

Al & ML – Why, What, How & Beyond

August 2018



What is this talk about? (and what it is not!)

What is this talk about:

- Broad Framework to think about AI & its techniques
- Highlight relationship between AI, ML & Deep Learning
- Articulate the impact of AI & ML in Business Decision Making

What this talk is not:

- Does not deal with cost-benefit analysis of AI & ML
- Does not cover moral, ethical dimensions of AI & ML
- Does not cover any math behind the techniques

How delivered: I am going to put myself in your shoes, ask & answer key questions that you might have in your mind as you embark on this course!

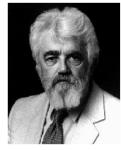
Q1: Artificial Intelligence brings images of Terminator,
Robots, Enthiran etc. What is the simplest way to
understand AI?



What is Artificial Intelligence?

Artificial Intelligence refers to the theory and development of computer systems & machines with the ability to perform tasks normally requiring human intelligence

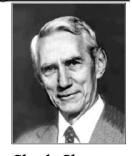
1956 Dartmouth Conference: The Founding Fathers of AI



John McCarthy



Marvin Minsky



Claude Shannon



Ray Solomonoff

Alan Newell



Herbert Simon



Arthur Samuel



And three others...
Oliver Selfridge
(Pandemonium theory)
Nathaniel Rochester
(IBM, designed 701)
Trenchard More
(Natural Deduction)



What constitutes Human Intelligence?

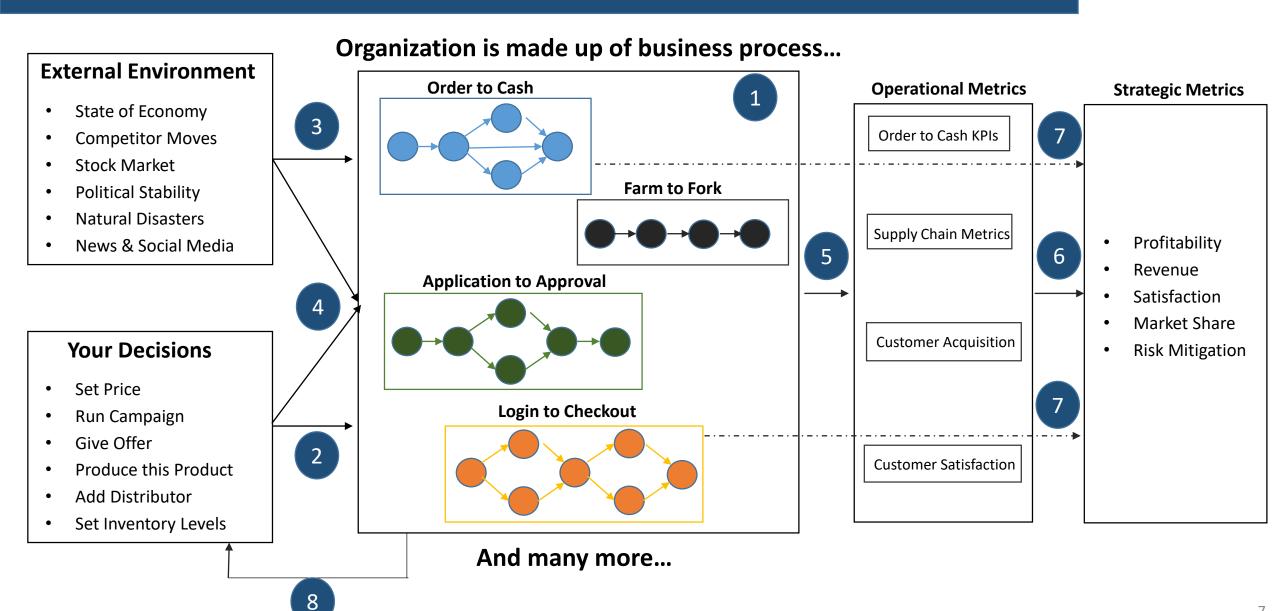


- 1. <u>Perceive</u> the world, detect signals and collect data
- Make sense of the world using data (Insights, Inference, Predictions etc.)
- 3. <u>Decide</u> on the next course of action
- 4. Act in the Real World

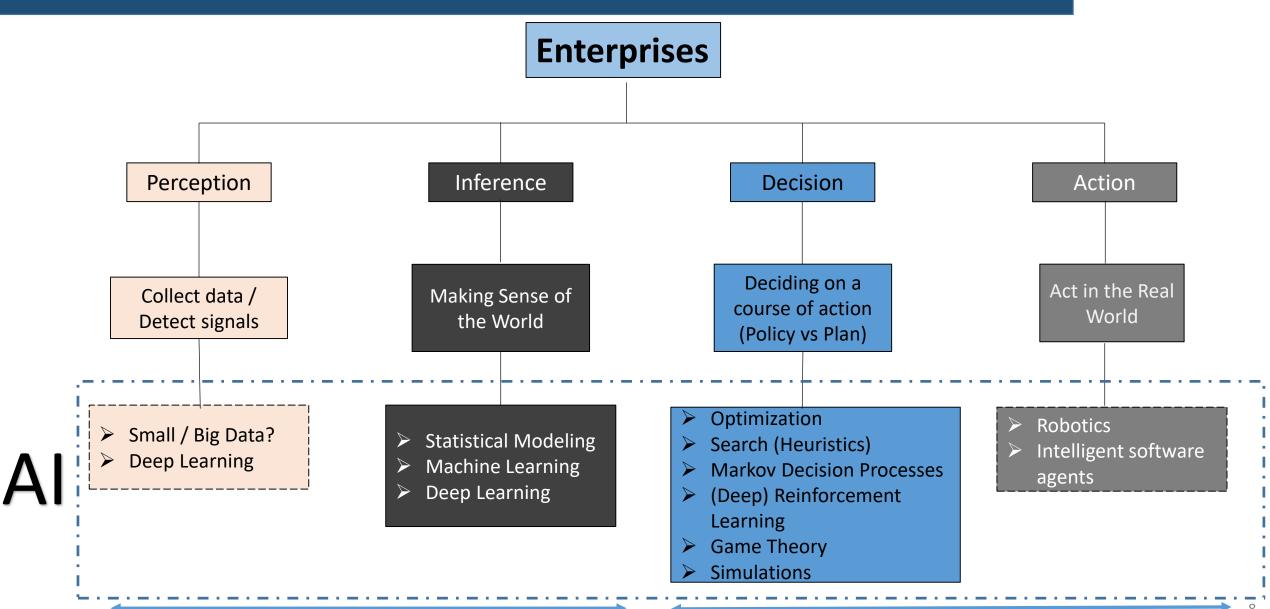
Q2: Ok. I kinda understand what constitutes Human Intelligence. How is it relevant for enterprises?



Business Decision Making is complex but worth it...



Al Techniques in Enterprises – Parallels to Human Intelligence

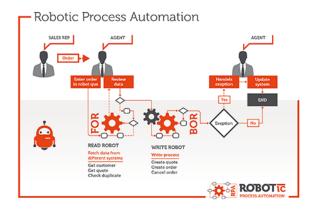


Descriptive, Diagnostic & Predictive Analytics

Prescriptive Analytics

3 Categories of Al in Enterprises

Assisted Intelligence



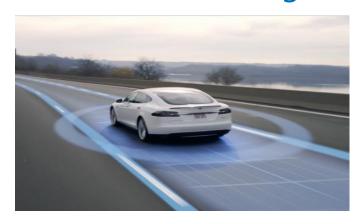
- Assisted intelligence amplifies the value of existing activity
- Assisted intelligence tends to involve clearly defined, rules-based, repeatable tasks. Ex: Robotic Process Automation (RPA)

Augmented Intelligence



- Augmented Intelligence fundamentally alters the nature of the task, and business models change accordingly.
- They involve advanced forms of machine learning and NLP, plus specialized interfaces tailored to your company and industry. Ex. Netflix using ML to build a recommendation engine.

Autonomous Intelligence

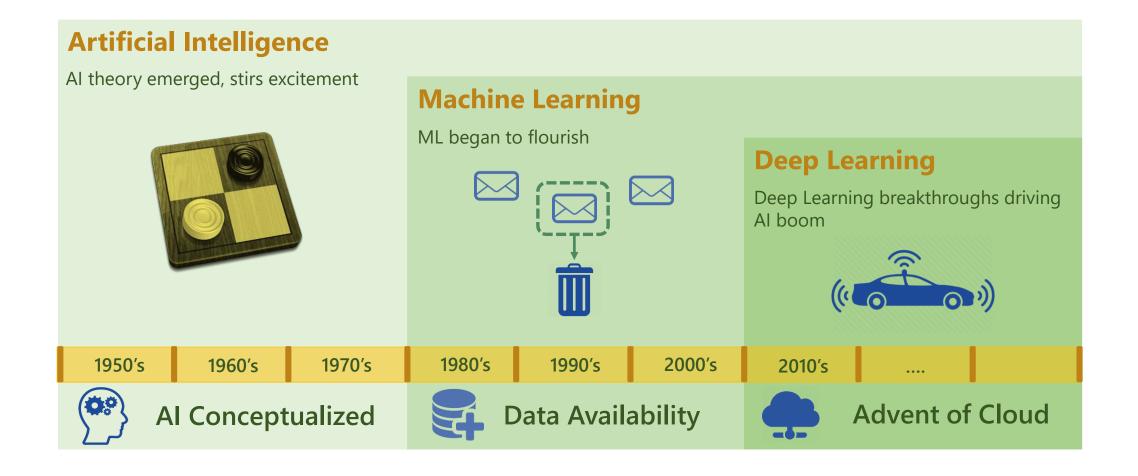


- Systems that make decisions without direct human involvement or oversight
- They will do so only after the human decision maker starts trusting the machine or becomes a liability for fast transactions. Ex. Autonomous cars, robots that dispose of bombs

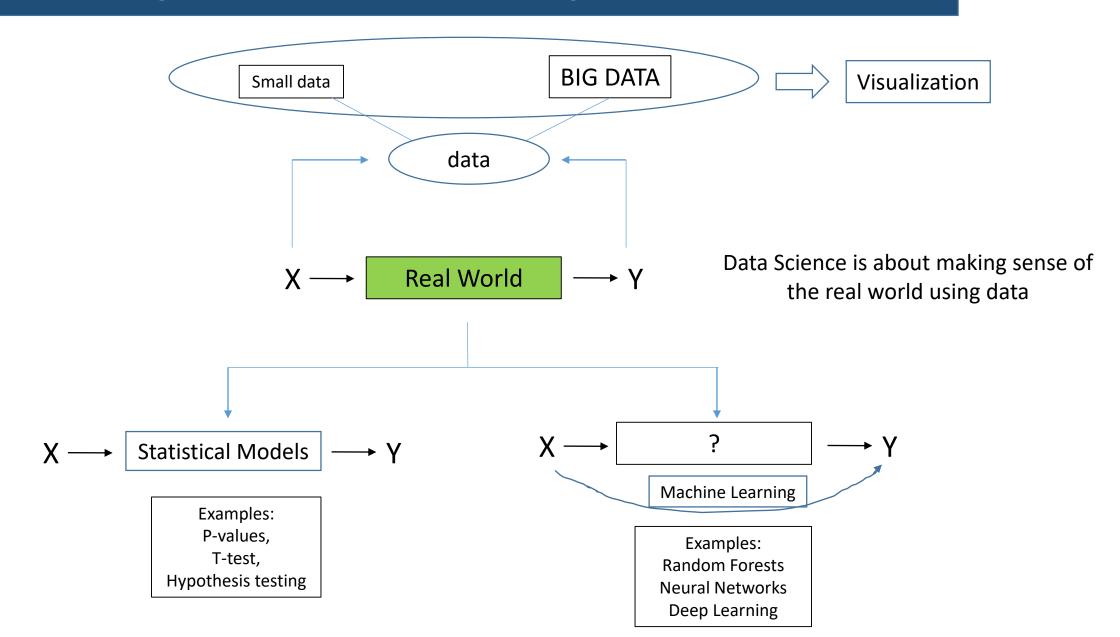
Q3: What is the relationship between AI, ML & DL?



Al in relation to ML & Deep Learning



ML & DL - Making Sense of the World (using Data)

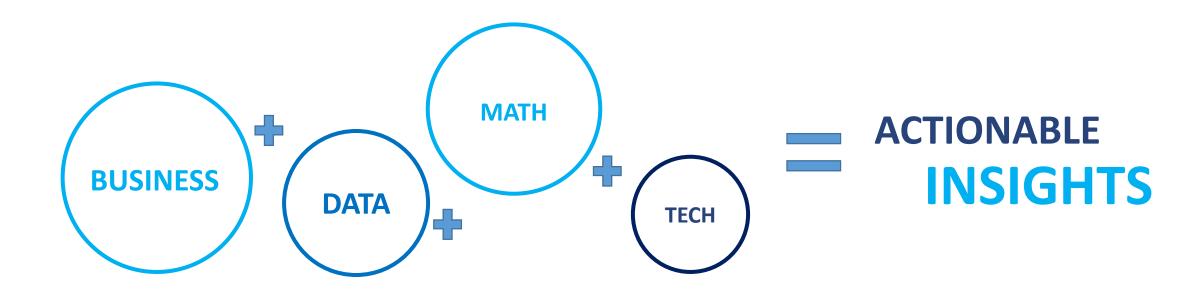


Q4: Enough of gyan on frameworks / high-level details.

Practically, what skills do I need to acquire to solve
problems? And can you show real-world examples?



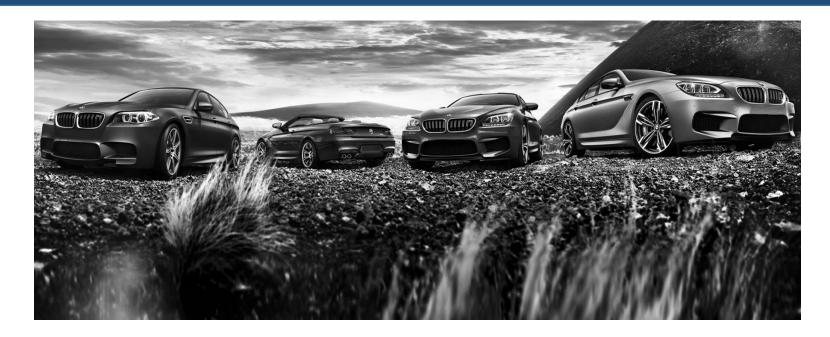
What skills are required to deliver 'Actionable Insights'?



Case Study 1: Famous Automobile Manufacturer

<u>Starting Point:</u> 3 Years of vehicle sensor data collected across 108 countries along with data on warranty claims

Case Study 1: Customer Behavior Modeling



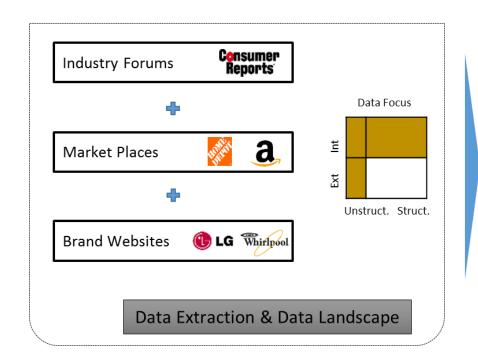
Salient Points from Analytics perspective:

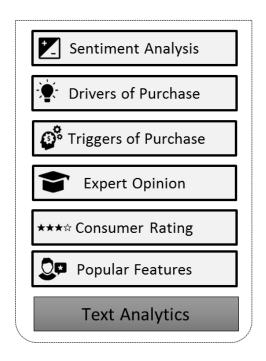
- Business: Warranty costs were high & rising. Urgent need to control costs & increase customer satisfaction
- Data: Sensor (semi-structured) data collected from cars running in 100+ countries
- Math: Clustering done on data to identify driving styles which is then correlated with warranty claims to predict defects
- **Technology:** Spark on the Cloud platform called Databricks, User Interface for self-service

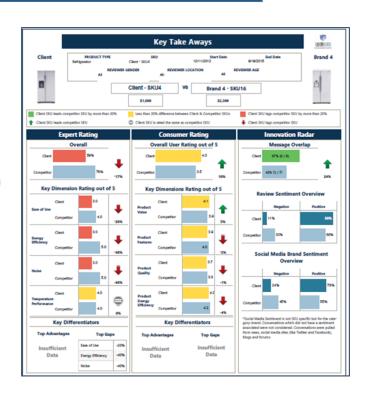
Case 2: Large Consumer Durables Company

<u>Starting Point:</u> Purchase drivers were determined by post-facto analysis of POS data at stores and survey data resulting in delays of up to eight months to get consumer feedback on product features.

Case Study 2: Social Data to Drive Innovation







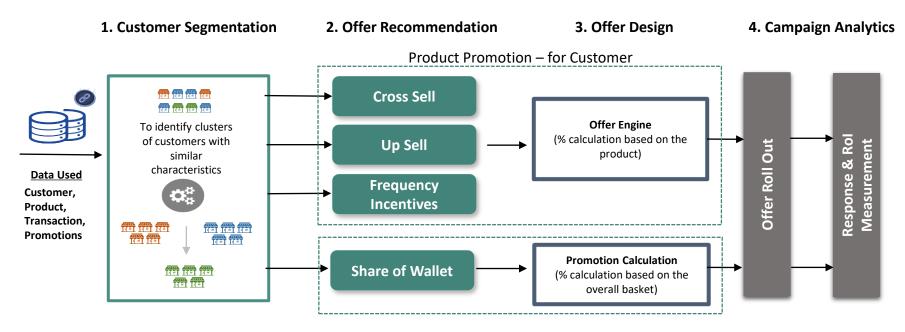
Salient Points from Analytics perspective:

- Business: Can we identify opportunities for Innovation using external data?
- Data: Reviews & Social Interactions captured across the globe. Unstructured data in the form of text
- Math: Sophisticated Natural Language Processing Techniques to extract insights from unstructured data
- **Technology:** Automated data pipeline to ingest & analyze data. Visualization using Tableau

Case 3: World's Largest Food Distribution Company

Starting Point: Customer & transactional data related to sales of food products to over 500,000 customer locations including restaurants, healthcare & educational facilities and other food service customers. They wanted to drive high margin product sales through effective cross-sell & upsell

Case Study 3: Recommendation Engine to Increase Sales



Promotion on Additional Spend

Salient Points from Analytics perspective:

- Business: Can we identify opportunities for cross-sell / up-sell to sell more of high margin products?
- Data: Customer, Product, Transactions and Promotions
- Math: Clustering followed by Collaborative Filtering (Recommendation Engine)
- **Technology:** Automated pipeline that generates recommendations for every sales person

Q5: Business, Data, Math, Technology...hmm...that's easy...so why should it take time & effort to acquire this knowledge?



Dimensions of Analytics

Use Case **Interpret Analytics** Domain Business Formulation Output **Expertise** Acquisition & Data Visualization & Signals from data Data (subtract noise) Wrangling **Story Telling** Math / **Statistical Modeling** Select the right Evaluating the techniques & code output of algos vs ML Quant Tech / Data Engineering / Understand the IT Software Ecosystem **Pipelines** Engineering / SDLC Software

My Analytics Mindmap

Global Trends in Society

Macro-economy

Business Fundamentals

Specific Industry Domain

Analytical use cases



Analytical
Platforms &
Techniques

Data Management

Reporting & Self-service

Quantitative Techniques

Performance Mgmt

Insight Delivery

Analytics for Business Value http://bit.ly/31KArT8

Scan for New Products

Evaluate Maturity



Monitor Ecosystem

Leverage Resources

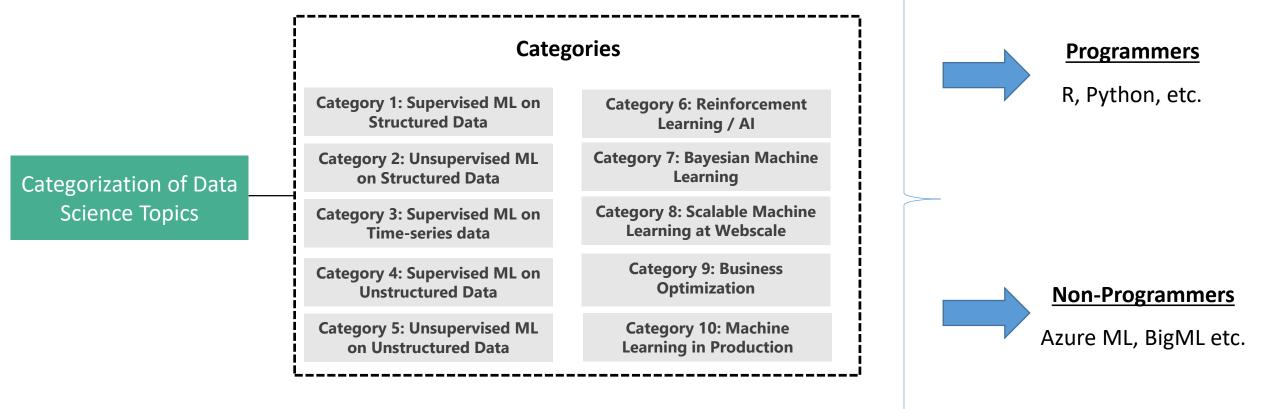
Q6: There could be many techniques and it is not possible to learn everything in a short timeframe? Any tips on how to keep track of them and learn as you go along?



Data Science Techniques – There are a lot of them!



Develop your own personal map



Example: Category 1

Is the focus on data **Navigation** or on the process **Data** Type of Data **Structured Not Webscale** Volume of data Is it a time-series? Has Label / DV? No Yes Category 1: Supervised ML on Structured Data DV - Continuous or Categorical? **Continuous Categorical** Regression Classification

Details

- Exploratory Data Analysis (EDA)
- > Data Pre-processing Outliers, Missing data, Variable Transformations
- Feature Selection & Dimensionality Reduction
- Feature Engineering
- Algorithms Standalone vs Ensembles
- Algorithms Parametric vs Non-Parametric
- Algorithms Linear vs Non-linear
- Cross validation
- Hyper-parameter Tuning
- Predict on Test set

Q7: What are the useful components in the data science toolbox?



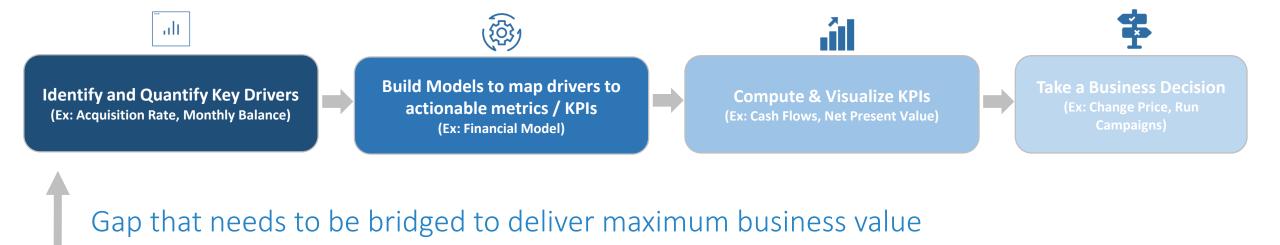
Data Science Toolbox

- ➤ Maths / Stats orientation (Not a tool but...)
- > Atleast 1 programming language Python (Jupyter notebooks), R
- > Atleast 1 GUI based ML platform H2o, Azure ML, BigML
- ➤ 1 Cloud based platform (Nice to have) AWS, Databricks
- > Github
- > Kaggle (Competition & Kernels), Analytics Vidhya
- Database / SQL knowledge (preferable)

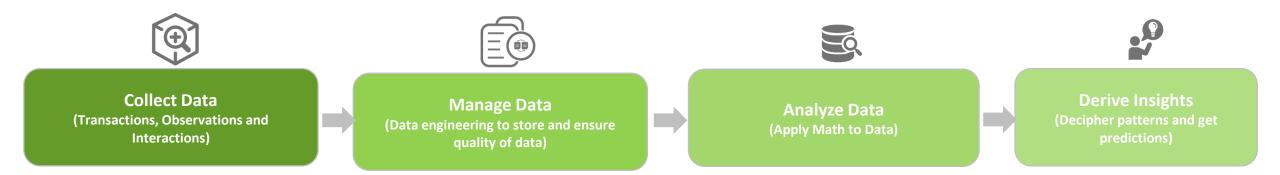
Q8: Other than the analytical techniques themselves, what are the top 2 skills that needs to be developed?



Business Orientation is the cornerstone of Analytics



Business Decision Making Pipeline



Data Science Pipeline

Think Technology Landscape

- > Cloud
- Big Data
- Mobility
- Web Technologies
- Embedded Analytics in Applications
- Legacy Systems

Q9: What are the typical roles in the analytics space and entry possibilities for different experience levels?



Typical Roles in Analytics

Business Business Analyst Functional Expert Domain Expert Visualization Data **Data Analyst experts** Math / **Data Scientist Statisticians** Quant (Junior to Senior Level) AI / ML Engineer Tech / Tech Leads / **Project / Delivery Data Engineer Architects** Managers Software (Cloud, Big Data etc.)

Typically one will need all skills in different proportions

How to make the transition? – Fresher / Developer

	Can Aspire to be	Skills to Acquire	How to Acquire
Fresher / Junior Developer	Business Analyst	Business OrientationFunctional Knowledge(in 1 or 2 areas)	Domain / FunctionalCertificationsMBA
	Data Analyst	 SQL Skills / DB knowledge Translate business requirements to data needs Basic Stats knowledge 	 Specialized courses Online Tutorials Technical certifications MOOCs
	Data Engineer	 SQL Skills Hands-on coding expertise in Big Data tools Cloud Platform knowledge 	 Focused Big Data & Cloud Courses Online Courses MOOCs

How to make the transition? – Experienced Techie (6-12 years)

	Can Aspire to be	Skills to Acquire	How to Acquire
Lead / Architect	Data Engineer	 Strong SQL & Programming skills in Java, Scala, etc. Design data pipelines for analytics 	 Technical certifications Online Tutorials Focused Courses
	Big Data / Cloud Specialist	 Design Big Data Systems Expertise in using databases / cloud platforms in the Big Data context 	> Technical certifications in areas of specialization
	Mid-Level Data Scientist	 Good Stats / Math knowledge Intuitive understanding of algorithms Hands-on coding expertise in ML/Data Science (R, Python etc.) 	 Specialized Analytics Programs MOOCs Build a portfolio of ML projects Online competitions (Ex: Kaggle, AnalyticsVidhya)

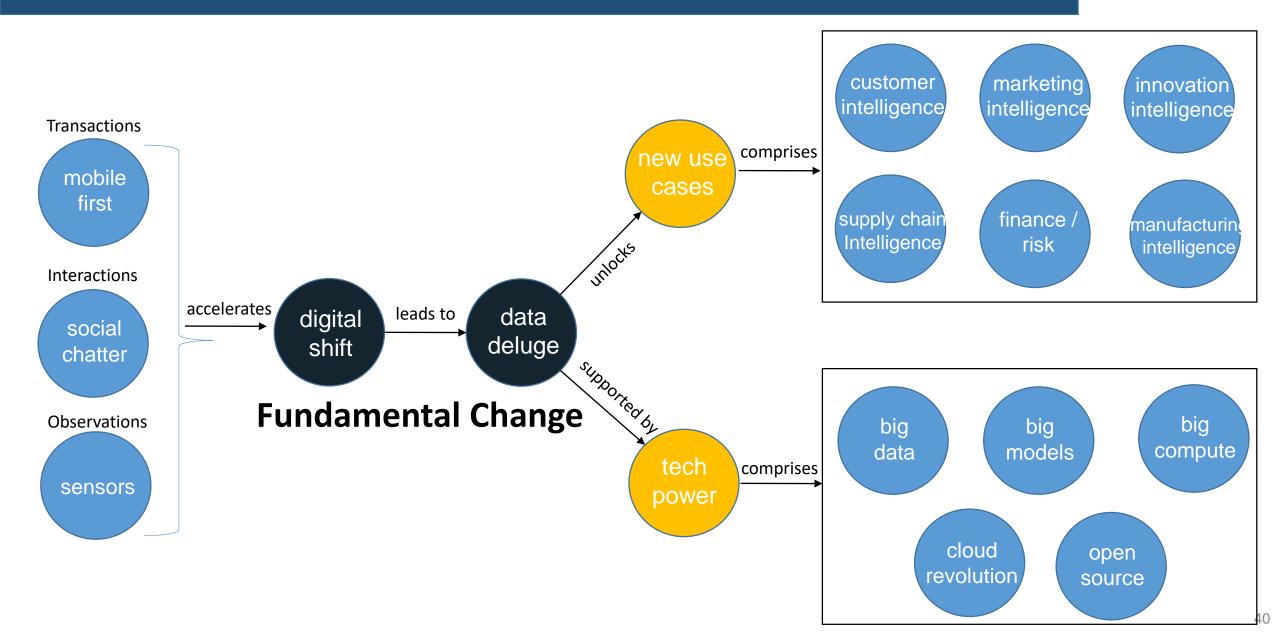
How to make the transition? – Senior Professionals

Can Aspire to be Skills to Acquire How to Acquire **Strong Functional / Domain Executive MBA programs** Delivery Manager / **Functional / Domain** Knowledge **Specialized Analytics Expert Business Head Conceptual Knowledge of Analytics** programs (Online / Offline) On the job SDLC as applicable to analytics / **Project / Delivery MOOCs (Case study** big data projects Manager Conceptual knowledge of based approach) **Business + Data + Math Good Stats / Math knowledge Specialized Analytics Programs** Intuitive understanding of **MOOCs** Mid-Level **Data Scientist** algorithms **Build a portfolio of ML projects** Hands-on coding expertise in Online competitions (Ex: Kaggle, ML/Data Science (R, Python etc.) AnalyticsVidhya)

Q10: How are you sure that AI & ML techniques are for the long-term and is not just a fad?



Digital Shift – Fundamental, Irreversible Change

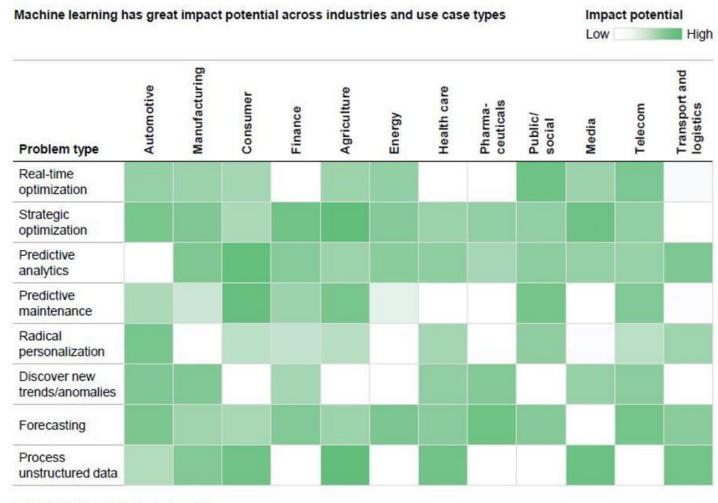


Data Science & ML can have great impact on industries

MCKINSEY GLOBAL INSTITUTE

THE AGE OF ANALYTICS:
COMPETING IN A
DATA-DRIVEN WORLD

DECEMBER 2016



SOURCE: McKinsey Global Institute analysis

More stories for inspiration...

- **Predictive Policing:** https://en.wikipedia.org/wiki/Predictive_policing
- Genome Sequencing: https://www.techemergence.com/machine-learning-in-genomics-applications/
- Self-correcting Machines: https://www.ge.com/reports/ge-takes-predix-cloud-edge/
- AlphaZero: https://www.extremetech.com/extreme/260215-alphazero-new-chess-champion-harbinger-brave-new-world-ai
- Self-Driving Cars: https://en.wikipedia.org/wiki/Autonomous car









Strong Motivation – Data Science is a journey

Curiosity – Ask yourself, others & internet the right questions

Connecting the Dots – Learn & Assimilate

Skill - Should enjoy working with numbers

Q&A



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