Savvy forecasters learn to ferret out telltale clues before the rest of us.[17]

How does one go about teasing subtle signals noisy news flows? To observe, one has to first quieten the mind. And then one has to look for slow gradual changes that are taking place. The way to do that is focus on long-term changes and not quarterly changes. These could be changes in the quality of the balance sheet, the earnings statement and the cash flow statement. And those changes should be related to a qualitative analysis of the reasons. Often such analysis creates unique insights.

Another aspect of noise vs signal is that the Bayesian investor has to be very very careful about what goes inside his head. When he is made aware of an "event" he has to follow Bevelin's advice when he writes:

> Make sure "facts" are facts - Is it really so? Is this really true? Did this really happen?

He quotes Montaigne:

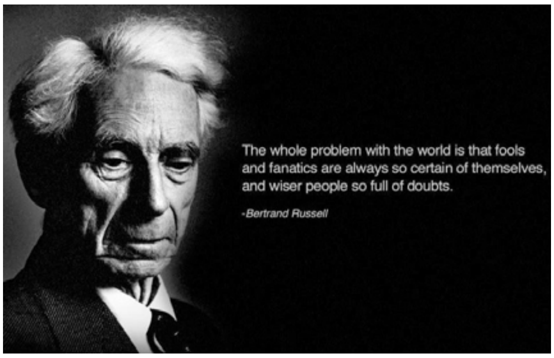
> I realize that if you ask people to account for "facts", they usually spend more time finding reasons for them than finding out whether they are true...They skip over the facts but carefully deduce inferences. They normally begin thus: "How does this come about?" But does it do so? That is what they ought to be asking. (Montaigne)

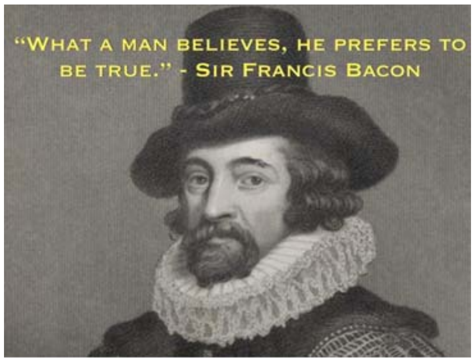
He has to follow the advice of Sherlock Holmes, who, as Bevelin quotes said:

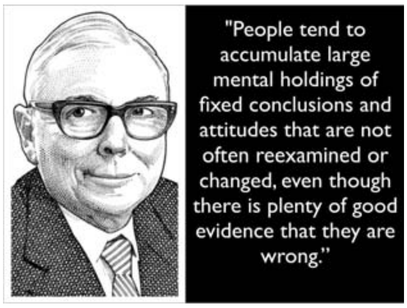
> I consider that a man's brain originally is like a little empty attic, and you have to stock it with such furniture as you choose. A fool takes in all the lumber of every sort that he comes across, so that the knowledge which might be useful to him gets crowded out, or at best is jumbled up with a lot of other things so that he has a difficulty in laying his hands upon it. (Holmes; A Study in Scarlet)
>
> Now the skilful workman is very careful indeed as to what he takes into his brain-attic. He will have nothing but the tools which may help him in doing his work, but of these he has a large assortment, and all in the most perfect order. It is a mistake to think that that little room has elastic walls and can distend to any extent. Depend upon it there comes a time when for every addition of knowledge you forget something that you knew before. It is of the highest importance, therefore, not to have useless facts elbowing out the useful ones.(Holmes; A Study in Scarlet)
>
> I say now, as I said then, that a man should keep his little brain-attic stocked with all the furniture that

> he is likely to use, and the rest he can put away in the lumber-room of his library, where he can get it if he wants it. (Holmes; The Five Orange Pips)[18]

5. Actively Seek Disconfirming Evidence







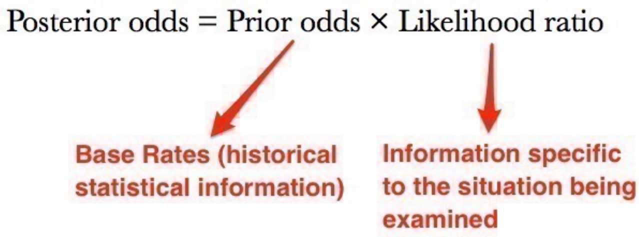
Clearly, Bayesian thinkers don't have this problem. The Bayes rule specifically requires one to estimate the probability of an alternative hypothesis being true.

6. Don't Forget That You Are Operating in a Pari-Mutuel System

Finally, investors should remember that they are not trying to maximise the odds of having their hypothesis being correct. Rather, their goal should be to maximise returns without taking excessive risks of permanent capital loss.

The key is not how often one is right. The key is how much money one makes when one is right and how much one loses when one is wrong.

In a pari-mutuel system of the stock market, unlike most games in a casino, one is betting not against the house, but against other investors. And in a such a system, the behavior of other investors changes the odds. When, for example, an exceptionally well-managed niche business hiding inside a commodity industry is valued by the market as a commodity business, it represents an opportunity. While the thoughtful Bayesian investor has taken care not to lose sight of the fact that business belongs to a commodity industry (low prior odds), he has also factored in key evidence specific to the business which makes it exceptional resulting in a high likelihood ratio.



Therefore, for him, the posterior odds are far better than those implied by the stockmarket's assessment of the business. And that is an exploitable prejudice.

Basically, what Bayes Rule tells you is to be a bit less prejudiced. You may have a prejudice against family owned businesses, or Hyderabad companies, or Delhi based companies or turnaround situations or highly leveraged businesses or holding companies etc. That prejudice is reflected in your prior odds. At the same time, however, you should recognize the possibility that this particular business which you are evaluating could be *different* from the statistical class to which it belongs.

Reverend Bayes is telling us: Don't be a racist.

Sanjay Bakshi
October 9, 2015
Mumbai

Ends

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[1] Riccardo Rebonato, Plight of the Fortune Tellers: Why We Need to Manage Financial Risk Differently [Kindle Edition]. loc. 762.

[2] Peter Bevelin, A Few Lessons from Sherlock Holmes.

[3] Charlie Munger at 39th Annual meeting of Wesco Financial's Shareholders in 1998

[4] Charlie Munger in "A Lesson on Elementary, Worldly Wisdom as it Relates to Investment Management and Business."

[5] A Visual Guide to Bayesian Thinking, https://youtu.be/BrK7X_XlGB8.
Also see:
How one Equation Changed the Way I think, http://youtu.be/za7RqnT7CM0
Think Rationally via Bayes' Rule by Julia Galef, https://youtu.be/NEqHML98RgU

[6] Nate Silver, The Signal and the Noise: Why So Many Predictions Fail but Some Don't

[7] Riccardo Rebonato, Plight of the Fortune Tellers: Why We Need to Manage Financial Risk Differently [Kindle Edition]. loc. 688.

[8] Think Rationally via Bayes' Rule by Julia Galef, https://youtu.be/NEqHML98RgU

[9] Philip Tetlock and Dan Gardner, Superforecasting: The Art and Science of Prediction [Kindle Edition]. loc. 2568.

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[13] Daniel Kahneman, Thinking, Fast and Slow [Kindle Edition]. loc. 8894.

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[15] Daniel Kahneman, Thinking, Fast and Slow [Kindle Edition]. loc. 2796.

[16] Nate Silver, The Signal and the Noise: Why So Many Predictions Fail but Some Don't [Kindle Edition]. loc. 4254.

[17] Philip Tetlock and Dan Gardner, Superforecasting: The Art and Science of Prediction [Kindle Edition]. loc. 4124.

[18] Peter Bevelin, A Few Lessons from Sherlock Holmes [Kindle Edition]. loc. 103.