

# The Case for Leading Indicators and Signal from Noise – An Experiential Summary

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# Agenda

Purpose

Background

Leading Indicators

Signal from Noise

Conclusion

# Purpose

This presentation seeks to enlighten the entire measurement food chain from those first recording or collecting data to those decision-makers who must act on the data

The enlightenment comes in two forms:

- 1) providing actionable data, and
- 2) discerning signal from noise in data

Merely reviewing what has occurred leaves the audience with a great leap in determining how to act

Failing to delineate signal from noise can cause the audience to either miss opportunities to act, as well as, act when they should not to the detriment of the work system

We hope the measurement food chain will recognize the need for leading indicators in addition to lagging indicators, and to proactively seek out signal from noise in both lagging and leading indicators

# Background

Both the advent of Six Sigma and CMMI High Maturity highlighted the need for actionable leading indicators as well as delineating signal from noise.

Six Sigma taught us that *predictive models* using statistics, probabilistic modeling and simulation were essential to dramatic business improvement and competitive position.

CMMI High Maturity taught us that such predictive models needed to contain *controllable independent factors* (x factors) so that decision makers would have a way to influence success outcomes (y factors).

Six Sigma taught us that *variation is the enemy to quality*. This training included concepts such as common and special cause variation, and using techniques such as statistical process control charts and confidence/prediction intervals to sort signal from noise.

Likewise, CMMI High Maturity taught us to pursue *qualitative and quantitative process control* using those same techniques.

# Leading versus Lagging Indicators



- Managing a project or organization with only lagging indicators is akin to driving a car by only looking in the rear view mirror
- Additionally looking out the windshield with leading indicators enables a driver to anticipate and act

# Leading Indicators Come in Different Forms

There can be simple to complicated leading indicators

Leading indicators can be simply univariate, e.g. a trend of a single measure

Leading indicators can be multivariate, e.g. predictions of an outcome based on 2+ other informative measures

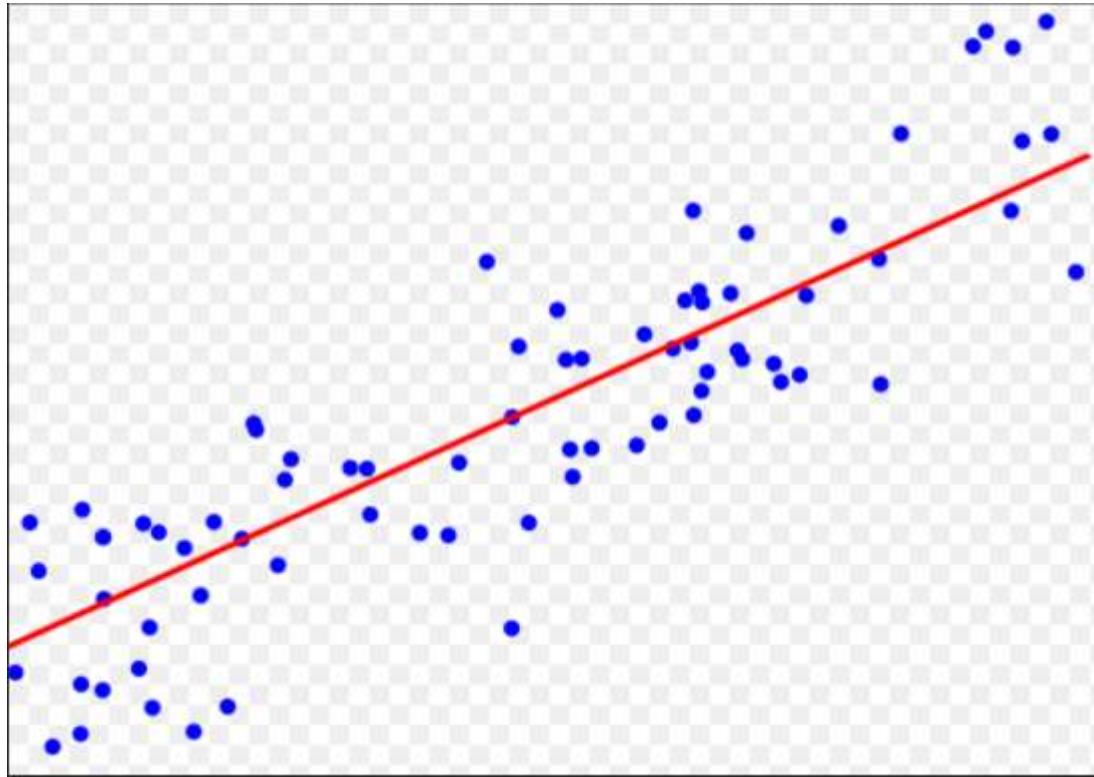
Leading indicators can be based on a time series analysis with cycles

Leading indicators can be statistical, probabilistic, simulation, or AI-based

Leading indicators can be correlational or causal inferential in nature

***We will discuss each of these in the coming slides***

# Simple Univariate Leading Indicators



Single measure across time

These are considered weakest as the only information is from a single measure

# Multivariate Leading Indicators

## *Multivariate Regression Model*

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \varepsilon$$

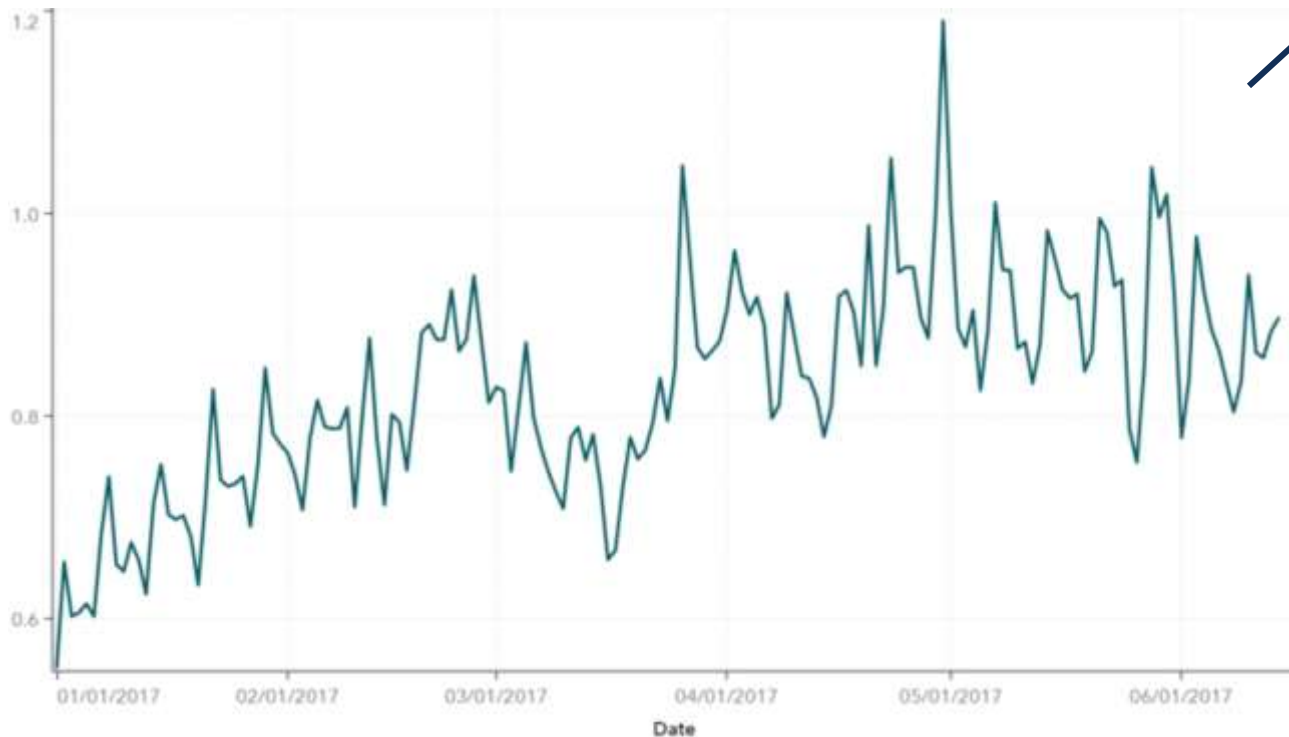
**y is the DEPENDENT variable**

**Each of the  $x_j$  is an INDEPENDENT variable**

**The OLS estimates  $b_0, b_1, b_2, b_3, \dots$   
are sample statistics used to estimate  
 $\beta_0, \beta_1, \beta_2, \beta_3, \dots$  respectively**

These are more informed from multiple data items and generally more trustworthy

# Time Series Leading Indicators



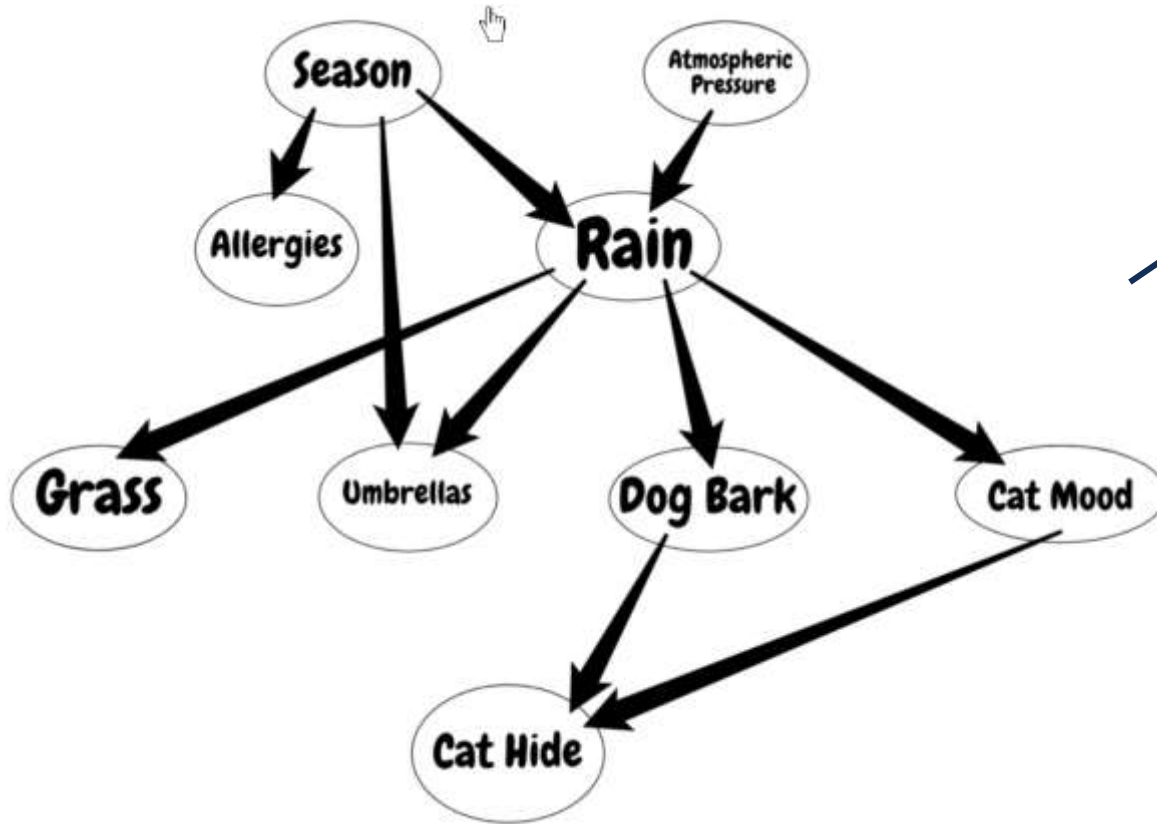
These are good at modeling expected cycles in data across time

# Statistical Leading Indicators

Regression modeling most commonly includes but is not limited to:

1. Univariate regression: simple linear regression of one factor across time, e.g. regression line of a productivity measure (linear and nonlinear modeling!)
2. Multivariate regression: more informed regression based on 2+ factors
3. Logistic regression: regression in which the prediction is binary or categorical
4. Without time modeled, a simple confidence or prediction interval of collected data

# Probabilistic Leading Indicators

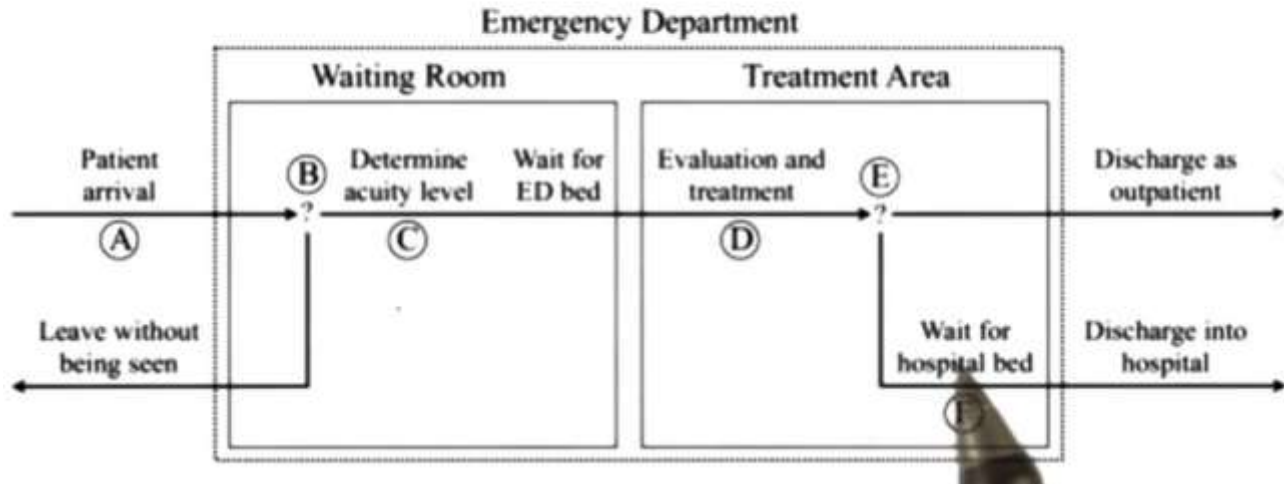


## Bayesian Belief Networks are useful:

1. Avoid unrealistic statistical assumptions,
2. Can predict and diagnose,
3. Can operate on both objective and subjective data,
4. Can operate with incomplete information in current situation,
5. Use Bayesian updating to update probabilistic outcome for all unobserved nodes in the model

# Simulation Leading Indicators

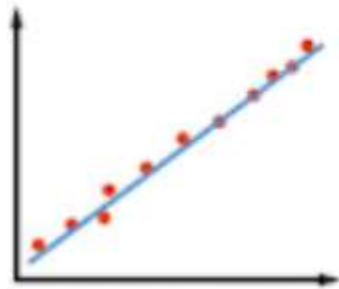
DISCRETE EVENT SIMULATION



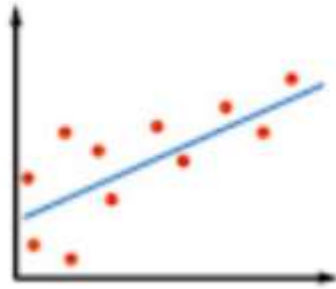
Discrete and dynamic simulation modeling can mimic real life processes to allow one to:

1. Visualize flow, bottlenecks etc without learning from actual experience,
2. Monitor resource utilization,
3. Measure rework, waste, cycle times, queue lengths and wait times, throughput of items

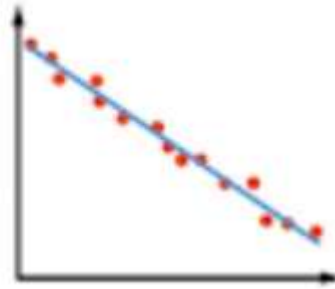
# Correlation based Leading Indicators



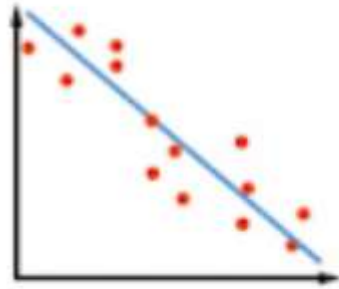
**STRONG POSITIVE CORRELATION**



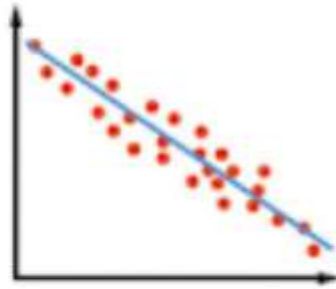
**WEAK POSITIVE CORRELATION**



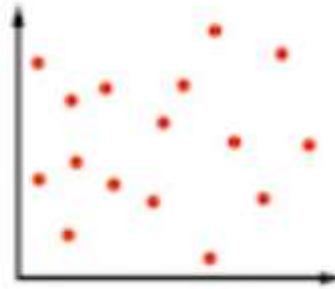
**STRONG NEGATIVE CORRELATION**



**WEAK NEGATIVE CORRELATION**



**MODERATE NEGATIVE CORRELATION**



**NO CORRELATION**

Correlation-based leading indicators are useful when you have a known correlation between A and B, and ability to anticipate future behavior of B lets you better anticipate future behavior of A

# Causal Inferential Leading Indicators

Causal inference goes beyond correlation to distinguish true cause-effects in data from spurious correlation

Correlation can mislead and give absolutely wrong answers in situations, especially where decision-makers/stakeholders want to intervene and improve a situation

Modern causal inference consists of 1) causal search within a data set to arrive at a causal structure normally depicted as a causal directed-acyclic graph, and 2) causal estimation in which direct, indirect, mediated, and moderated effects as well as counterfactual questions may be answered.

**Models intended to advise decision-makers what actions to take to influence future outcomes really should be based on causal models!**

# Techniques to Determine Signal from Noise

Confidence intervals

Prediction intervals

Statistical process control charts

Intervals around regression lines

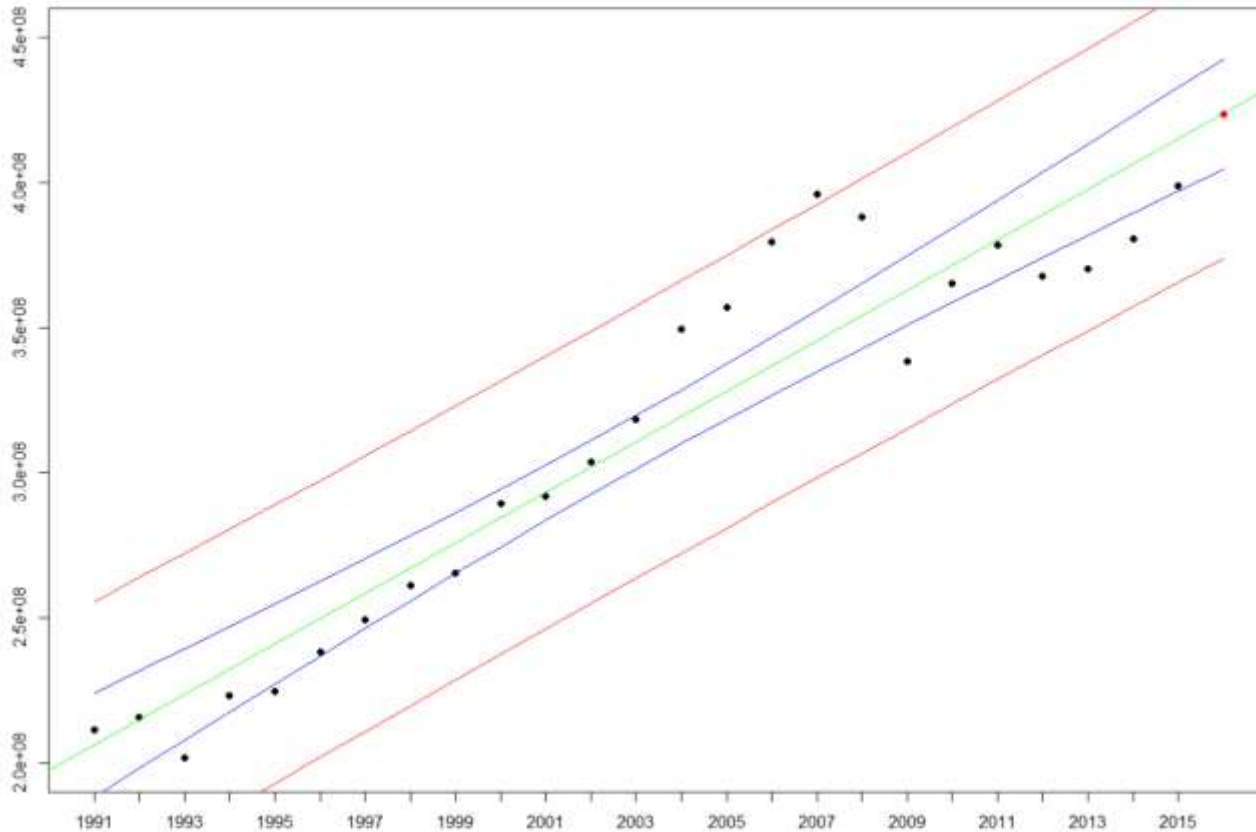
Probability density intervals in Bayesian probabilistic analysis

Outlier analysis

Hypothesis testing with alpha and beta error

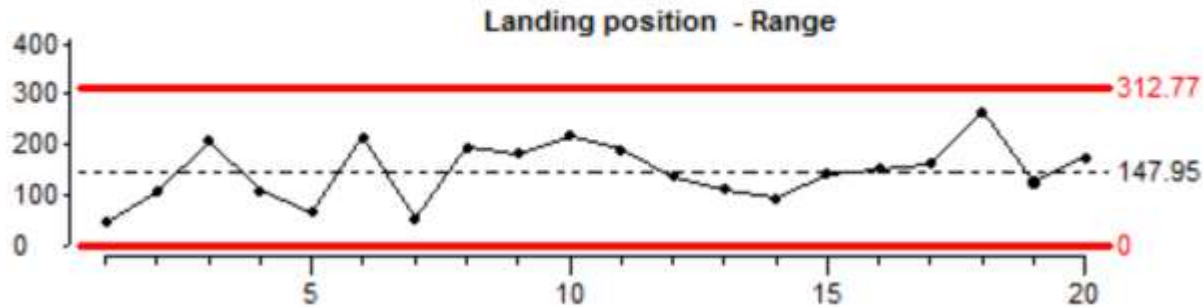
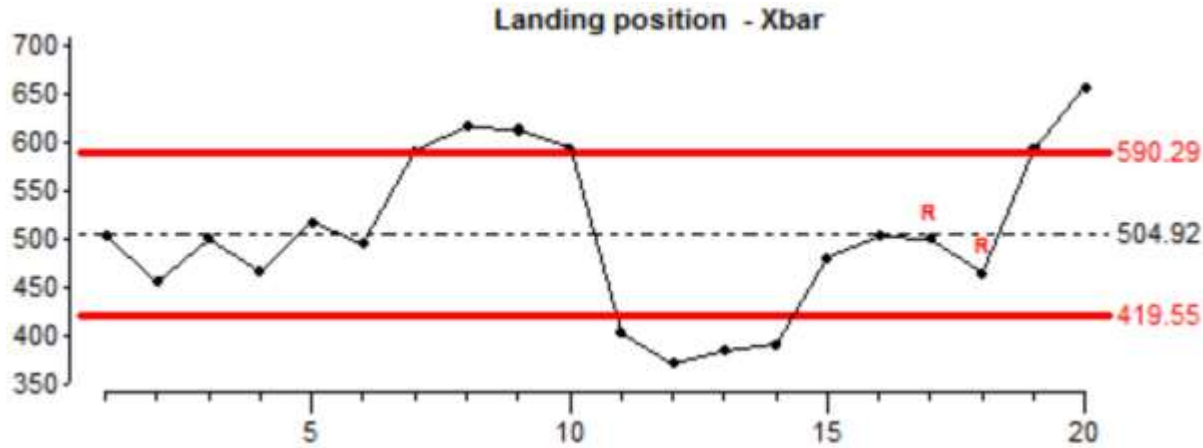
Power analysis with statistical sampling

# Confidence and Prediction Intervals



The narrow blue confidence interval represents where short term average behavior is expected while the wider red prediction interval is where individual data point behavior is expected

# Statistical Process Control Charts



“Run rules” and behavior outside of the statistically-determined control limits indicate a process is out of control, e.g. quite unexpected; SPC enables distinguishing common cause from special cause variation; management generally should only react to special causes of variation

# Probability Density Intervals within Bayesian Analysis

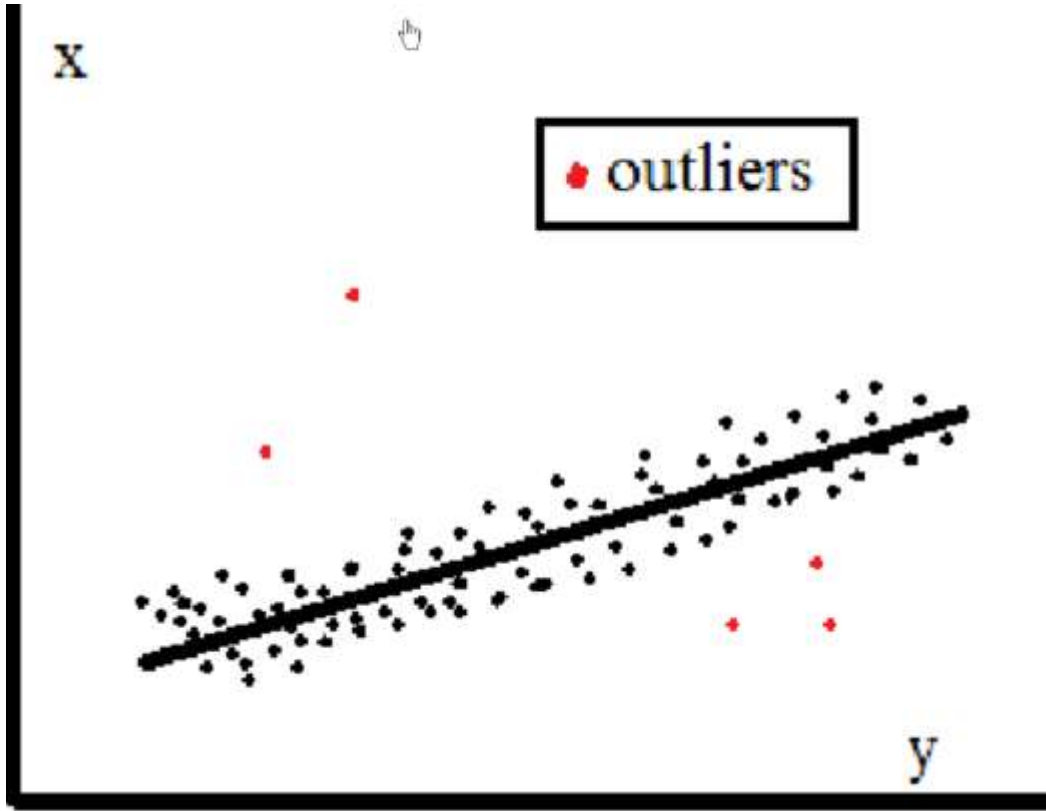
Bayesian data analysis is an alternative to Null Hypothesis testing

Tools and training on this are relatively new

Researchers have shown that Bayesian Data analysis is superior in specific situations and philosophically superior to Null Hypotheses testing

Famous examples in medical science and even game shows depict the benefits of Bayesian data analysis

# Outlier Analysis



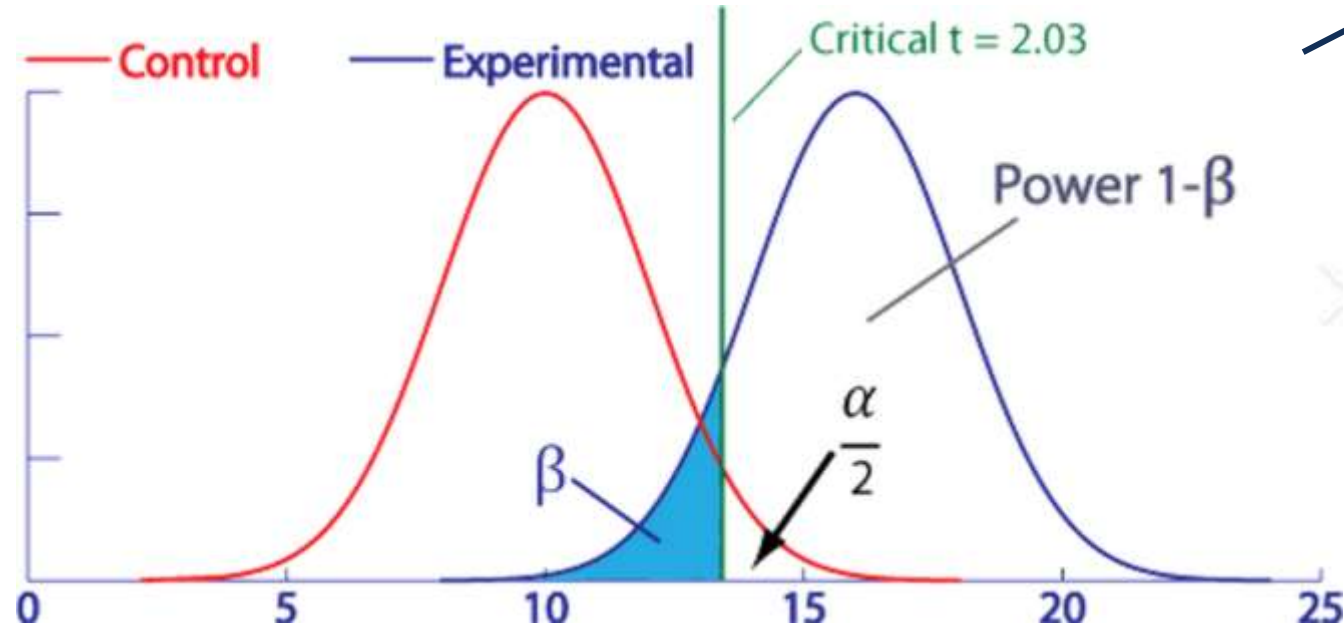
Data quality and integrity should be scanned before creating leading indicators. Many methods exist to detect and deal with outliers; one method is called the Interquartile Method

# Null Hypothesis Testing

		Conclusion about null hypothesis from statistical test	
		Accept Null	Reject Null
Truth about null hypothesis in population	True	Correct	Type I error Observe difference when none exists
	False	Type II error Fail to observe difference when one exists	Correct

Null Hypothesis Significance Testing (NHST) remains a method to take a sample of data and conclude what is going on; Practitioners make the mistake in the field to assume they have population data when they really have sample data and should use NHST!

# Power Analysis for Data Sampling



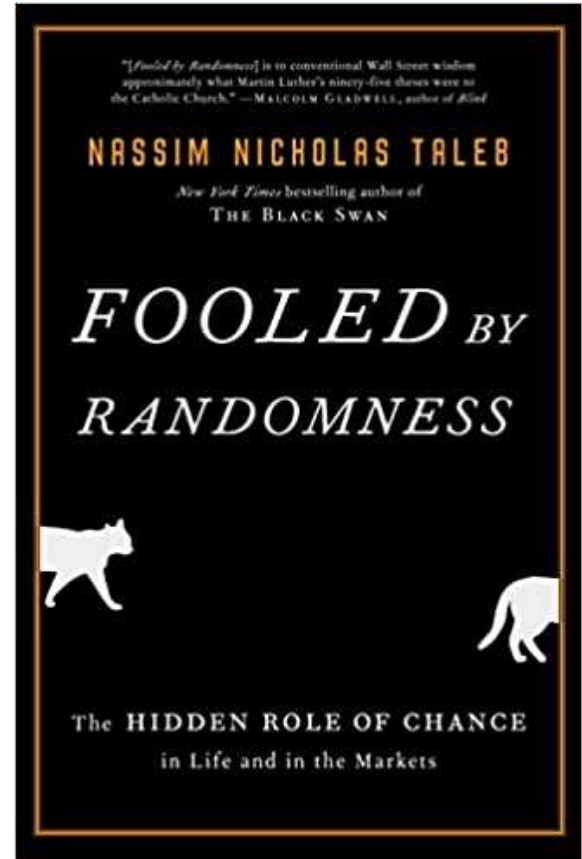
Any approach to sampling data to render a conclusion should conduct a power analysis to ensure a proper sample size is taken to enable seeing the effect one desires to show a decision-maker

# Favorite References Reinforcing Signal vs Noise Thinking

*the signal and the noise and the noise and the noise and the noise why so many and predictions fail – but some don't th and the noise and the noise and the nate silver noise noise and the noi*

By Nate Silver

By Nassim Taleb



# Reacting to Noise Instead of Signal with Potentially Negative Consequences

1. A drop in a productivity measure during a month or quarter
2. Higher defects noted in a unit of code or document review
3. Seemingly high number of slips to a subsequent Agile sprint
4. High number of employee turnovers
5. Seemingly high project financial variance to plan
6. High or low response values on customer or employee surveys
7. Seemingly high number of milestones late or missed
8. Seemingly high or low number of CRM submitted comments
9. Seemingly high or low number of test failures
10. Seemingly high or low number of reported effort hours
11. Seemingly high or low number of security incidents

# These Two Principles have Transformed Organizations

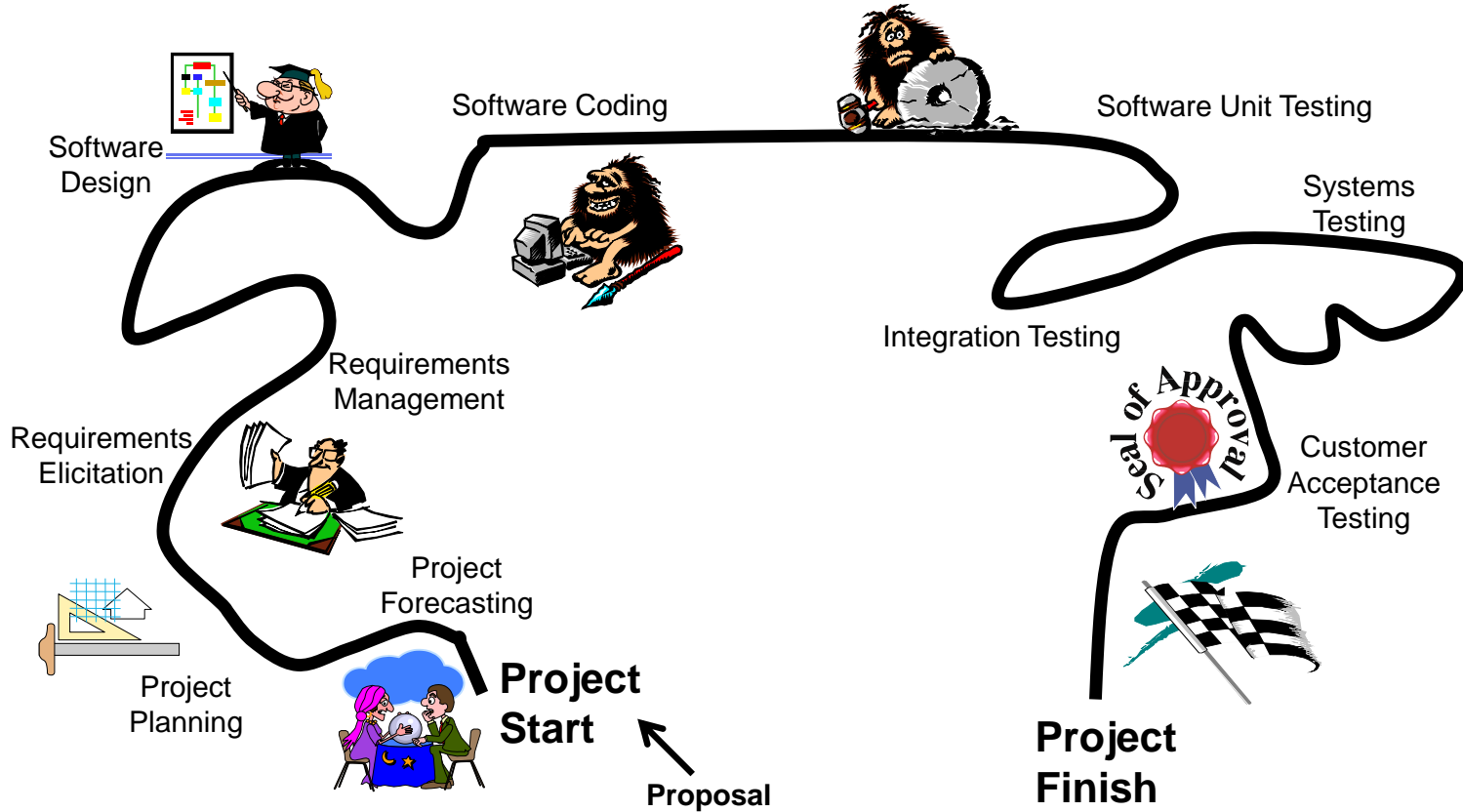
Organizations adopting leading indicators went as far as to require 1-2 leading indicators for every existing lagging indicator

These same organizations transformed the nature of senior management/leadership meetings so that more than half of meeting time spent discussing leading indicators and how to change the future

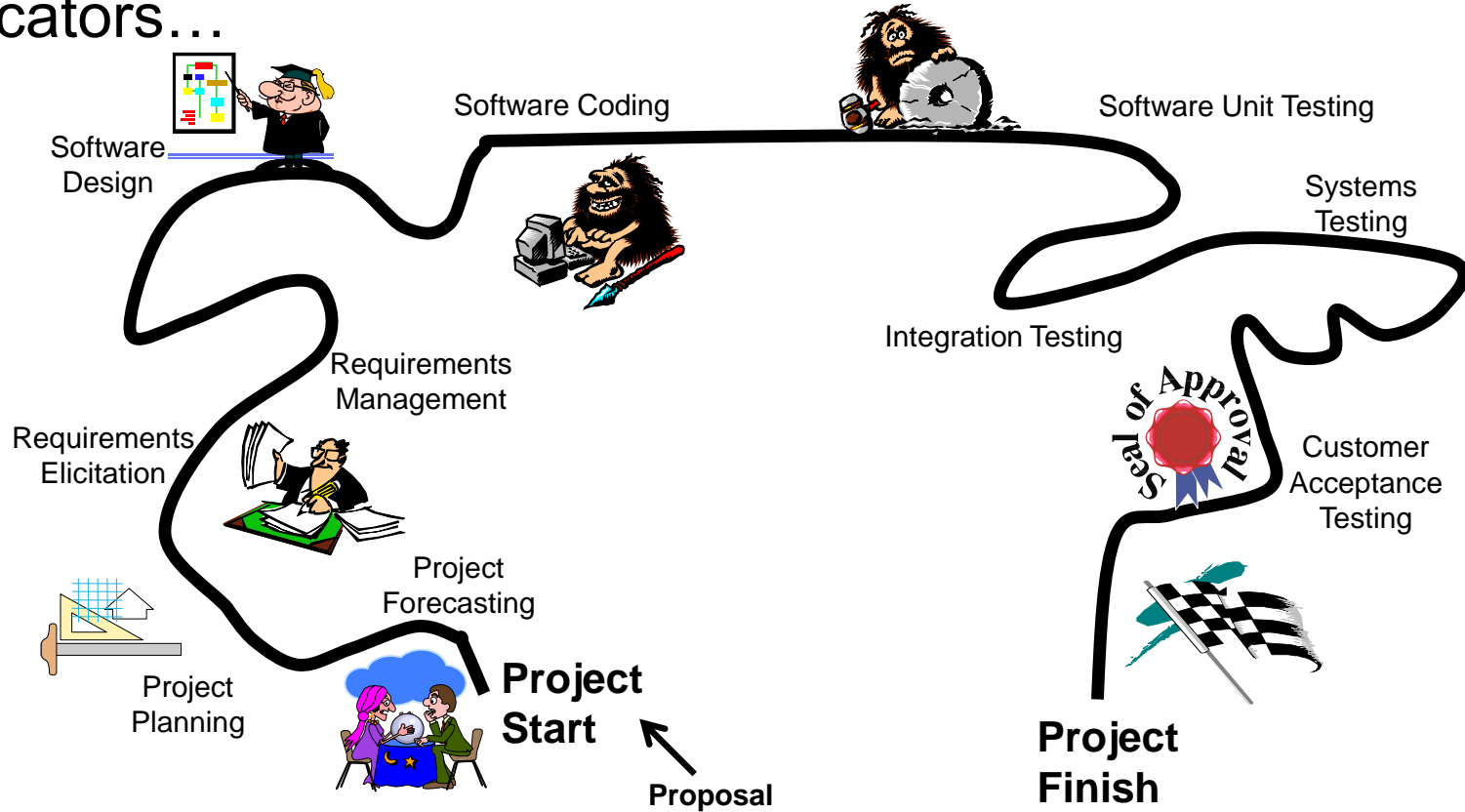
Likewise, Six Sigma studies of U.S. manufacturing quality experiences since WWII show that up to 40% of manufacturing issues were caused by management intervening in a work process when they should not have, e.g. reacting to noise

There are case studies across a broad range of industries in which violations of these principles caused enough serious internal work issues that entire product lines were discontinued due to quality and profitability issues

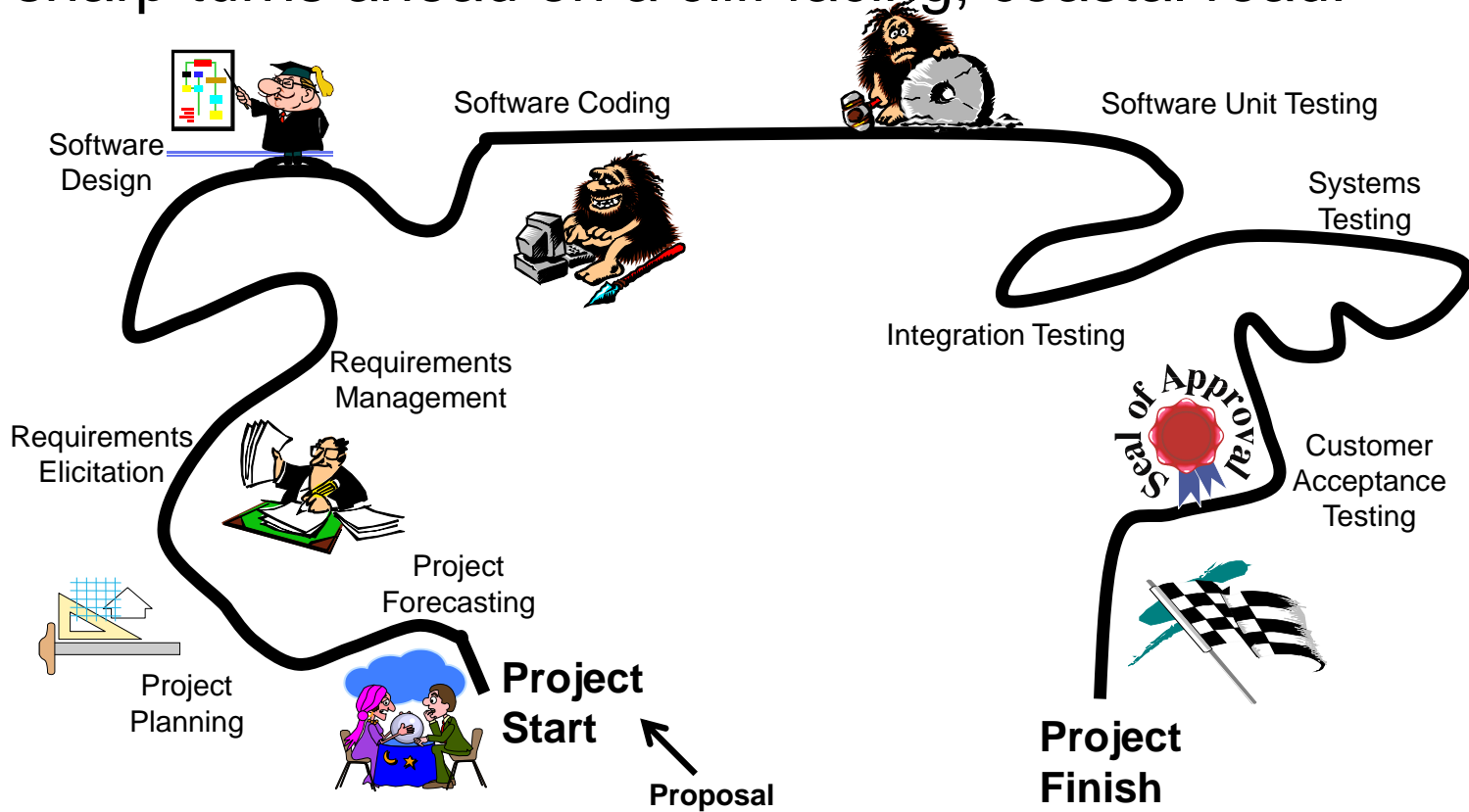
# Leading Indicators remain Situational and Dynamic...



# Straightaways in the Project, Require Less Leading Indicators...



# While Other Activities in the Project Require Much Attention, e.g. sharp turns ahead on a cliff facing, coastal road!



# Decision-Makers, Process Owners and Measurement Experts Must Work Together

Decision-makers must become educated consumers of data and information

Process owners must add transparency to signal and noise and develop leading indicators for decision-makers

Measurement experts must ensure data has quality and integrity suitable for the intended purpose

***Implies all three groups must communicate and coordinate on the management dashboard contents for fitness for use!***

# Just as Risks Come and Go, so Do Leading Indicators

In my industry experience with Texas Instruments and Motorola Mobility, we developed an average 1-2 new leading indicators every calendar month to address the changing landscape of risk and issues

Designing new indicators via the models listed in this presentation became a new and valued job role for analysts and Six Sigma Black Belts

We also adopted Schmidt, Kiemele and Berdine's book on Knowledge Based Management (KBM) and included laminated badge card which detailed on both front and back:

- The 14 key questions management should always be asking their people, and
- The 14 key questions management should always be prepared to answer.

# Conclusion

GBSD (Gov't, NGC and subs) should strive towards management dashboards that include both lagging and leading indicators

There should be a defined and active pipeline of leading indicator development to address the changing landscape of risks and issues

Fitness-for-use of the leading indicators necessarily requires transparent communication and coordination among the data recorders/collectors, analysts and modelers, and consumers of the information

Models to be used to guide management intervention need to be based on causal inference

Management and process owners should take great pain to react to signal and not noise