### The Quality 4.0 Revolution: Reveal Hidden Insights Now With Data Science and Machine Learning

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https://aws.amazon.com/blogs/machine-learning/build-an-autonomous-vehicle-on-awsand-race-it-at-the-reinvent-robocar-rally/ Cameras on front of remote-controlled cars sampled at 20 images/second

Based on patterns in the photos, give car steering instructions

**Goal**: Keep them on the road up to max speed!

(AWS with multilayer neural net in Python/TensorFlow in Jupyter notebooks)



"... a leading car manufacturer... was experiencing recurrent faults, and therefore high warranty costs, on the rear tail-lights. The engineers had been looking at the rear of the vehicle for the answer (and not succeeding) however the software quickly found the root cause of the fault to be located in the roof of the vehicle, a part of the car that had not even been investigated as a possible source.

Sometimes prior experience, or being too close to a problem, can inhibit a solution if an old hypothesis is applied to a new problem."

From http://www.gmtmag.com/display\_eds.cfm?edno=9665074





Chen, X., Liu, F., Hou, Q., & Lu, Y. (2009, August). Industrial high-temperature radar and imaging technology in blast furnace burden distribution monitoring process. In Electronic Measurement & Instruments, 2009. ICEMI'09. 9th Intl Conference on (pp. 1-599). IEEE.



### New Ways to Solve Old Problems

#### You will:

1.Understand **what Quality 4.0 is** and the value propositions it presents.

2.Identify the **types of problems** to which you can apply these new methods in your organization.

3.Explain how these technologies support engagement and collaboration to promote a connected and empowered workforce.

4.Explore ways to incorporate data science and machine learning into your work, whether you are drowning in data or just starting your digital transformation.





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#### Previously:

•Project Manager, Solution Architect, Engagement Manager // Meteorological Research, Telecom, Manufacturing, Software, High Tech 1995-2002

•Division Head, Software, Green Bank Observatory, 2002-2006

•Assistant Director of End to End Operations, National Radio Astronomy Observatory, 2006-2009

•Associate Professor of Data Science & Production Systems, James Madison University, 2009-2018; taught data science & applied machine learning from 2009-2018



## 1: Quality 4.0

### and value propositions enabled by data science



Quality as: 1.0 - Inspection 2.0 - Design 3.0 - Engagement



	Quality Planning	Quality Assurance/ Quality		Quality Improvement
		Control		
•	Establish quality goals Understand organizational context (mission, vision, values, strategy, position, capabilities) Understand business environment Identify customer & stakeholder needs – Voice of Customer (VoC) Design products/services to meet needs, implement design controls Design processes for consistent production & related controls	<ul> <li>Evaluate process performance</li> <li>Compare performance with quality goals         <ul> <li>Manage "quality events" and update controls</li> <li>Audits</li> <li>Management reviews</li> <li>Nonconformances</li> <li>Incidents/near misses</li> <li>Complaints</li> </ul> </li> <li>Out-of-control production</li> <li>Act to close the gaps</li> <li>Integrate lessons learned into Quality Planning</li> </ul>	•	<ul> <li>Build capabilities (people and technical)</li> <li>Build infrastructure</li> <li>Identify and justify needs and gaps</li> <li>Conduct improvement activities and establish</li> <li>controls to maintain them</li> <li>Quick wins (PDCA)</li> <li>Process improvement (DMAIC, Lean)</li> <li>Process design or redesign (DMADV)</li> <li>Business process mgmt (BPM) or Robotic Process Automation (RPA)</li> <li>Confirm/Validate changes</li> </ul>

### **Quality Events**

indicate that quality goals are not being met and action is needed

- Nonconforming product
- Incidents/near misses
- Customer complaints
- Audit findings
- Recalls/warranty calls
- Deviations (from SOP)
- Out-of-control Action Plans
- Industry-specific events (e.g. MDRs)



# Quality Controls

to prevent or correct unwanted or unexpected change  $\rightarrow$ stability and consistency

- Calibrations
- Maintenance
- Inspections
- Sampling incoming parts
- Process validation
- Mistake-proofing
- In-situ process monitoring
- Environment monitoring
- Professional testing/ competency assessment
- Training programs and reminders
- Corrective actions taken
- Information security/ network security

### Why Quality Systems Work



From Kovach, J. V., & Fredendall, L. D. (2013). The influence of continuous improvement practices on learning: An empirical study. *The Quality Management Journal*, *20*(4), 6.



### AI/ML Can Enhance & Accelerate Organizational Learning

People	Intelligent Systems
As people learn about the work environment, they update: • policies, • procedures, • practices, and • heuristics to improve the performance of	<ul> <li>When Al/ML systems learn, they update how they:</li> <li>predict,</li> <li>classify,</li> <li>find patterns, and</li> <li>identify important predictors to improve the performance of</li> </ul>
people, projects, processes & the bottom line.	people, projects, processes & the bottom line.

\* Jim Duarte (ASQ TV) also noticed that the algorithms do what we've been used to doing as quality professionals... just iteratively, and much faster.

# Quality as: 1.0 - Inspection 2.0 - Design 3.0 - Engagement 4.0 - Discovery

AI/ML evolves data-driven decision making to be *self-aware* & adapt to changing environments, circumstances, and customer/stakeholder needs





**Gartner Analytic Continuum** 

@doug\_laney



From http://www.mkomo.com/cost-per-gigabyte

### Data Science Venn Diagram v2.0



## **Scientific Method vs Data Science**



Newman, M. E. (2003). The structure and function of complex networks. SIAM review, 45(2), 167-256.

### POLICYFORUM

#### **BIG DATA**

#### The Parable of Google Flu: Traps in Big Data Analysis

David Lazer, 1.2\* Ryan Kennedy, 1.3.4 Gary King, 3 Alessandro Vespignani 5.6.3

n February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. Nature reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (1, 2). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (3, 4), what lessons can we draw from this error?

The problems we identify are not limited to GFT. Research on whether search or social media can Large errors in flu prediction were largely avoidable, which offers lessons for the use of big data.

> run ever since, with a few changes announced in October 2013 (10, 15).

Although not widely reported until 2013, the new GFT has been persistently overestimating flu prevalence for a much longer time. GFT also missed by a very large margin in the 2011-2012 flu season and has missed high for 100 out of 108 weeks starting with August 2011 (see the graph). These errors are not randomly distributed. For example, last week's errors predict this week's errors (temporal autocorrelation), and the direction and magnitude of error varies with the time of year (seasonality). These patterns mean that GFT overlooks considerable information that could be extracted by traditional statistical methods.

'...GFT overlooks information that could be extracted by traditional statistical methods.'

' "**Big data hubris**" is the often implicit assumption that big data are a substitute for, rather than a supplement to, traditional data collection and analysis.'

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: traps in big data analysis. Science, 343(6176), 1203-1205.





# What is Big Data?

- Lots of it (volume)
- It's coming at you fast (velocity)
- Different formats and sampling frequencies (variety)
- Huge variations in data quality (**veracity**)
- Different people/organizations produce it or own it (governance)
- It could easily change or disappear (control)
- There may be restrictions on how you use it (**policy**)

"... Big Data is anything bigger or more complex than what your organization is currently prepared to handle."

-- one of the world's experts on cyberinfrastructure for Big Data at a National Science Foundation panel (2013)





Type of data Inventory management		Transportation management	Customer and supplier relationship management		
Sales	How can sales data be used with detailed customer data to improve inventory management either in terms of forecasting or treating some inventory as "committed" based on specific shoppers requirements?	How can more current sales data be used to re-direct shipments in transit? How can sales data, integrated with detailed customer data, be used for more efficient and effective merge-in-transit operations?	How can more granular sales " data from the wide variety of sources that exist be used to improve visibility on the one hand and trust on the other, between trading partners?		
Consumer	How can face profiling data for shopper identification, emotion detection, and eye-tracking data be used to determine which items to carry and stock at particular shelf locations?	How can delivery preferences captured in online purchases be used to manage transportation mode and carrier selection decisions?	How can customer sentiment about products purchased based on "Likes," "Tweets," and product reviews be used to collaborate on forecasts?		
Location and time	How can sensor data used to detect location in store, be used to improve inventory management, including departmental merchandising decisions?	How can sensor data in the distribution center be used to anticipate transportation requirements?	How can location and time-stamp data of shoppers be used for collaborative assortment and merchandising decisions?		

From Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77-84.



Radziwill, N. M. (2018, October). Let's Get Digital: The many ways the fourth industrial revolution is reshaping the way we think about quality. *Quality Progress*, p. 24-29. <u>http://qualityprogress.com</u>

### Quality 4.0 = C I A

Connectedness

Intelligence

Automation

# **Degrees of Automation**

- 1. Human specifies process and computer only implements
- 2. Computer assists by determining options
- 3. Computer assists by determining options and suggests choice
- 4. Computer assists by determining options and selects choice human has option to do it, or not
- 5. Computer selects and implements options if human approves
- 6. Computer selects option and automatically implements, but gives human chance to stop the process flow
- 7. Computer selects and implements options, then tells human about results
- 8. Computer selects and implements options, but only tells human about results if asked for report
- 9. Computer selects and implements options, but only tells human about results if asked, only reports some information
- 10. Computer performs whole job; may or may not tell human

From Sheridan, T. B., & Verplank, W. L. (1978). Human and computer control of undersea teleoperators. MASSACHUSETTS INST OF TECH CAMBRIDGE MAN-MACHINE SYSTEMS LAB.

Increasing autonomy

INTFLFX

# **2: Types of Problems**

& how to identify challenges that are well supported by DS/ML







From Carlson, R. O., Amirahmadi, F., & Hernandez, J. S. (2012). A primer on the cost of quality for improvement of laboratory and pathology specimen processes. *American journal of clinical pathology*, *138*(3), 347-354.





From Carlson, R. O., Amirahmadi, F., & Hernandez, J. S. (2012). A primer on the cost of quality for improvement of laboratory and pathology specimen processes. *American journal of clinical pathology*, *138*(3), 347-354.

# Quality 4.0 Ecosystem



Radziwill, N. M. (2018, October). Let's Get Digital: The many ways the fourth industrial revolution is reshaping the way we think about quality. *Quality Progress*, p. 24-29. <u>http://qualityprogress.com</u>



Machine Learning Tasks	Data Science Tasks			
<ol> <li>Prediction</li> <li>Classification</li> <li>Pattern Identification</li> <li>Data Reduction</li> <li>Anomaly Detection</li> <li>Pathfinding</li> </ol>	<ol> <li>Frame the problem(s)</li> <li>Explore the data</li> <li>Build models</li> <li>Evaluate model performance</li> <li>Deploy models and real-time processing <b>pipelines</b></li> <li>Uncover high-value insights</li> <li>Tell stories</li> <li>Do it again and again</li> </ol>			



From Duarte, J. (2017). Data Disruption. Quality Progress, 50(9), 20-24.

"Data can take several forms, such as data at rest and data in motion. Data that are sitting in warehouses waiting to be analyzed are referred to as **data at rest**...

**Data in motion** (data analyzed in real time as the event occurs, such as click streams and sensors) flow through a connected device to a database on the receiving end for immediate analysis... used to fine tune the [predictive] models... and analytics at the edge... deploys information to control processes in real time."

-- Jim Duarte

Quality Problem	Machine Learning	Feasibility	
Audio anomalies	Classification (CNN)	Feasible	
Checking for leakage	Image classification	Potential	
Setting up engines	Reinforcement learning	Unnecessarily complicated	
Supervising testing	Image classification	Potential	
Feature detection	Image classification	Unnecessarily complicated	
Cause diagnosis	Multidimensional Regression, association rule learning Multidimensional	Potential	
Machine adjustments	Regression	Potential	
Surface defects	Image classification	Feasible	
Assembly gaps	Image Regression	Unnecessarily complicated	
Part identification	Image classification	Unnecessarily complicated	
Machine error cause	Image classification	Unnecessarily complicated	
Field quality detection	Association rule learning	Unnecessarily complicated	
Field quality cause analysis	Association rule learning	Feasible	
Predictive maintenance	Classification	Feasible	
Control chart pattern detection	Classification	Feasible	
Optimizing production parameters	Classification	Potential	

Granstedt Möller, E. (2017). The Use of Machine Learning in Industrial Quality Control. Thesis, KTH Vetenskap Och Konst (Stockholm, Sweden).

### Value Propositions for Quality 4.0



Radziwill, N. M. (2019). Value Propositions for Quality 4.0. Manuscript in review.

### 3: Engagement & Collaboration

with Quality 4.0









Radziwill, N. M. (2019). The Relationship Between Engagement and Quality Outcomes. *Manuscript in review*.

- Ensures alignment
- Supports collective efforts
- Achieves consistency
- Deploys strategy broadly & deeply









#### Not Just for Manufacturing, Not Just for Germany

While the focus of Plattform Industrie 4.0 has, without doubt, been very much on German manufacturing, it is by no means an exclusive club for any particular industry or region. Gartner's recent definition of the term Industrie 4.0 underlines this point, calling it "a business-outcome-driven digital transformation approach to generate value from the collaboration of multiple partners in ecosystems across value chains and industries."

In other words, it is not simply about technologies such as the Internet of Things (IoT) and artificial intelligence (AI) increasing production efficiency at any one site or even one company. Industrie 4.0 enables integration across entire enterprises, powering the creation of brand new ecosystems that can span multiple industries.

I have spoken many times about the importance of openness – in terms of technologies, development mindsets, partnerships, and collaborations. Industrie 4.0 is for me another great example of the crucial role openness plays in successful digitalization. On the one hand, there are the individual interorganizational networks that Industrie 4.0 helps to create – ecosystems that connect companies and industries in completely new value chains. But on a broader scale, cooperation and openness between many different types of organizations across Germany, Europe, and indeed the globe are required to fully exploit the advantages of digitalization. And among the various goals the Plattform Industrie 4.0 pursues, the promotion of networking between global consortia and stakeholders, and the coordination of this exchange is a clear priority.

Bernd Leukert, Executive Board SAP, at <u>https://news.sap.com/2018/01/industrie-4-0-why-openness-and-collaboration-make-all-the-difference/</u>



### **4: Reveal Hidden Insights Now**

incorporate DS/ML & ensure readiness for the future



# I want my QMS/IMS to...

- Help me make better decisions
   about my processes
- Audit itself and alert me when I need to do something
- Tell me where to **focus** my resources for maximum added value
- Based on risk assessments and theory of constraints, tell me how should I prioritize work
- Alert me when an important **change** occurs at the systems level





# DS in the Cloud: <a href="http://rstudio.cloud">http://rstudio.cloud</a>



Example to follow: <u>https://qualityandinnovation.com/2015/07/14/a-simple-intro-to-bayesian-change-point-analysis/</u>











## **Example 2: Wine Quality**

library(tidyverse)
library(randomForest)

url <- "https://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/winequality-white.csv"
wine <- as.tibble(read.delim(url,header=TRUE,sep=";"))</pre>

#### > wine

# A tibble: 4,898 x 12

fixed.acidity	v volatile	.acidity	citric.acid	residual.su	ıgar chlorides	free.sulfur.diox~
<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<<	dbl> <dk< td=""><td>ol&gt; <dbl></dbl></td><td></td></dk<>	ol> <dbl></dbl>	
17.00	0.270	0.360	20.7	0.045	50 45	
2 2	6.30	0.300	0.340	0 1.60	41	

# ... with 4,888 more rows, and 5 more variables: density <dbl>, pH <dbl>, sulphates <dbl>,
alcohol <dbl>,quality <int>

> wine\$taste <- as.factor( ifelse(wine\$quality <= 6,'bad','good') )</pre>

### **Build the ML Model**

```
> train <- wine[1:3000, ]</pre>
> test <- wine[3001:4898, ]</pre>
> ml.model <- randomForest(taste ~ . - quality, data=train)</pre>
> print(ml.model)
Call:
 randomForest(formula = taste ~ . - quality, data = train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 3
        OOB estimate of error rate: 9.7%
Confusion matrix:
      bad good class.error
bad 2276
           83
                 0.0351844
good 208 433
                 0.3244930
```

### **Check Performance of ML Model**

> pred <- predict(ml.model, newdata=test)</pre> ml.model > table(pred, test\$taste) bad good pred bad 1233 191 good 246 228 > ml.model\$importance 0.20 MeanDecreaseGini fixed.acidity 64.47684 Error volatile.acidity 84.14794 0.10 citric.acid 61.37304 residual.sugar 91.95227 chlorides 86.69503 free.sulfur.dioxide 82.76855 0.05 total.sulfur.dioxide 80.33434 125.57005 density рΗ 81.95264 78.01374 100 200 300 400 sulphates 0 169.45978 alcohol trees plot(ml.model, log="y")

**INTELEX** 

OOB

bad

good

500

### Drowning in Data

Set up data **governance** processes. Bust silos, encourage collaboration, continue systems integration.

Invest in **cybersecurity**: physical, behavioral, and technical

**Be selective**: archive only most critical information, or "compute at the edges" & store aggregated values

Put **controls** in place to avoid the Data Swamp/Graveyard problem

Haven't Started Yet

**Digitize!** Make data capture part of what's expected in each work process

Practice good data hygiene: one observation per row, one variable per column

**Keep learning** key concepts, get your feet wet and play

Wait it out! Gartner says ~40% of data science tasks will be automated by 2020.

### In a perfect world, my QMS would tell me...

From Kendall, K. (2017). The Increasing Importance of Risk Management in an Uncertain World. The Journal for Quality and Participation, 40(1), 4.

# **INTELE**<sup>%</sup>

Integrated Management Systems for Environment, Health & Safety, and Quality Management (EHSQ)

Established in 1992.

Worldwide client base.

More than 500 employees.

Over 1,200 global customers.

Over 1.5 million users.

Peer reviewed as best managed company.



#### Quality 4.0 is...

### Connectedness

### Intelligence

### **Automation**

... for discovering insights into performance.

#### QUALITY 4.0 SUMMIT ON DISRUPTION, INNOVATION, AND CHANGE

Organizational Excellence in the Digital Age

November 12 – 13, 2018 Dallas, TX



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