

# Data Science

An Introduction

Setia Pramana

# Data, data and data everywhere.....

Big Data is affecting people everywhere.

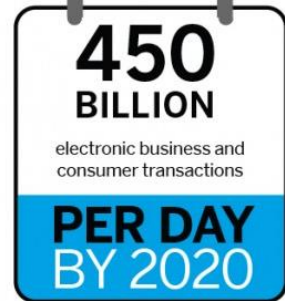


Big Data is changing business



Big data industry estimated to be worth \$100 BILLION+

IDC believes that within five years..... companies will finally be able to run a real-time enterprise that simultaneously transacts, analyzes and acts on big data.



SAP is helping customers get real value from Big Data

MKI performs genome analysis with SAP HANA

"...with this (SAP HANA) we've found a way to shorten the genomic analysis time from several days down to only 20 minutes."

YUKIHISA KATO, CTO AND DIRECTOR OF MKI

eBay uses predictive analytics to gain new insights

"With the speed of HANA great people become exceptional at what they do because of the speed that they can interact with the data. That is truly awesome."

DANIEL SCHWARZBACH, VP & CFO EBAY NORTH AMERICA AT EBAY INC.

Bigpoint solves big data challenges with SAP HANA

Our expectation – and it actually seems to be coming true – is that the use of this technology and the methods behind it helps us realize sales growth spurts of 10 – 30%.

MICHAEL GUTSMANN, CFO BIGPOINT



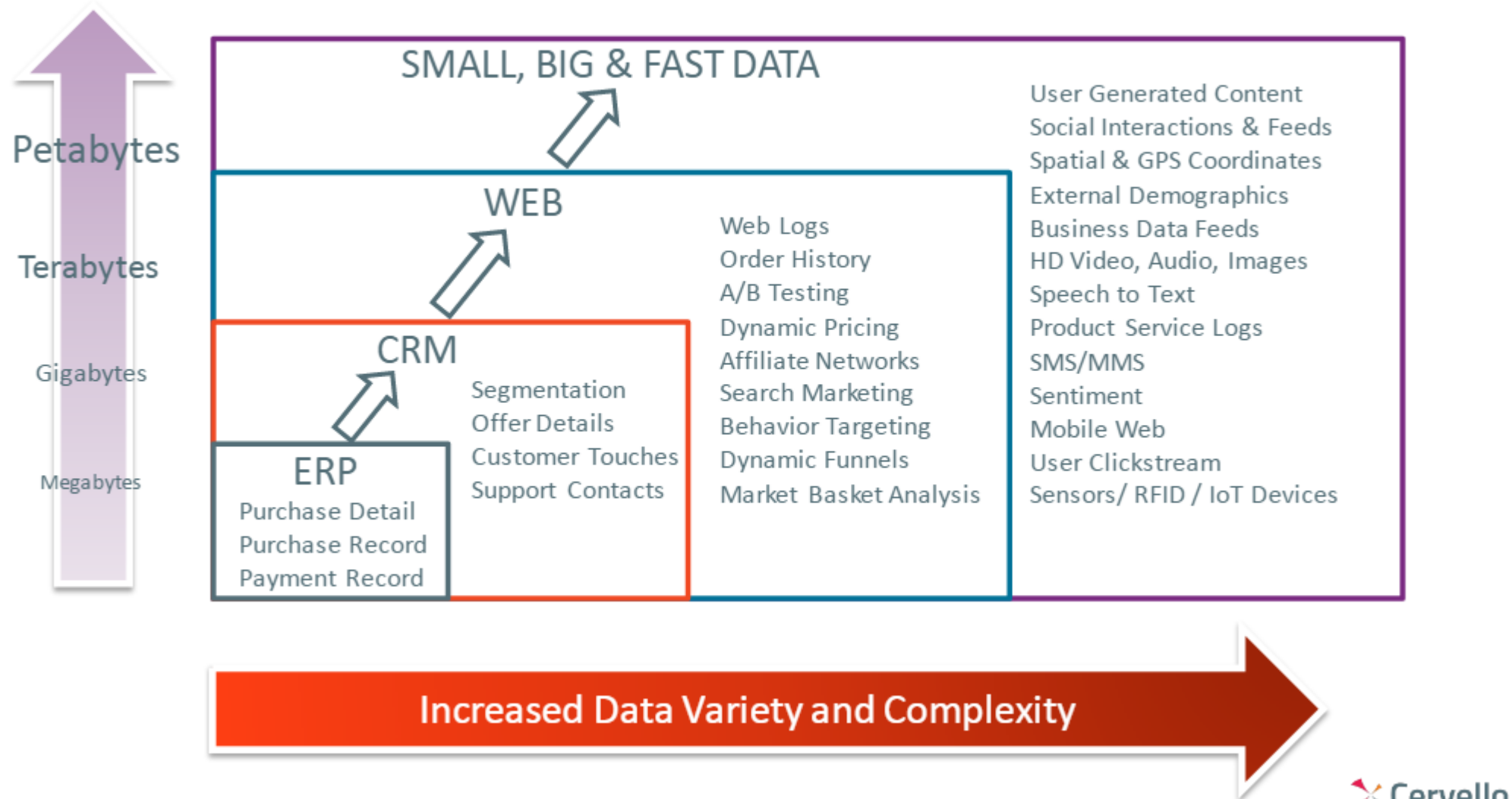
Find out what opportunities Big Data holds for you.

Follow us on Twitter @asiarunbetter Visit [www.sap.com/bigdata](http://www.sap.com/bigdata) Contact SAP

Garner: The Nexus of Forces Boosts Information Governance and MDM, 2012 | IDC: IDC Predictions 2012: Competing for 2020 | IDC: Ingraining Insights into the DNA of People and Process, 2013 | International Telecoms Union, 2013 | Economist, 2013 | SAP, 2013



# Data = Transactions + Interactions + Observations





# THE WORLD OF DATA

NUMBER  
OF EMAILS  
SENT  
EVERY SECOND

2.9

MILLION

DATA  
CONSUMED BY  
HOUSEHOLDS  
EACH DAY

375

MEGABYTES

VIDEO  
UPLOADED TO  
YOUTUBE EVERY  
MINUTE

20

HOURS

DATA PER  
DAY  
PROCESSED  
BY GOOGLE

24

PETABYTES

TWEETS  
PER  
DAY

50

MILLION

TOTAL MINUTES  
SPENT ON  
FACEBOOK  
EACH MONTH

700

BILLION

DATA SENT  
AND RECEIVED  
BY MOBILE  
INTERNET USERS

1.3

EXABYTES

PRODUCTS  
ORDERED ON  
AMAZON PER  
SECOND

72.9

ITEMS



IN THE 21ST CENTURY, we live a large part of our lives online. Almost everything we do is reduced to bits and sent through cables around the world at light speed. But just how much data are we generating? This is a look at just some of the massive amounts of information that human beings create every single day.

SOURCES: Cisco, comScore, Netflix, Google Analytics, YouTube

# Type of Data

- Relational Data (Tables/Transaction/Legacy Data)
- Text Data (Web)
- Semi-structured Data (XML)
- Graph Data
- Social Network, Semantic Web (RDF), ...
- Streaming Data
- You can afford to scan the data once

# What to do?

- Aggregation and Statistics
  - Data warehousing and OLAP
- Indexing, Searching, and Querying
  - Keyword based search
  - Pattern matching (XML/RDF)
- Knowledge discovery
  - Data Mining
  - Statistical Modeling

# Analytics Approaches

- Descriptive: What happened or what is happening now?
- Diagnostic: Why did it happen or Why is it happening now?
- Predictive: What will happen next? What will happen under various conditions?
- Prescriptive: What are the options to create the most optimal/high value result/outcome?

# Data Science

“Applying advanced statistical tools to existing data to solve problems, generate new insights, improve products/services”

“Everything that has something to do with data: Collecting, analyzing, modeling..... yet the most important part is its applications --- all sorts of application”



# What is Data Science?

- Theories and techniques from many fields and disciplines are used to investigate and analyze a large amount of data to help decision makers in many industries such as science, engineering, economics, politics, finance, and education
  - Computer Science
    - Pattern recognition, visualization, data warehousing, High performance computing, Databases, AI
  - Mathematics
    - Mathematical Modeling
  - Statistics
    - Statistical and Stochastic modeling, Probability.

# Data Science: An Action Plan for Expanding the Technical Areas of the Field of Statistics

William S. Cleveland

*Statistics Research, Bell Labs*

DOI:10.1002/sam.11239

Published online in Wiley Online Library (wileyonlinelibrary.com).

**Abstract:** An action plan to expand the technical areas of statistics focuses on the data analyst. The plan sets out six technical areas of work for a university department and advocates a specific allocation of resources devoted to research in each area and to courses in each area. The value of technical work is judged by the extent to which it benefits the data analyst, either directly or indirectly. The plan is also applicable to government research labs and corporate research organizations. © 2014 Wiley Periodicals, Inc. *Statistical Analysis and Data Mining* 7: 414–417, 2014

## 1. SUMMARY OF THE PLAN

This article describes a plan to broaden the major areas of technical work of the field of statistics. Because the plan is ambitious and implies substantial changes, the new field will be called ‘data science’.

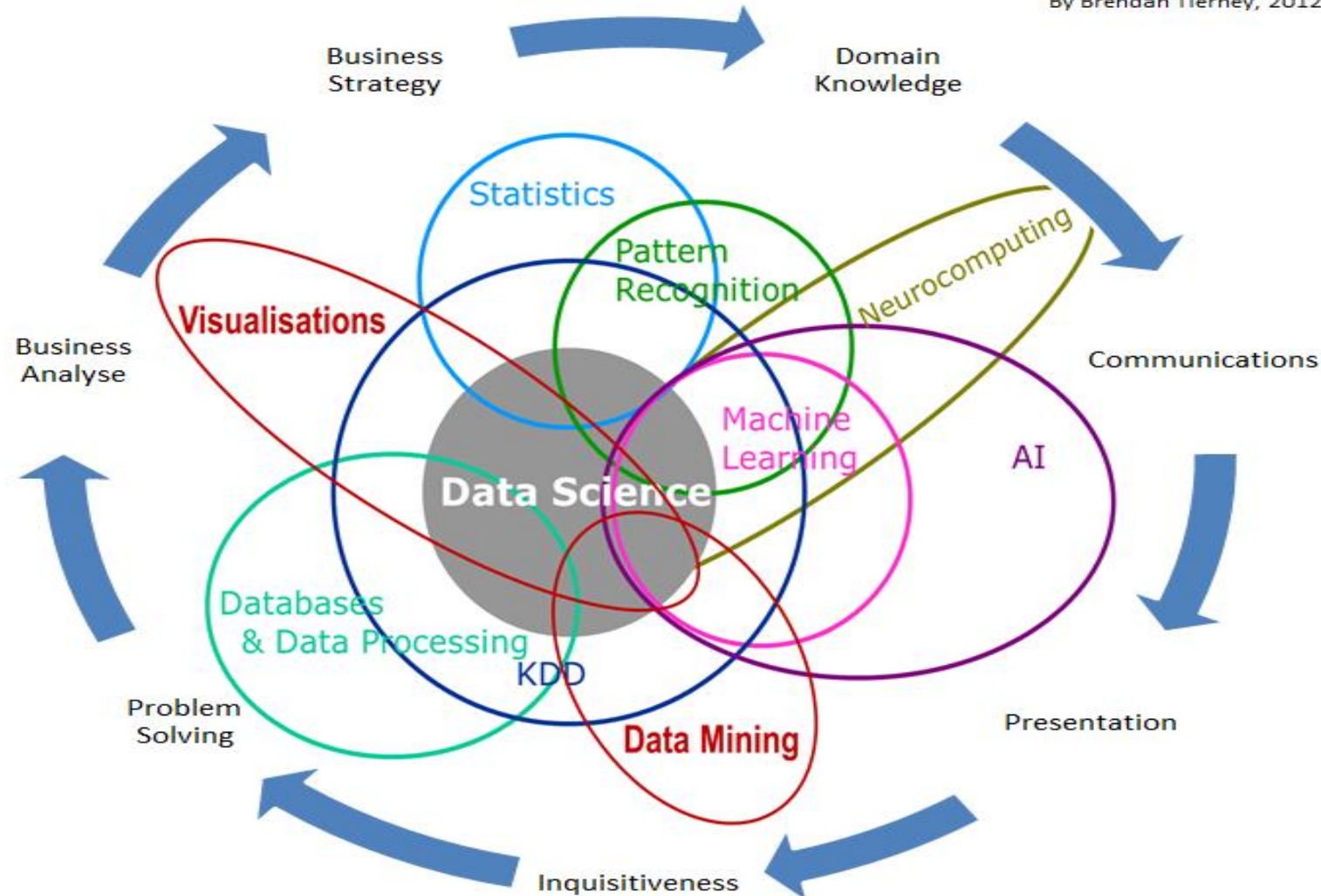
The focus of the plan is broadening the data analyst. A

- *Models and Methods for Data (20%)*: statistical models; methods of model building; and methods of estimation and distribution based on probabilistic

hardware systems;

# Data Science Is Multidisciplinary

By Brendan Tierney, 2012



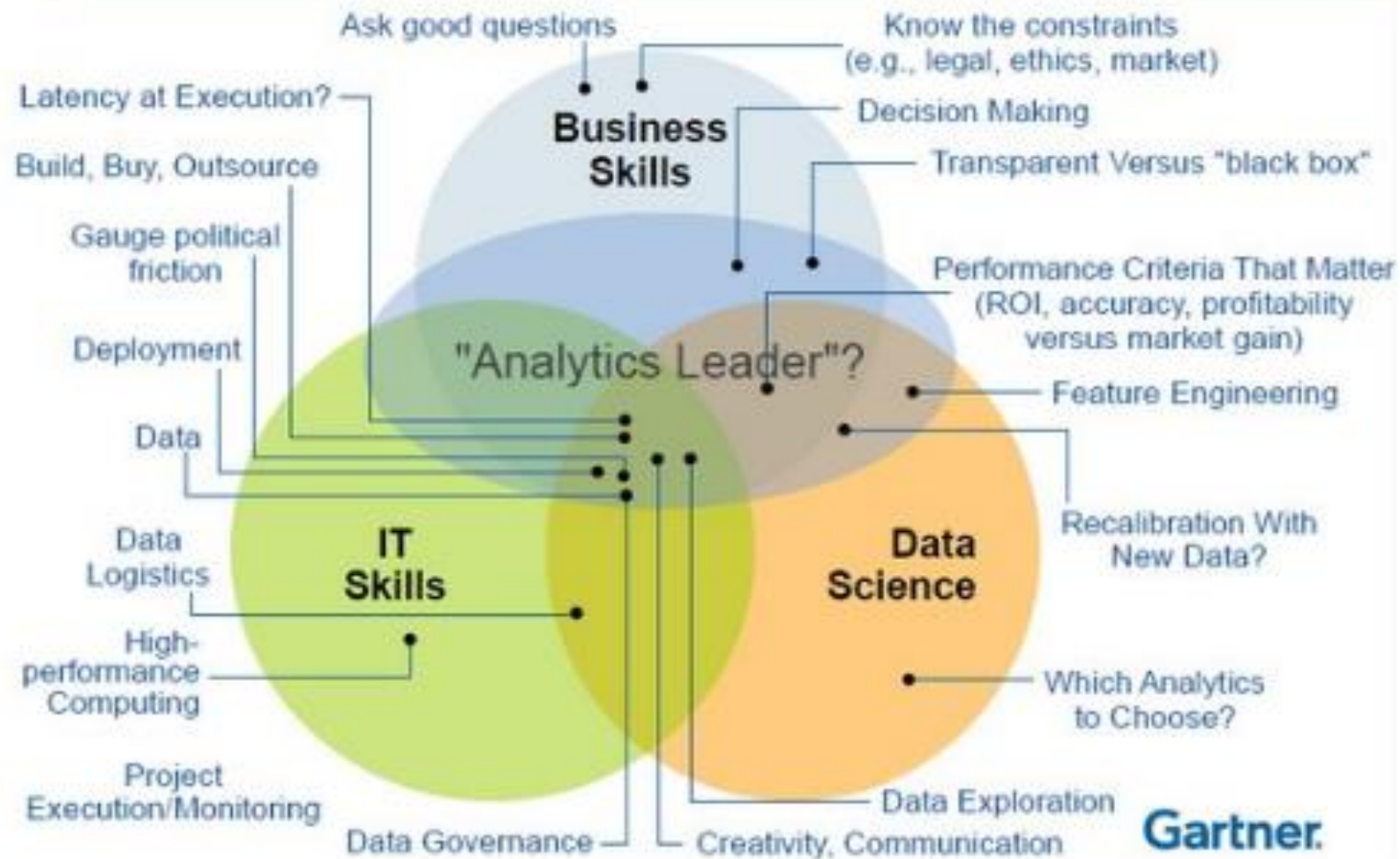
# Data Science

- A Mashed Up Discipline
- A multi-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data

Math and Theory	• Statistics, Linear Algebra, Optimization, Time Series, etc.
Applied Algorithms	• Machine Learning, Data Structures, Parallel Algorithms, etc.
Engineering and Technologies	• Storage and computing platforms, statistical tools ,etc.
Domain Expertise	• Text, Finance, Images, Econometrics etc.
Art	• Visualization, Infographics
Best practices and hacks	• Handle missed values in data, transform and represent data, etc.

# Data Science

## Driving the Success of Data Science Solutions: Skills, Roles and Responsibilities ...





# ANATOMY OF A DATA SCIENTIST

## SALARY

Average salary of data scientists is **\$120,000/year**

## BENEFITS

- Harvard Business Review called data science the **"Sexiest Job of the 21st Century"**
- One of the fastest growing careers in the United States
- **94%** of data science graduates have found jobs since 2011

## RESPONSIBILITIES

- Conduct research
- Extract, clean, and analyze data from varied sources
- Solve problems
- Build automation tools
- Communicate findings to management

## CAREER POSSIBILITIES

- The majority of data scientists work in the **technology industry.**
- Other options include marketing, consulting, healthcare and pharmaceuticals, finance, government, gaming, and many more.

## EDUCATION

- **88%** of all data scientists have at least a Master's degree
- **46%** of data scientists have a PhD

## SKILLS

- Programming languages (R, Python, SQL, Hive, etc.)
- Statistics
- Multivariable calculus and linear algebra
- Machine learning
- Software engineering
- Wrangle, visualize, and communicate data to management

operate

# MODERN DATA SCIENTIST

Data Scientist, the sexiest job of 21st century requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

## MATH & STATISTICS

- ☆ Machine learning
- ☆ Statistical modeling
- ☆ Experiment design
- ☆ Bayesian inference
- ☆ Supervised learning: decision trees, random forests, logistic regression
- ☆ Unsupervised learning: clustering, dimensionality reduction
- ☆ Optimization: gradient descent and variants

## DOMAIN KNOWLEDGE & SOFT SKILLS

- ☆ Passionate about the business
- ☆ Curious about data
- ☆ Influence without authority
- ☆ Hacker mindset
- ☆ Problem solver
- ☆ Strategic, proactive, creative, innovative and collaborative

## PROGRAMMING & DATABASE

- ☆ Computer science fundamentals
- ☆ Scripting language e.g. Python
- ☆ Statistical computing package e.g. R
- ☆ Databases SQL and NoSQL
- ☆ Relational algebra
- ☆ Parallel databases and parallel query processing
- ☆ MapReduce concepts
- ☆ Hadoop and Hive/Pig
- ☆ Custom reducers
- ☆ Experience with xaaS like AWS

## COMMUNICATION & VISUALIZATION

- ☆ Able to engage with senior management
- ☆ Story telling skills
- ☆ Translate data-driven insights into decisions and actions
- ☆ Visual art design
- ☆ R packages like ggplot or lattice
- ☆ Knowledge of any of visualization tools e.g. Flare, D3.js, Tableau



# THE DATA SCIENCE HIERARCHY OF NEEDS

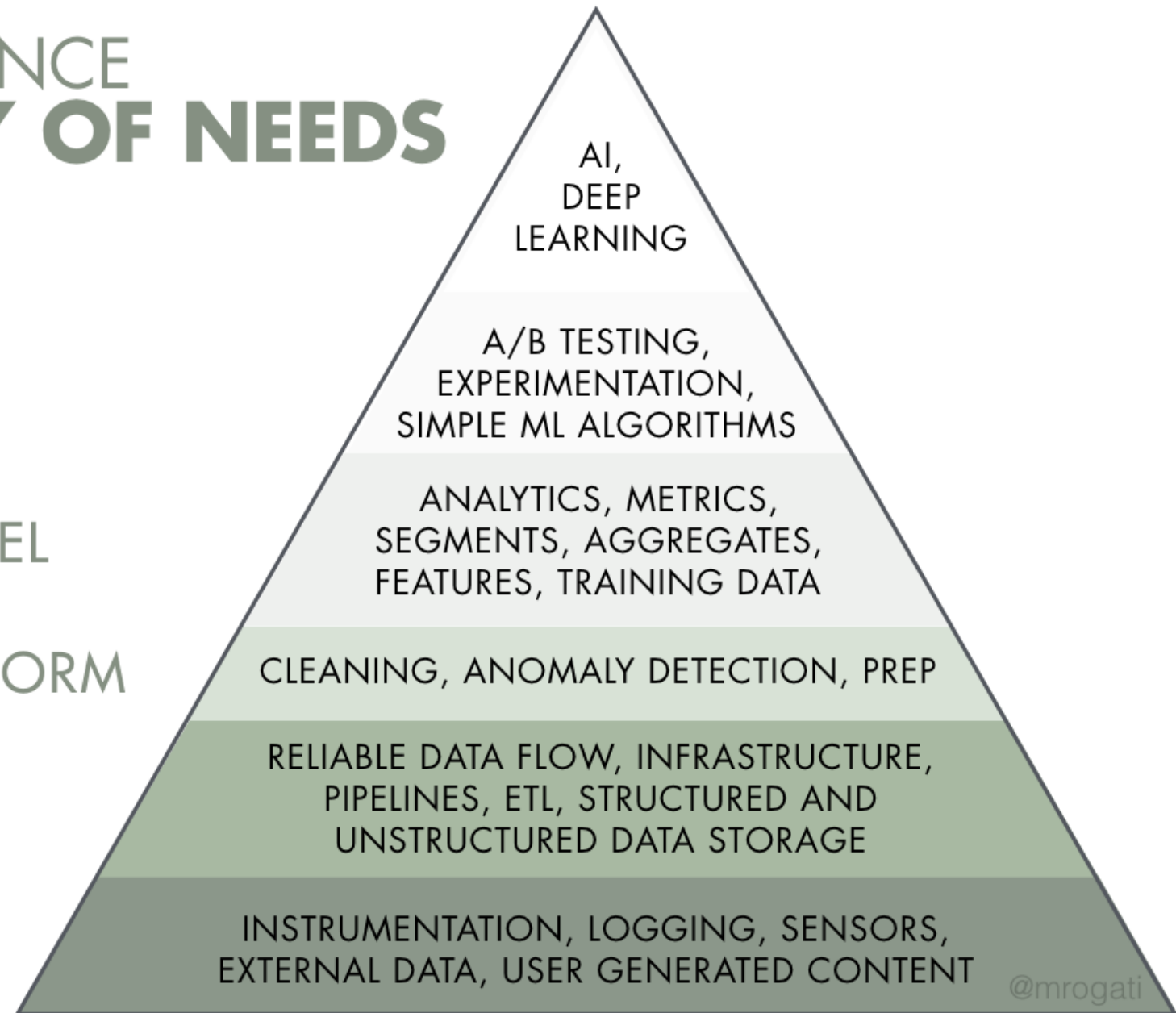
LEARN/OPTIMIZE

AGGREGATE/LABEL

EXPLORE/TRANSFORM

MOVE/STORE

COLLECT



# THE DATA SCIENCE HIERARCHY OF NEEDS

**Start Up**

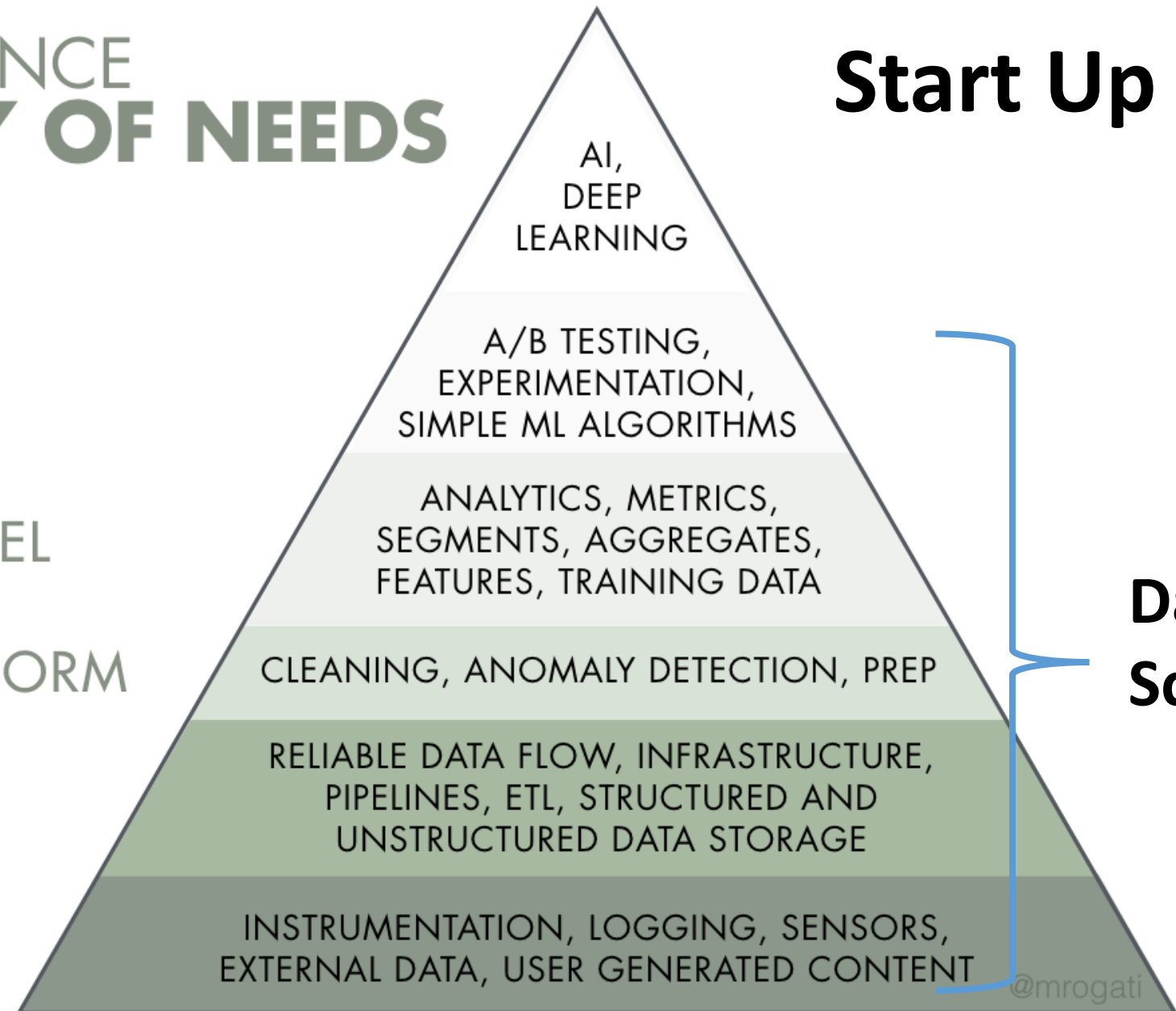
LEARN/OPTIMIZE

AGGREGATE/LABEL

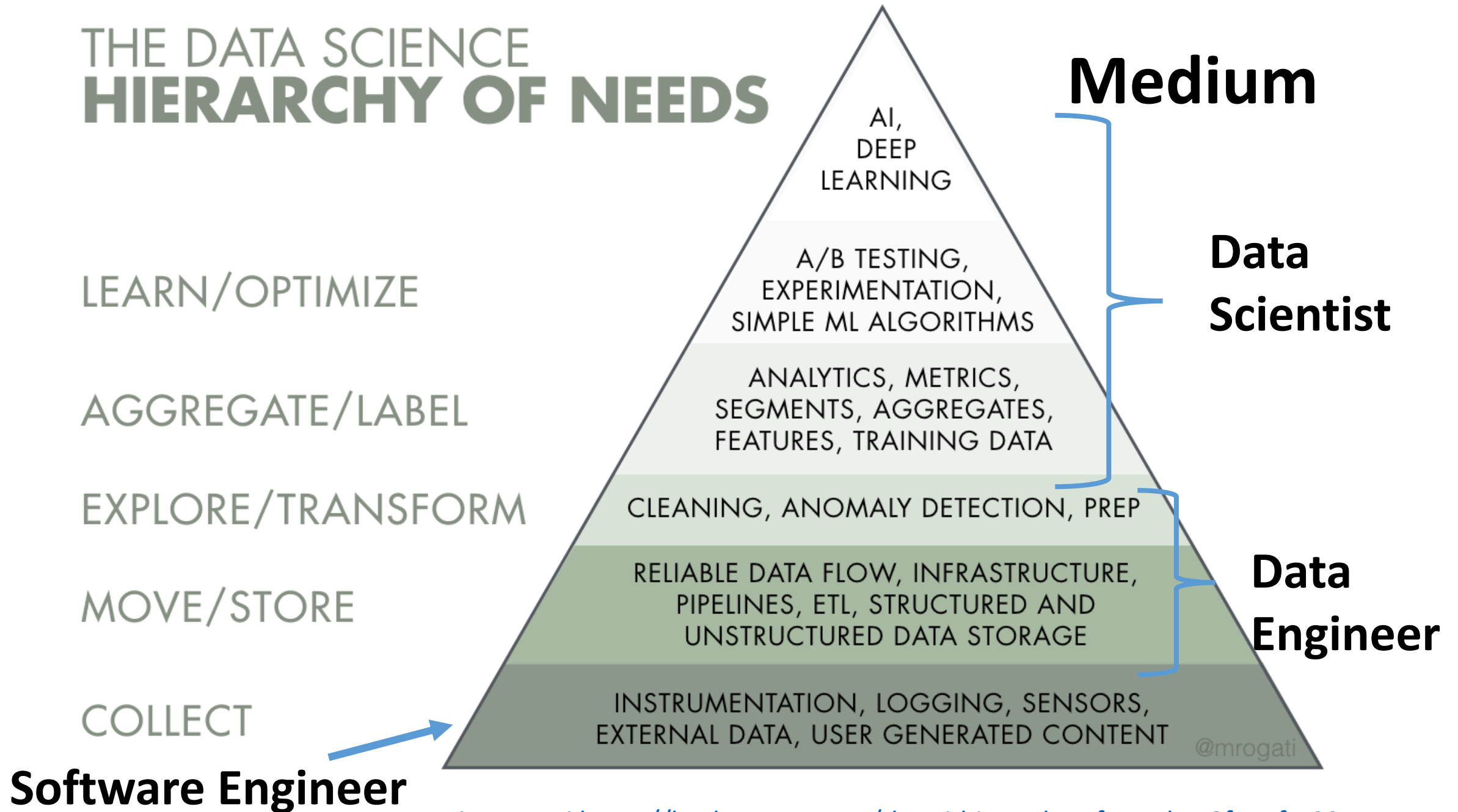
EXPLORE/TRANSFORM

MOVE/STORE

COLLECT

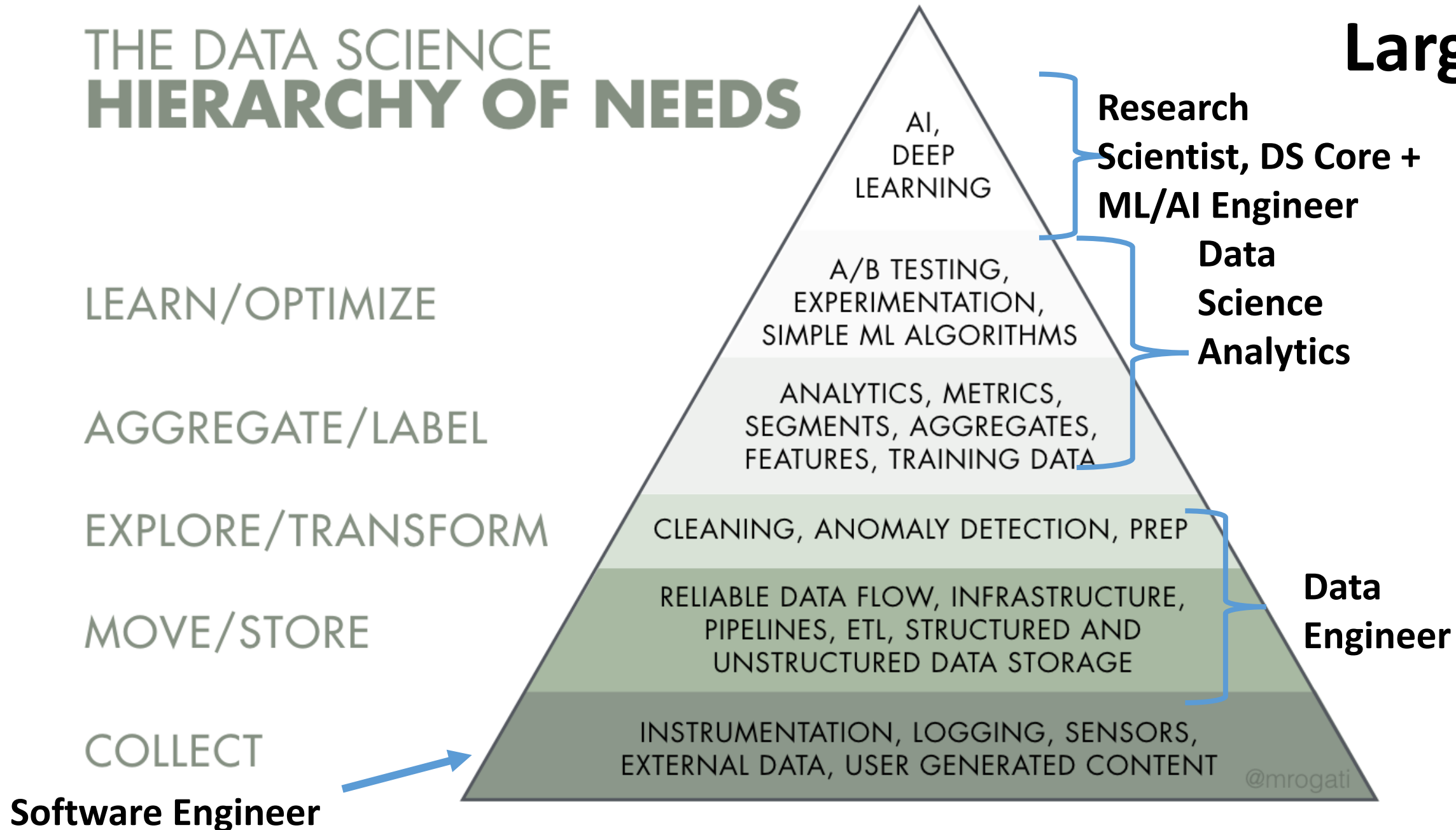


# THE DATA SCIENCE HIERARCHY OF NEEDS



# THE DATA SCIENCE HIERARCHY OF NEEDS

Large



# DATA Engineer



DataCamp  
Learn Data Science By Doing

# DATA Scientist

Develops, constructs, tests, and maintains architectures. Such as databases and large-scale processing systems.

Cleans, massages and organizes (big) data. Performs descriptive statistics and analysis to develop insights, build models and solve a business need.





# Languages, Tools & Software



Source: datacamp



## Data Scientist

also known as Data Managers, statisticians.



A data scientist will be able to take data science projects from end to end. They can help store large amounts of data, create predictive modelling processes and present the findings.

**Skills:** Mathematics, Programming, Communication



Will use programmes such as:  
SQL, Python, R

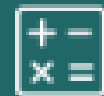
## Data Engineers

also known as database administrators and data architects.



They are versatile generalists who use computer science to help process large datasets. They typically focus on coding, cleaning up data sets, and implementing requests that come from data scientists.

**Skills:** Programming, Mathematics, Big data



Will use programmes such as:  
Hadoop, NoSQL, and Python

## Data Analysts

also known as business Analysts.



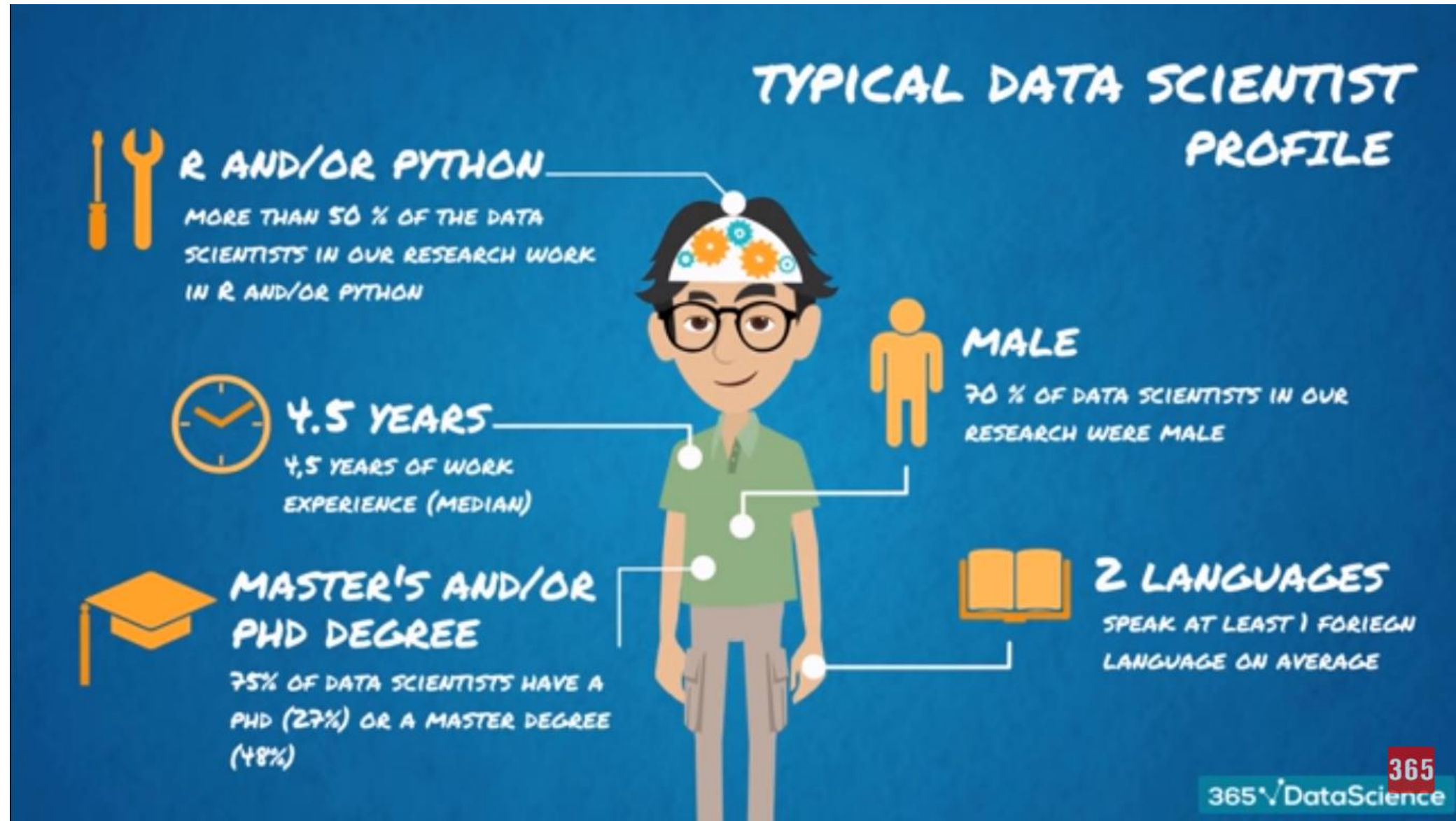
They typically help people from across the company understand specific queries with charts.

**Skills:** Statistics, Communication, Business knowledge

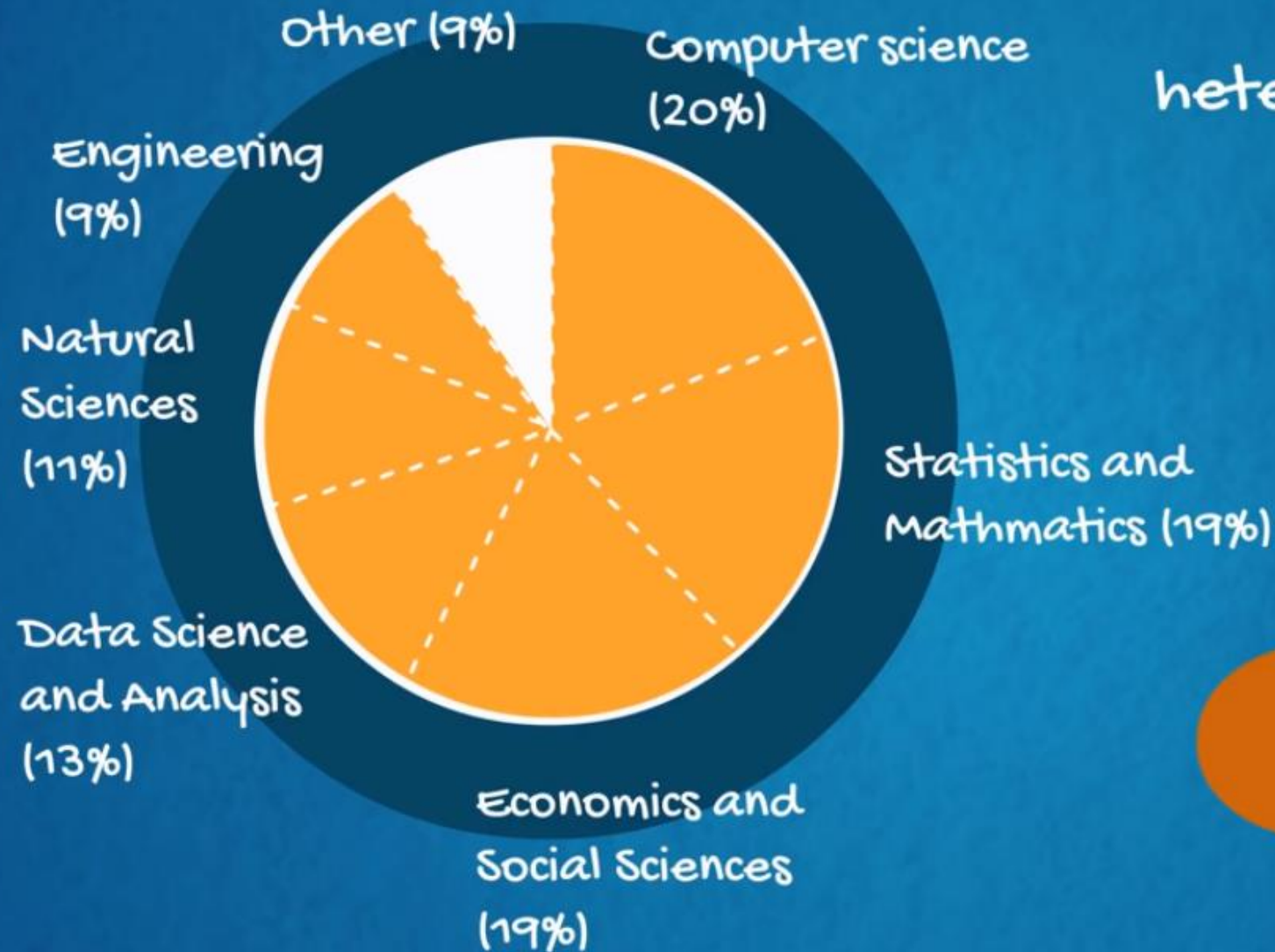


Will use programmes such as:  
Excel, Tableau, SQL

# Current Data Scientists Profile



Data scientists have  
heterogeneous academic  
profiles









91%

# Data Scientist: The Sexiest Job of the 21st Century

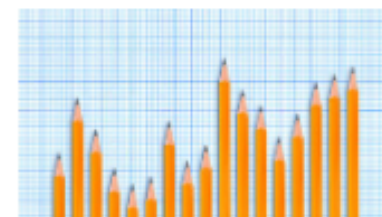
by [Thomas H. Davenport](#) and [D.J. Patil](#)

FROM THE OCTOBER 2012 ISSUE

 Summary  Save  Share  <sup>16</sup> Comment  Text Size  Print **\$8.95** Buy Copies

**W**hen Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social

## WHAT TO READ NEXT

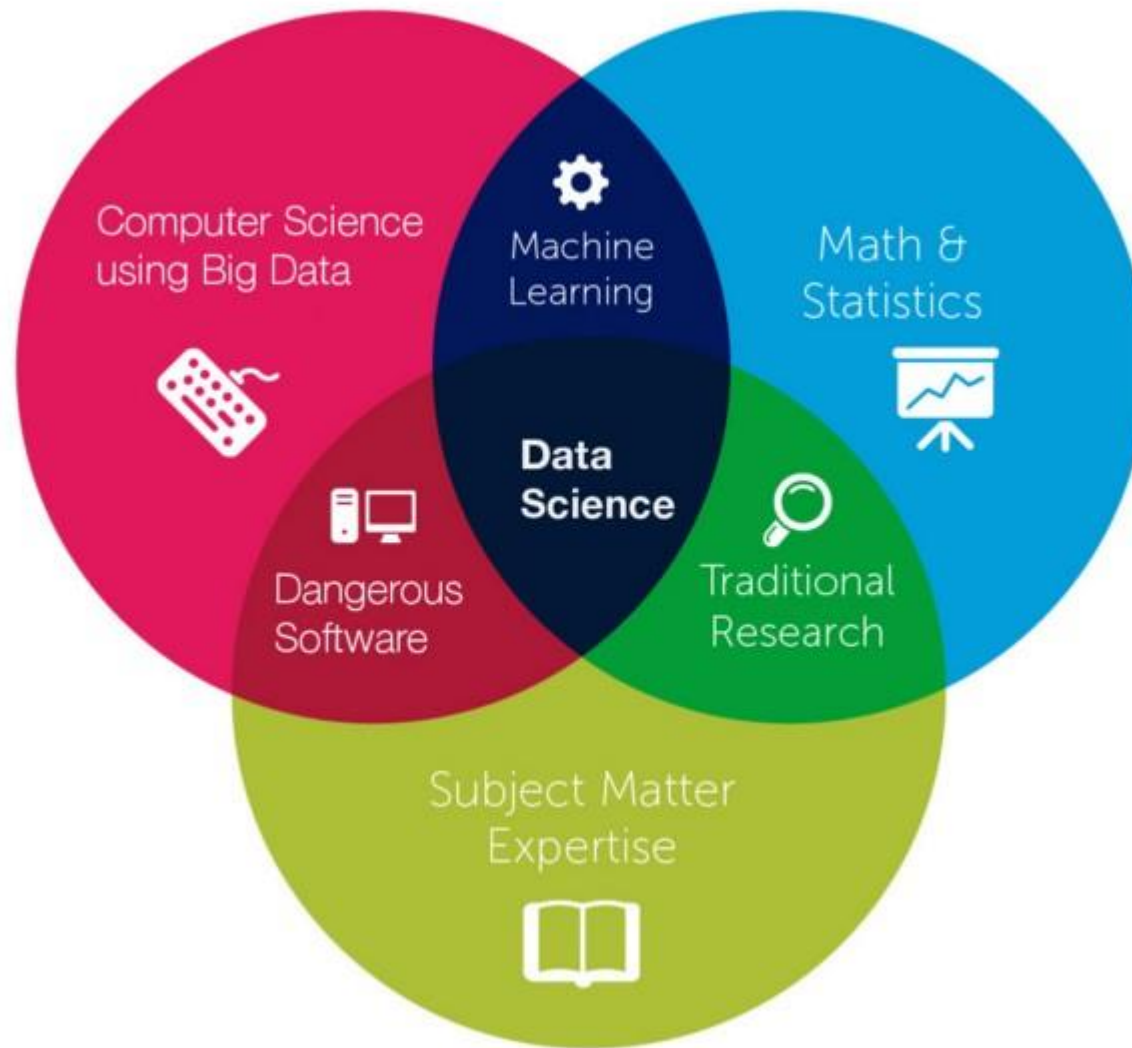


**What Data Scientists Really Do, According to 35 Data Scientists**

VIEW MORE FROM THE  
October 2012 Issue







# Methods

Sentiment  
analysis

Time series analysis

Data mining

Multilevel  
modeling

Missing data  
imputations

Classification and  
clustering

Survival analysis

Pattern recognition

Principal component  
and factor analysis

AB testing

Machine learning

Forecasting

Propensity score  
matching

Logistic, multinomial  
and multiple linear  
regression techniques

Network analysis



# Tools

## Languages

Python

R

SQL

Javascript

NodeJS

## Libraries

SciPy

Pandas

Scikit-learn

GPText

OpenNLP

Mahout

+many others

## Data Engineering

Profiling

ETL

Job notices

APIs

Optimized data  
pipelines

Optimized data  
storage/access

## Visualization

D3.js

Gephi

R

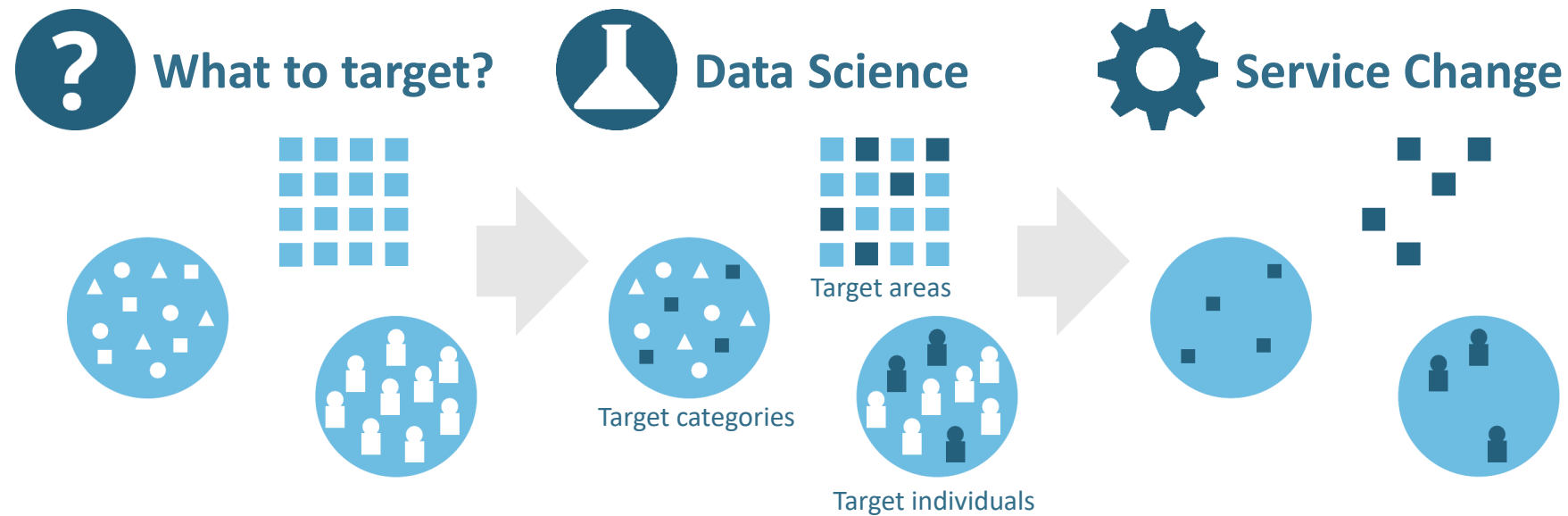
Leaflet

PowerBI

ggplot2

shiny

# Targeting: Find the needle in the haystack



**Service Issue:**  
Difficult to identify  
targets in a population

**Data Science Process:**  
Use existing data and  
predictive modeling to  
identify targets

**Service Change:**  
Engage with target  
subset of population

**Result:** Department resources are spent where most needed

# Prioritizing



## Service Issue:

Backlog is tackled via first in, first out (FIFO)

## Data Science Process:

Create a model to categorize and group past and current cases

## Service Change:

Prioritize cases based on categories in order of risk, need or opportunity

**Result:** Department addresses high priority cases first

# Predictions



## Service Issue:

Hard to predict future condition which leads to reactive services

## Data Science Process:

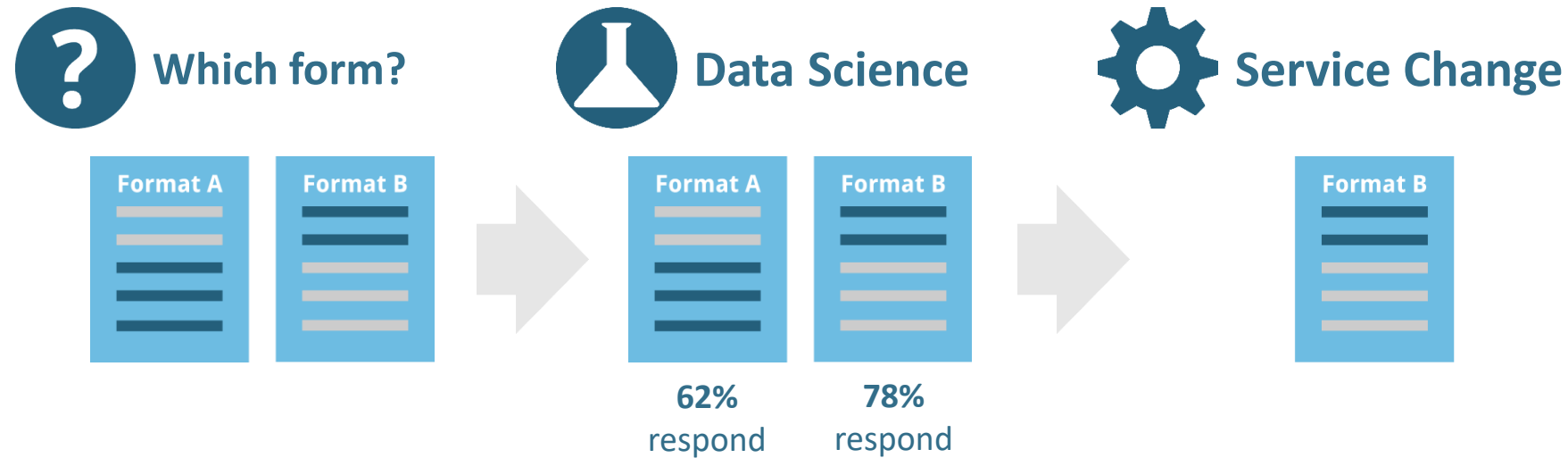
Use historical and current data to create estimate ranges for potential outcomes

## Service Change:

Use estimates to change and tailor intervention points

**Result:** Department provides pro-active early interventions

# A/B test



## Service Issue:

Costly outreach methods are not tested before implementation

## Data Science Process:

Statistical testing on outreach methods to identify which, when, and to whom to send

## Service Change:

Use statistically validated outreach method

**Result:** Department increases response rates

# Optimization



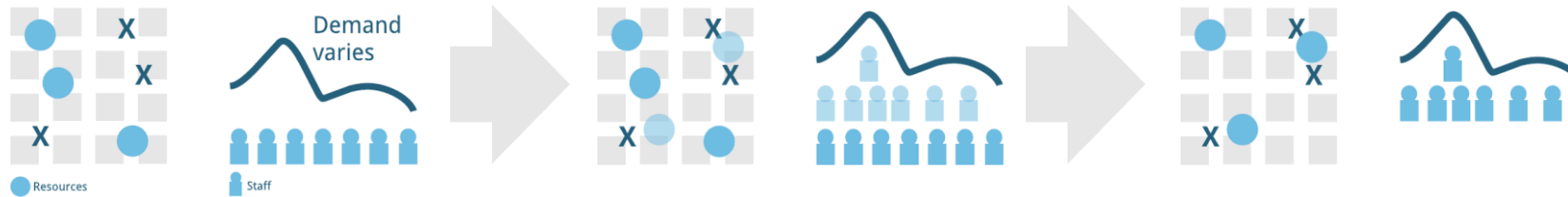
How to distribute?



Data Science



Service Change



## Service Issue:

Difficult to identify where to place or distribute resources to be most effective

## Data Science Process:

Use geospatial and/or other data to identify optimal distribution of resources

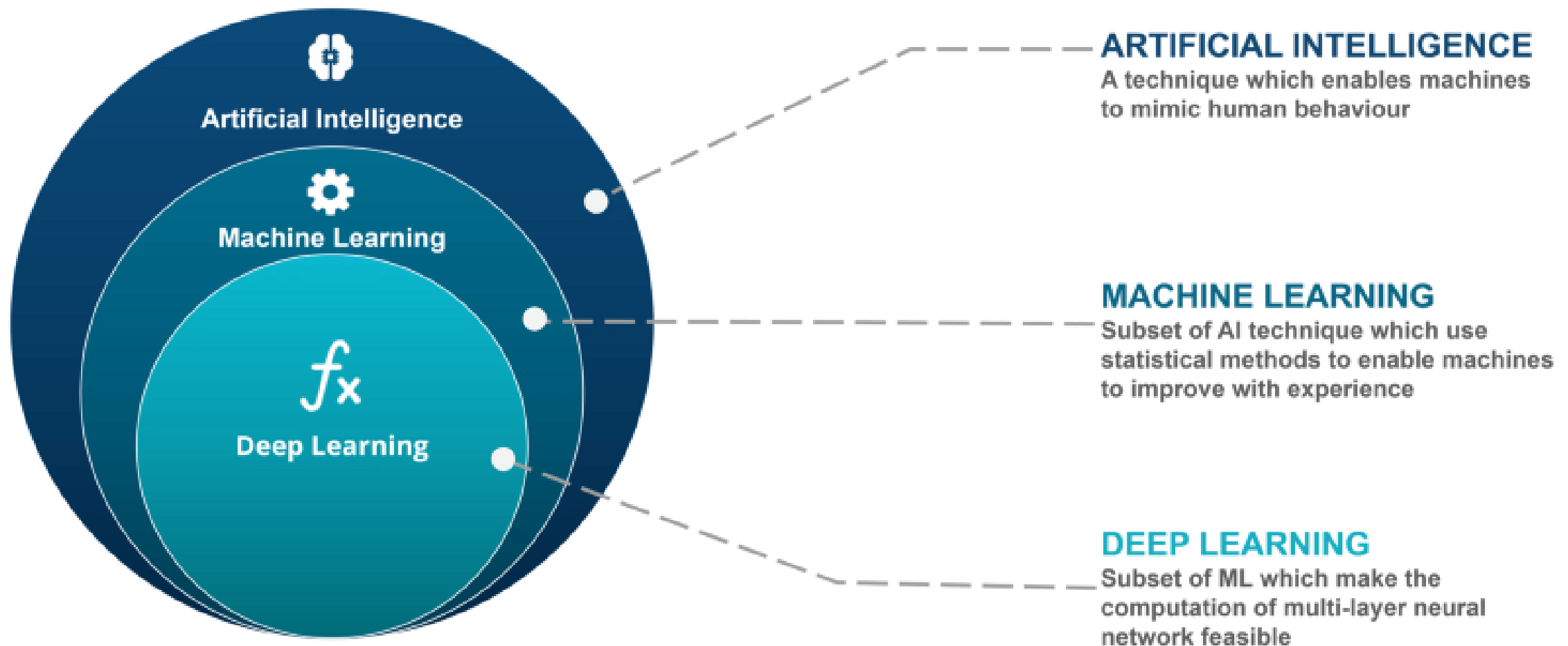
## Service Change:

Re-allocates resources to optimal distribution

**Result:** Department decreases response times; increases volume

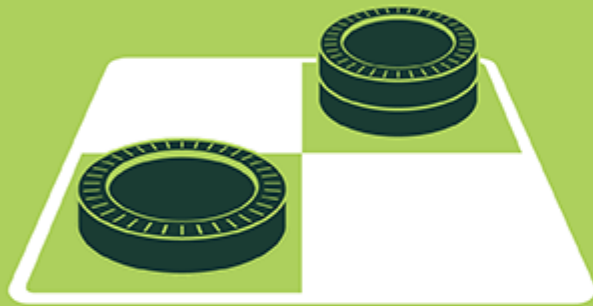






# ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



## MACHINE LEARNING

Machine learning begins to flourish.



## DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

1990's

2000's

2010's

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

# Data Mining, AI and Machine Learning

- **Data Mining:** extract existing information to highlight patterns, and serves as foundation for AI and machine learning.
- **Artificial Intelligence:** creating machines that perform functions that require intelligence when performed by people.
- **Machine Learning:** Offers data necessary for a machine to learn & adapt. The machine must automatically learn the parameters of models from the data. It uses self-learning algorithms to improve its performance at a task with experience over time

# AI in Sci-Fi Movies

- Terminator



<http://starwars.com/>

- Iron Man Marvel



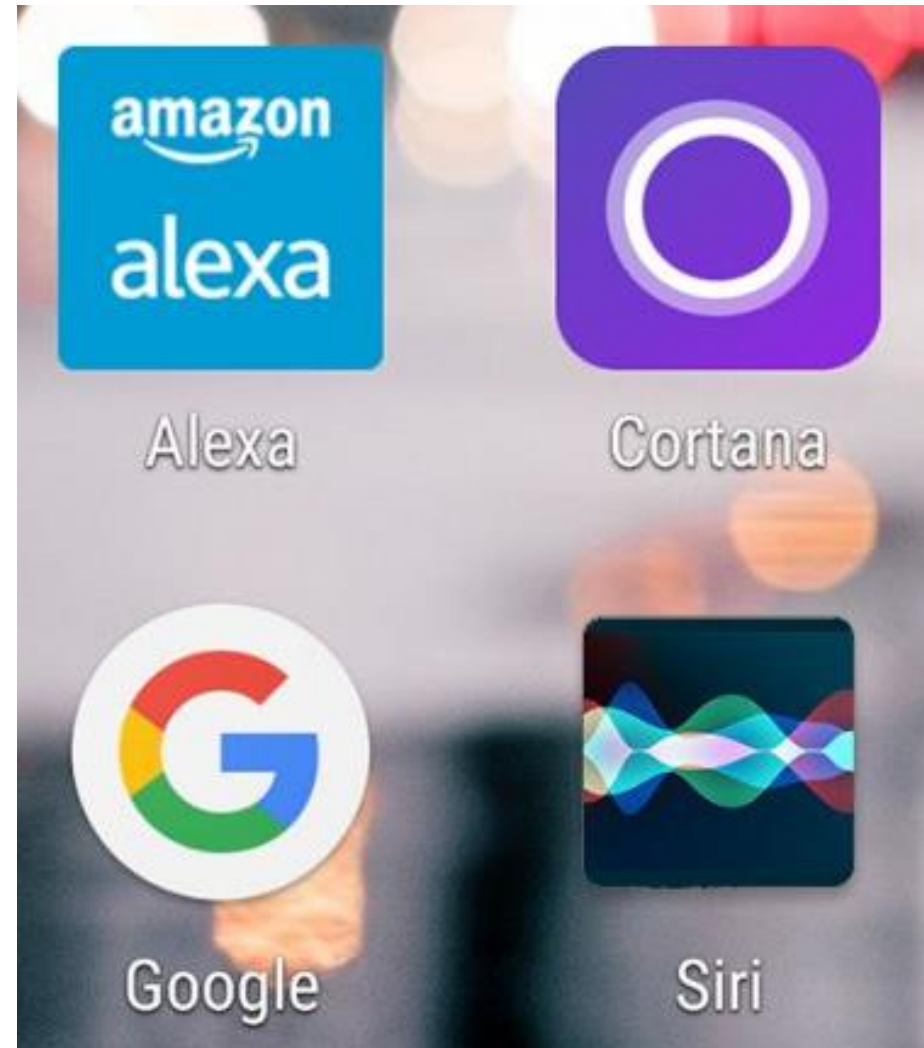
Just A Rather Very Intelligent System

# AI in Life

## Vacuum Cleaning Robot



## AI assistants





# AI in Life

- Kiva warehouse robot



# What is Artificial Intelligence ?

- The art of creating machines that perform functions that require intelligence when performed by people (Kurzweil, 1990)
- The study of how to make computers do things at which, at the moment, people are better (Rich and Knight, 1991)
- AI: acting humanly

# Machine Learning

Learning from  
Experience



Learning from  
Data

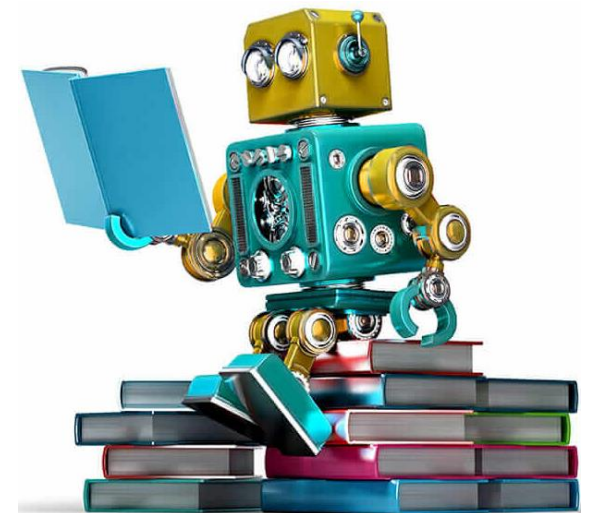


Follow  
Instructions

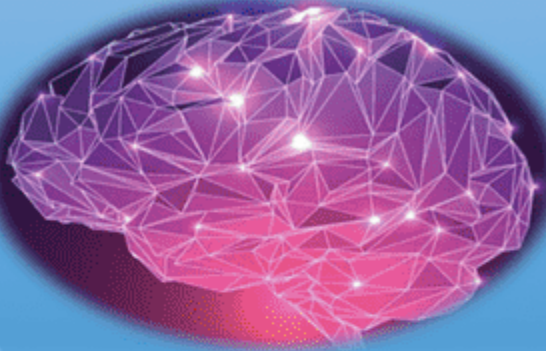


# Machine Learning

- Machine learning is aimed to optimize a certain task using example data or past experience
- The extraction of knowledge from data
- Machine learning is preferred approach to
  - Business Intelligence
  - Speech recognition, Natural language processing
  - Computer vision
  - Robot control
  - Computational biology
  - Crime predictions
  - Etc..



# Machine Learning & Some Use Cases



## Machine Learning

Where business and experience meet emerging technology and decides to work together”.



FB use it at extreme level for Spam control, discovering new content, recommendations and Ad sales



Google use it for many many reasons i.e. for maps, route calculations, data collection, translations, email spam and many more.

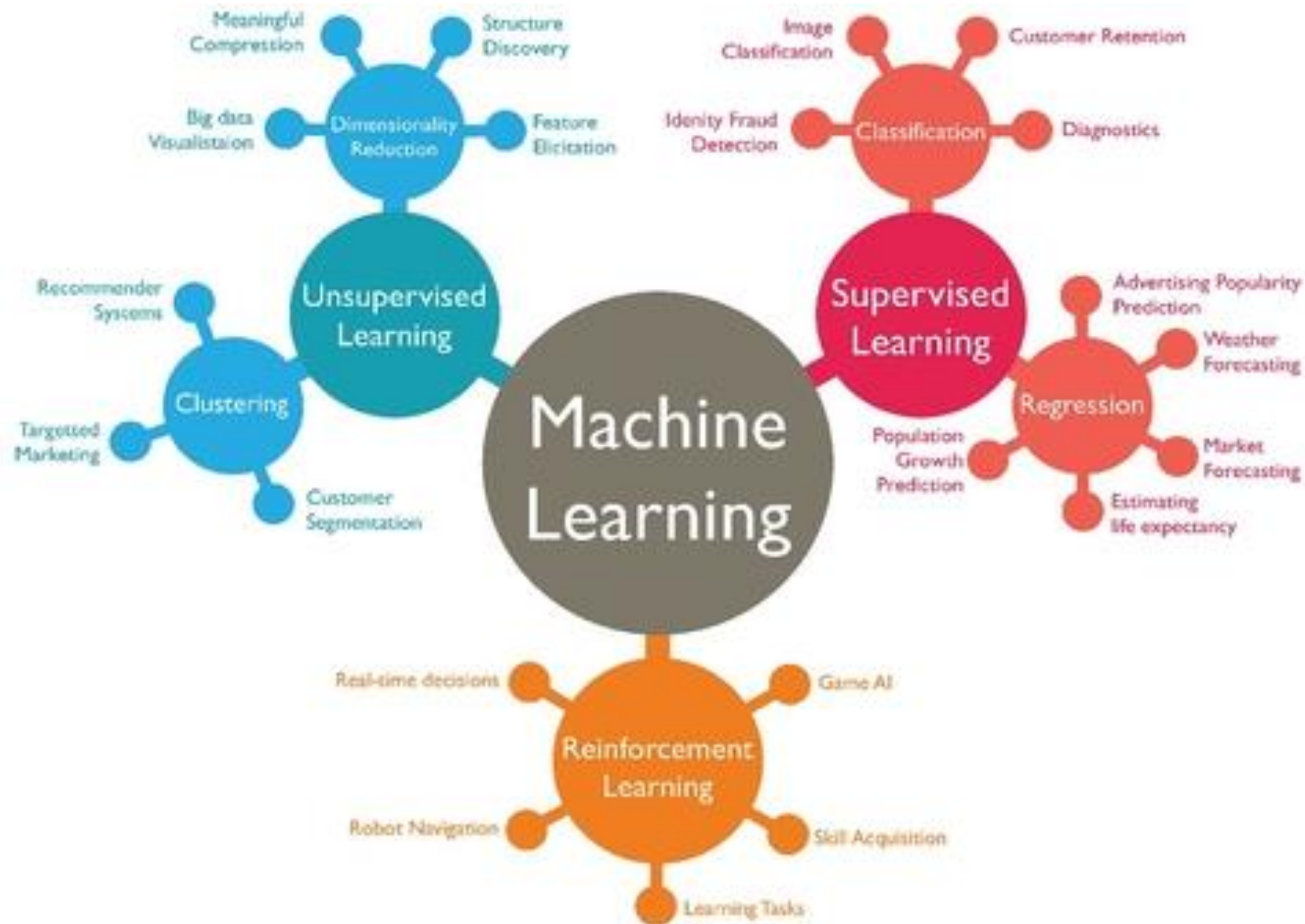


Credit Card Companies getting this now deeper and deeper to minimize the frauds and give safer transaction experience for customers

# Types of Learning

- **Supervised (inductive) learning**
  - Training data includes desired outputs
- **Unsupervised learning**
  - Training data does not include desired outputs
- **Reinforcement learning**
  - Rewards from sequence of actions





# Methods

- **Supervised learning**

- Decision tree induction
- Rule induction
- Naïve Bayes
- Neural networks
- Support vector machines
- Model ensembles
- Etc.

- **Unsupervised learning**

- Clustering
- Dimensionality reduction

- **Reinforcement learning**

- Decision making (robot, chess machine)

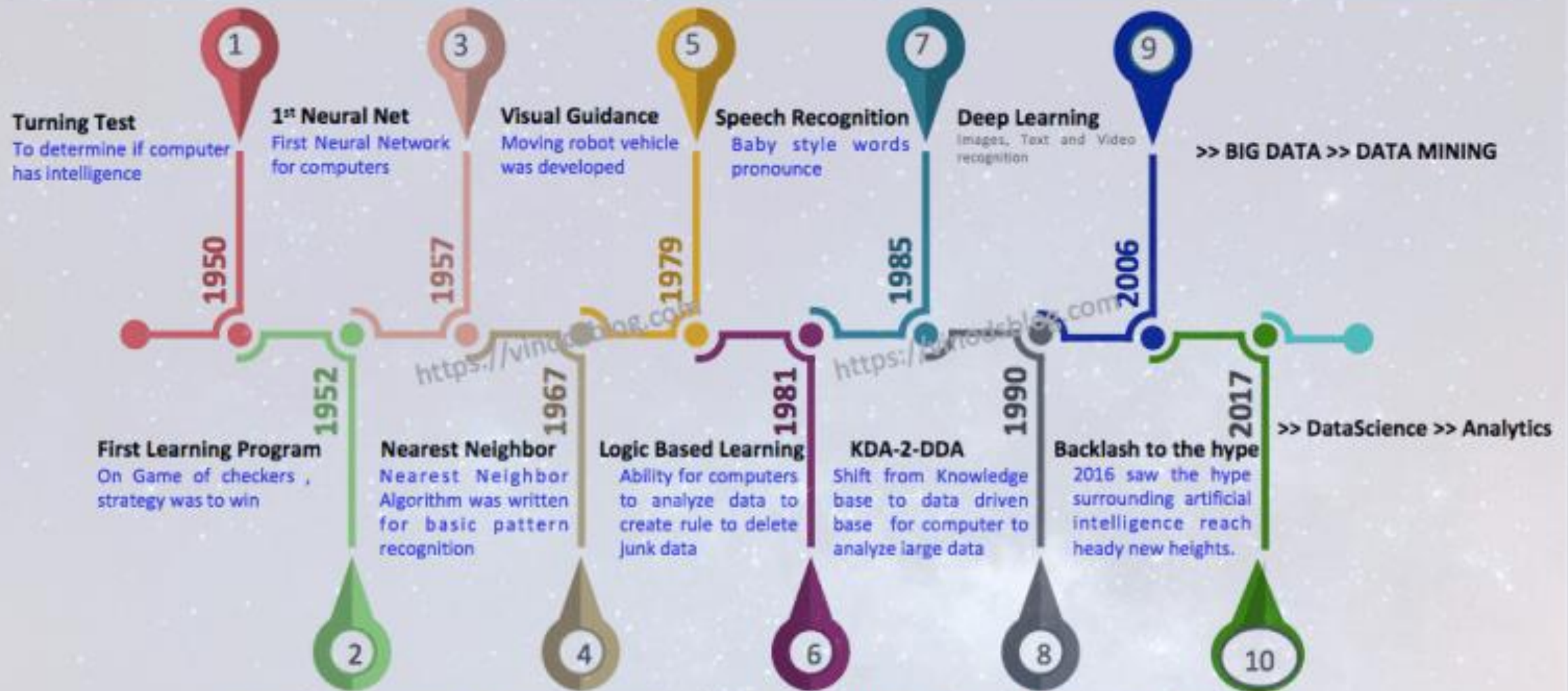
# From Data Mining to Knowledge Discovery in Databases

*Usama Fayyad, Gregory Piatetsky-Shapiro, and Padhraic Smyth*

■ Data mining and knowledge discovery in databases have been attracting a significant amount of research, industry, and media attention of late. What is all the excitement about? This article provides an overview of this emerging field, clarifying how data mining and knowledge discovery in databases are related both to each other and to related fields, such as machine learning, statistics, and databases. The article mentions particular real-world applications, specific data-mining techniques, challenges involved in real-world applications of knowledge

This article begins by discussing the historical context of KDD and data mining and their intersection with other related fields. A brief summary of recent KDD real-world applications is provided. Definitions of KDD and data mining are provided, and the general multistep KDD process is outlined. This multistep process has the application of data-mining algorithms as one particular step in the process. The data-mining step is discussed in more detail in the context of specific data-mining al-

# Machine Learning Evolution Over The Years



Data Source - Open Internet various sources

Image Source - <https://vinodsblog.com>

via @vinod1975

# Business Intelligence in Banking

- Customer account data and demographics
- Core banking data
- Transactional data at every level of detail
- Wire and payment data
- Trade and position data
- General ledger data including accounts payable, accounts receivable, cash management, purchasing information
- Support data from banking reporting

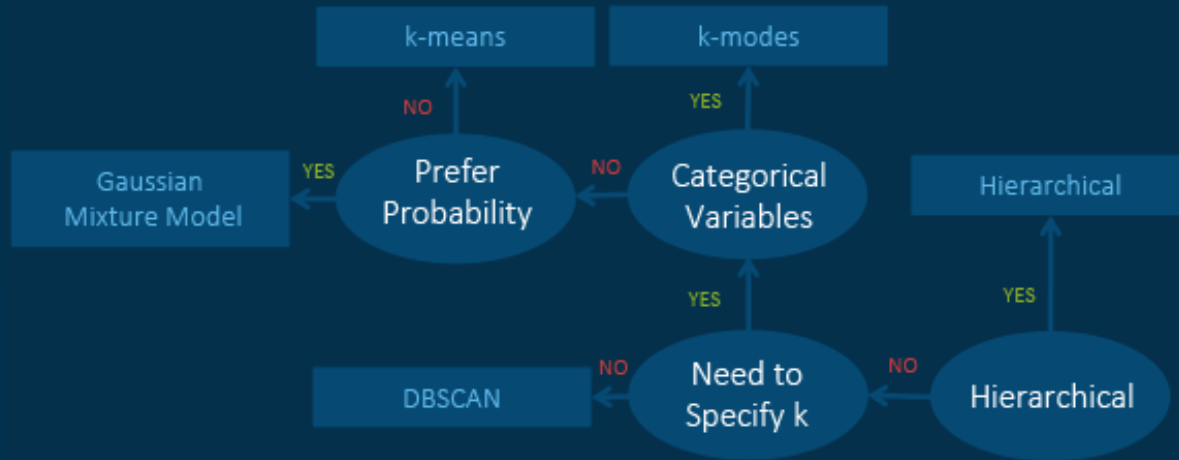
# Machine Learning in Finance

- Fraud prevention
- Portfolio and Risk Management
- Investment predictions
- Customer service
- Digital assistants
- Marketing
- Network security
- Loan underwriting
- Algorithmic trading
- Customer Service (Chatbot)
- Process automation
- Document interpretation
- Content creation
- Trade settlements
- Money-laundering prevention
- Custom machine learning solutions
- Sales/Recommendations of Financial Products
- Sentiment/News Analysis



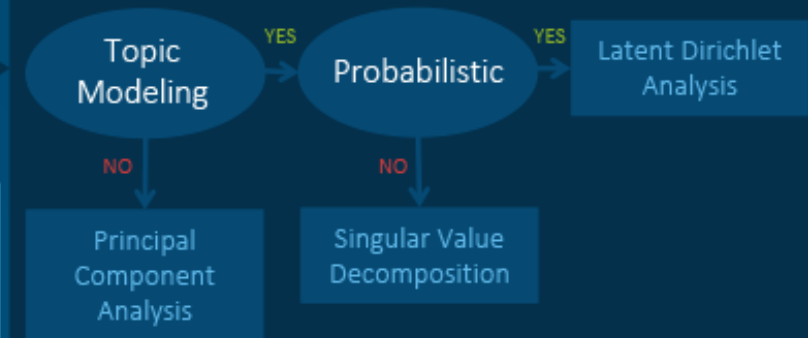
# Machine Learning Algorithms Cheat Sheet

## Unsupervised Learning: Clustering

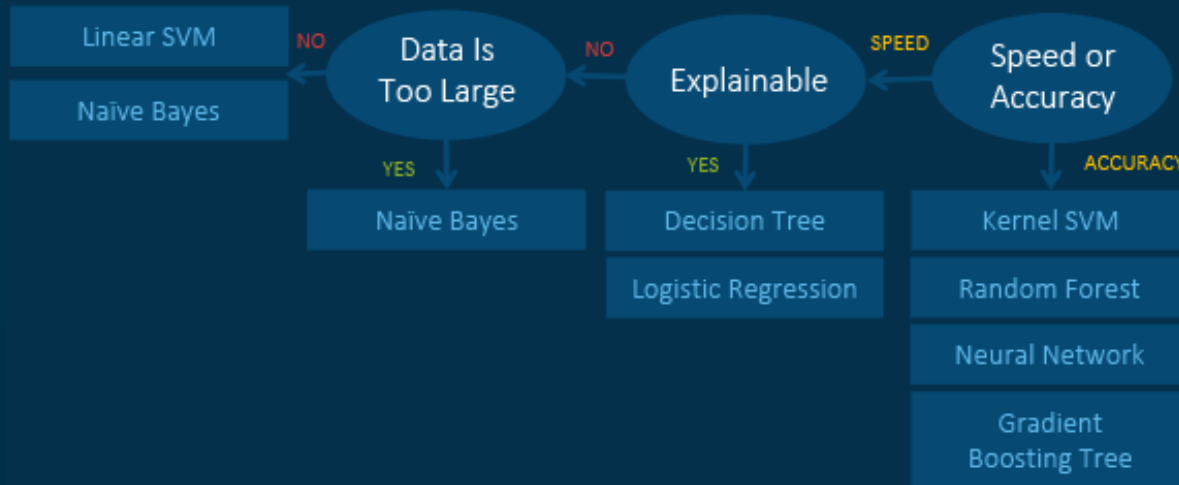


START

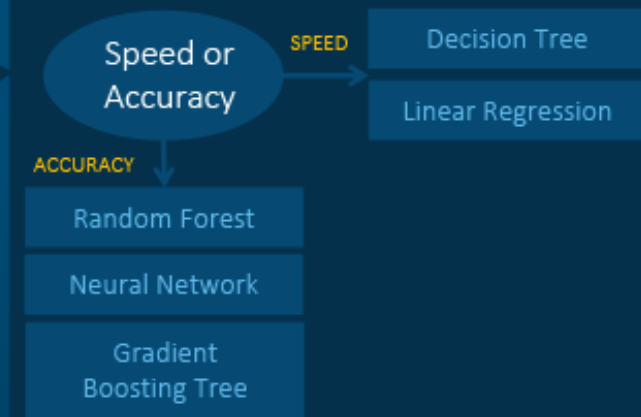
## Unsupervised Learning: Dimension Reduction



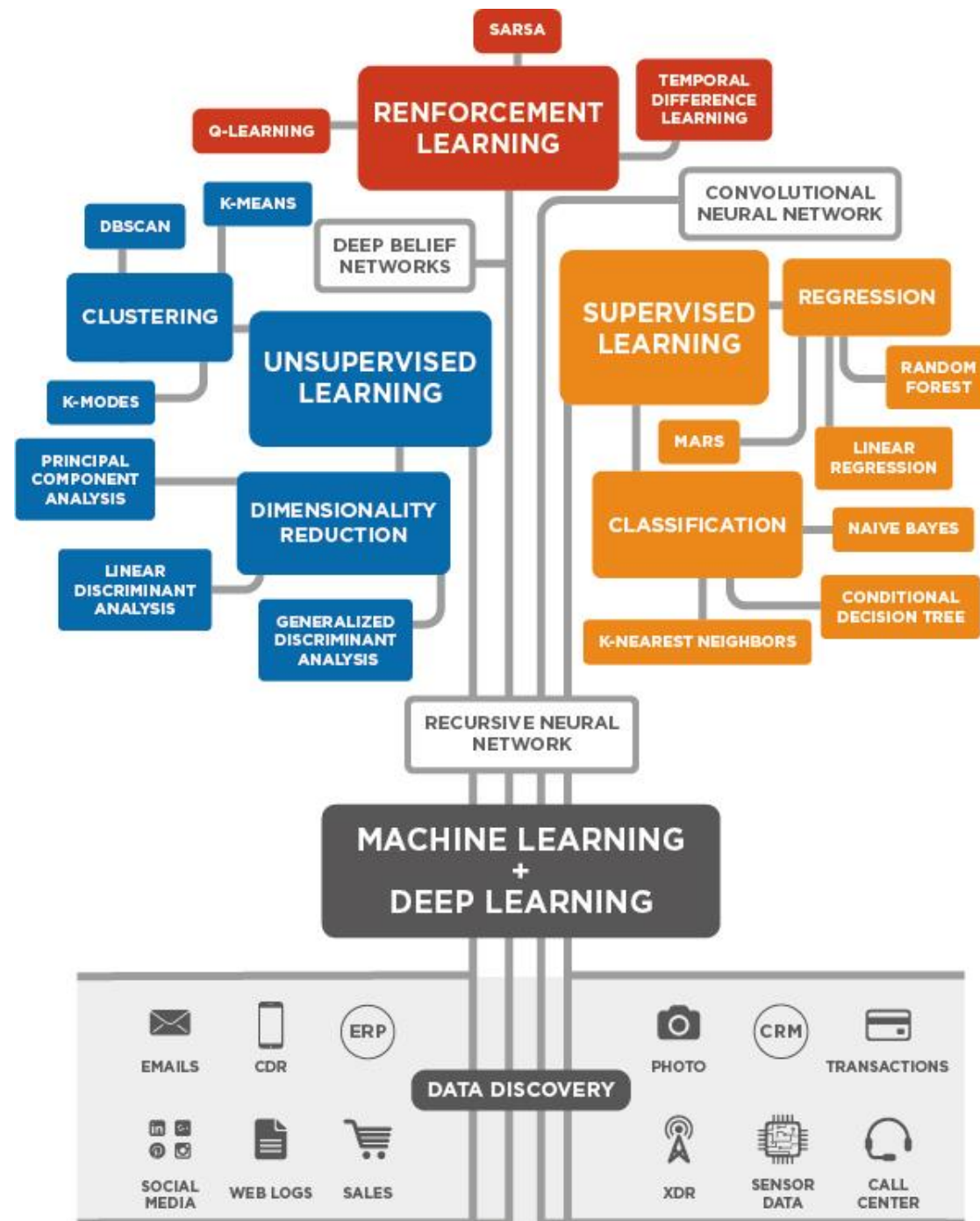
## Supervised Learning: Classification



## Supervised Learning: Regression



# Numerous (New) Algorithms



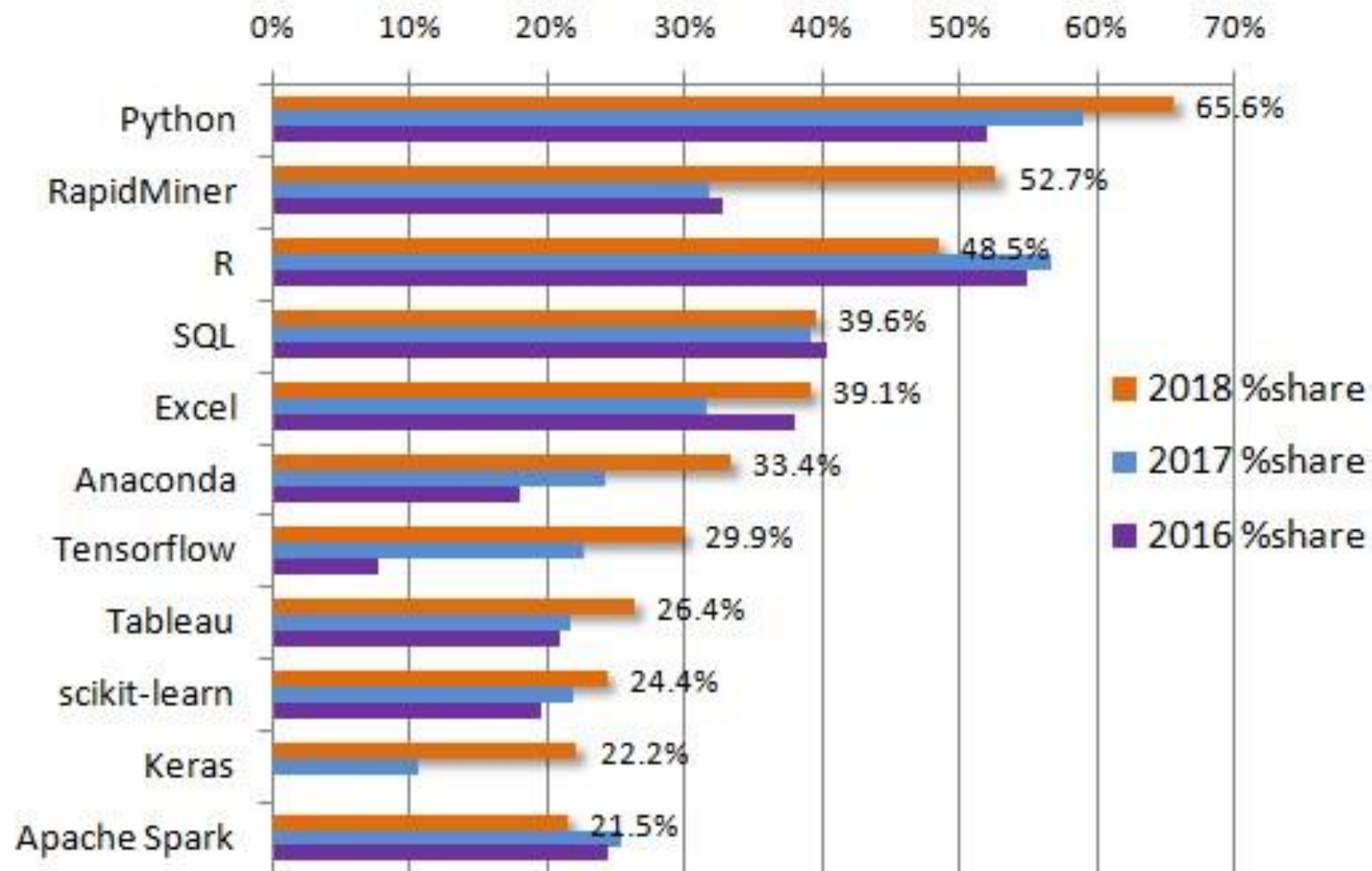
# Numerous (New) Algorithms

Classification algorithms considered in the benchmarking study.

	BM selection	Classification algorithm	Acronym
Individual classifier	n.a.	Bayesian Network	B-Net
		CART	CART
		Extreme learning machine	ELM
		Kernalized ELM	ELM-K
		k-nearest neighbor	kNN
		J4.8	J4.8
		Linear discriminant analysis <sup>2</sup>	LDA
		Linear support vector machine	SVM-L
		Logistic regression <sup>2</sup>	LR
		Multilayer perceptron artificial neural network	ANN
		Naive Bayes	NB
		Quadratic discriminant analysis <sup>2</sup>	QDA
		Radial basis function neural network	RbfNN
		Regularized logistic regression	LR-R
		SVM with radial basis kernel function	SVM- Rbf
		Voted perceptron	VP
Classification models from individual classifiers			16
Homogenous ensembles	n.a.	Alternating decision tree	ADT
		Bagged decision trees	Bag
		Bagged MLP	BagNN
		Boosted decision trees	Boost
		Logistic model tree	LMT
		Random forest	RF
		Rotation forest	RotFor
		Stochastic gradient boosting	SGB

Heterogeneous ensembles	n.a.	Simple average ensemble	AvgS
		Weighted average ensemble	AvgW
		Stacking	Stack
	Static direct	Complementary measure	CompM
		Ensemble pruning via reinforcement learning	EPVRL
		GASEN	GASEN
		Hill-climbing ensemble selection	HCES
		HCES with bootstrap sampling	HCES-B
		Matching pursuit optimization ensemble	MPOE
		Top- $T$ ensemble	Top- $T$
	Static indirect	Clustering using compound error	CuCE
		k-Means clustering	k-Mean
		Kappa pruning	KaPru
		Margin distance minimization	MDM
		Uncertainty weighted accuracy	UWA
	Dynamic	Probabilistic model for classifier competence	PMCC
		$k$ -nearest oracle	kNORA
Classification models from heterogeneous ensembles			17

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Next, we learn R... and Python....

