Tech Sector Speaker Series

Reality Check: AI, Machine Learning and Natural Language Processing

ARIZONA TECHNOLOGY COUNCIL
a place to connect and grow

University of Advancing Technology
UAT
Learn. Experience. Innovate.

SEPTEMBER 15, 2020

3:30-5:00 P.M. MST

Minky Kernacs
Mediato technologies
Moderator

INTRODUCTION

The panel will share how to avoid common pitfalls and successfully embark on the journey of artificial intelligence, machine learning, and other emerging technologies that are changing the way we work, play, live, and interact.

AGENDA

3:30 Welcome

Steve Zylstra, Arizona Technology Council

Presenting Sponsor: University of Advancing Technology

Minky Kernacs, Moderator

3:35 Introduction of panelists

Rinkan Patel, Technology Lead – Consultant, Washington University in St. Louis

Rebecca Clyde, Co-Founder and CEO, Botco.ai

Srikanth Balusani, Chief Technology Officer, MST Solutions

Sanjeev Katariya, Chief Technology Officer, InVision

3:45 Panel Discussion

4:45 Q&A

5:00 Event ends

MEET THE PANELISTS

Rinkan

Technology Lead, World Wide Technology

- Data Management Leader
- Mentor
- President, NAU Information Systems Advisory

World Wide Technology, Inc.

MEET THE PANELISTS

Rebecca

CEO & Co-Founder, Botco.ai

- Arizona Innovation Challenge awardee
- LatinX founder and entrepreneur
- Pioneering intelligent chat nurturing - powered by AI
- Co-managing director of Girls in Tech Phoenix
- AZ Business 2020 Most Influential Women in Arizona

MEET THE PANELISTS

Srikanth

CTO, MST Solutions

CTO & Co-Founder ShiftX

- Cloud
- SaaS
- AI & ML
- IoT

MEET THE PANELISTS

Sanjeev

CTO, InVision

AI Advisor

- University of Michigan
- Massachusetts Institute of Technology, Solve Center
- Credo.AI

Helped found major technological initiatives

- Windows NT
- Microsoft Internet Search Service
- Microsoft Teams
- Natural User Interface
  - Speech, Search, Natural Language Processing

in Enterprise

invision Enterprise.

InVision is the Digital Product Design platform used to make the world's best customer experiences.

Today, more than 7 million people use InVision to power a repeatable and streamlined design workflow.

Founded in 2011

600+ employees

7,000,000+ Users

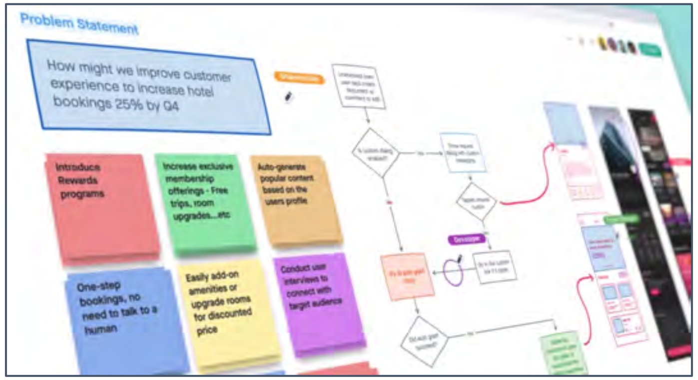
100% of Fortune 100

InVision Enterprise.

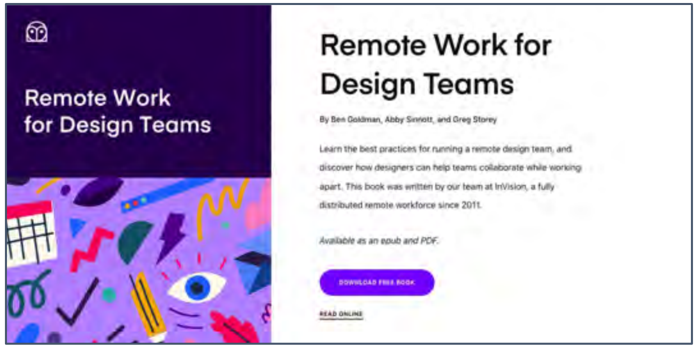
Fully distributed since day one.

InVision has nearly a decade of experience building a remote company. Currently we have employees across over 40 states and 25 countries!

We help our customers navigate the challenges of remote work through a combination of our products and our resources.



Productivity solutions



Remote work best practices

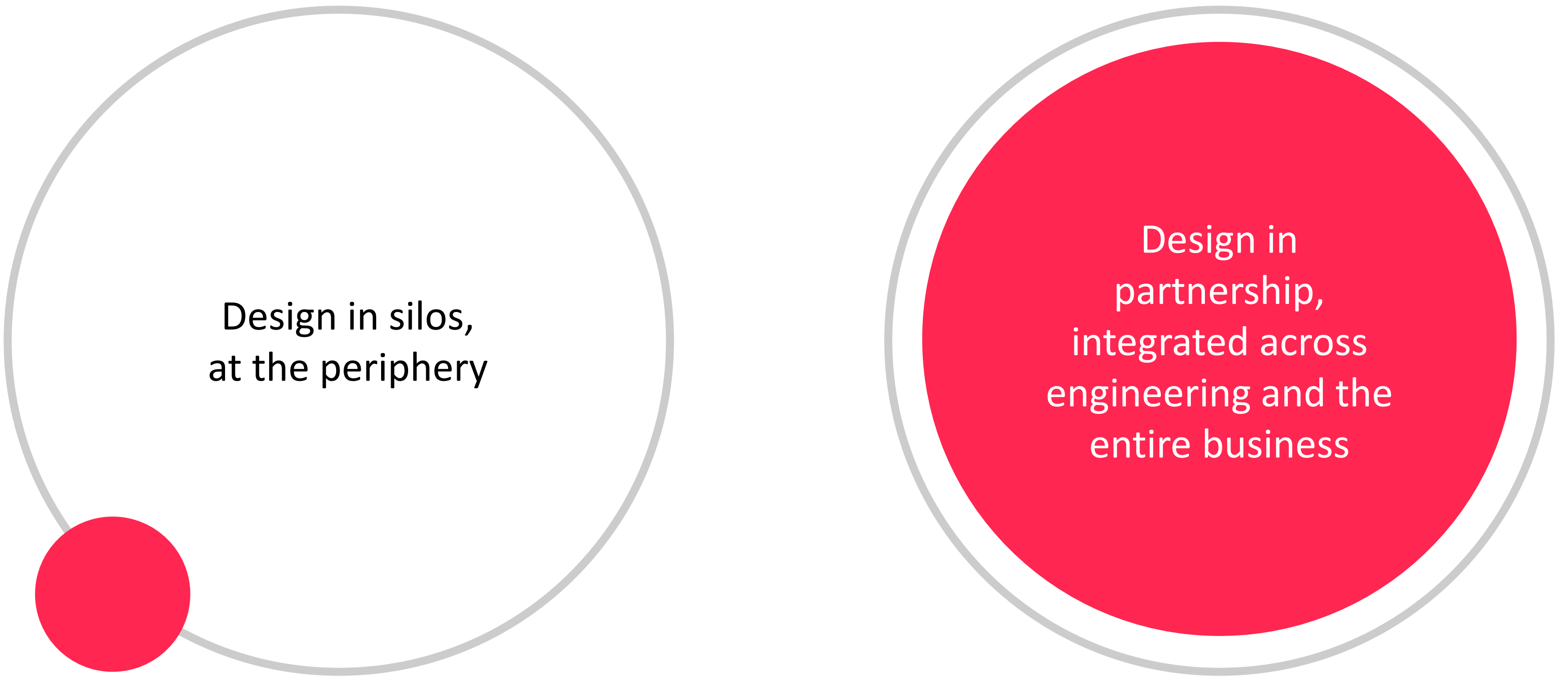
InVision Enterprise.

In every industry, the world's most successful brands innovate faster with InVision Enterprise

Enterprise.

The screen
has become
the most important
place in the world

How do your teams work together today?



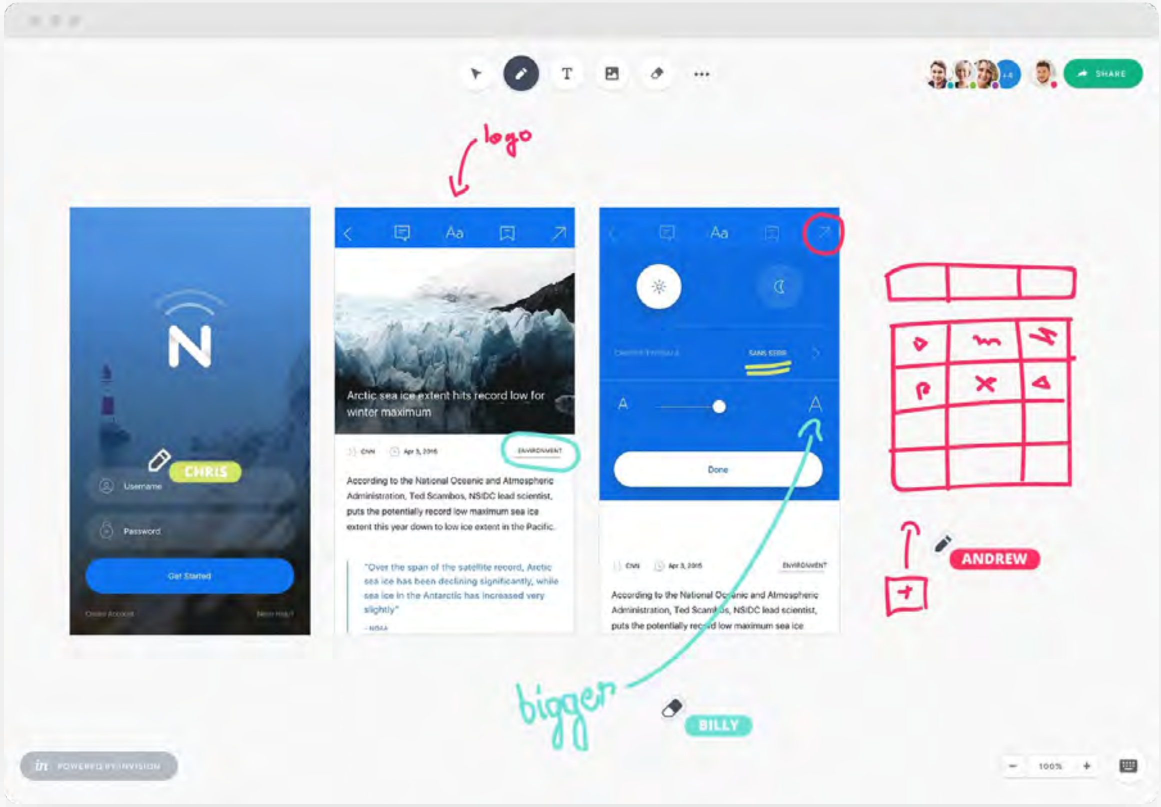
Business impact:
usability

Business impact:
revenue, speed to market,
valuation, patents, productivity, cost
savings…

invision Enterprise.

Freehand.

InVisionCloud



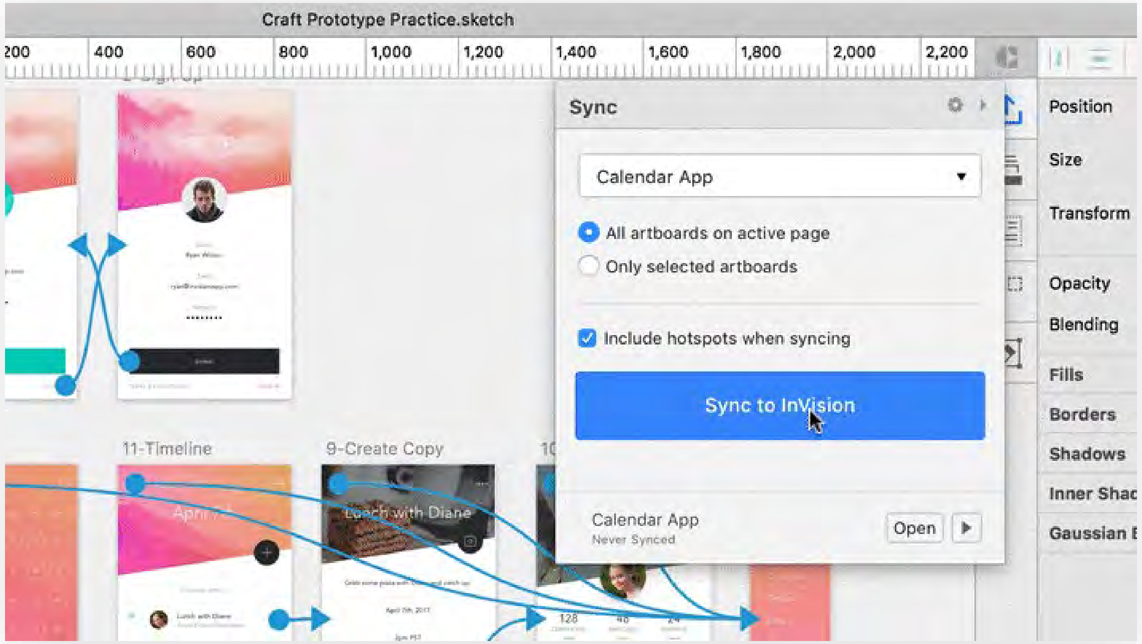
Make good ideas great by including stakeholders early in the design process–wherever they are, whenever they're free.

Nike's brand marketing team uses freehand to share work and ideas across 23 geographies.

InVision Enterprise.

Prototype.

InVisionCloud



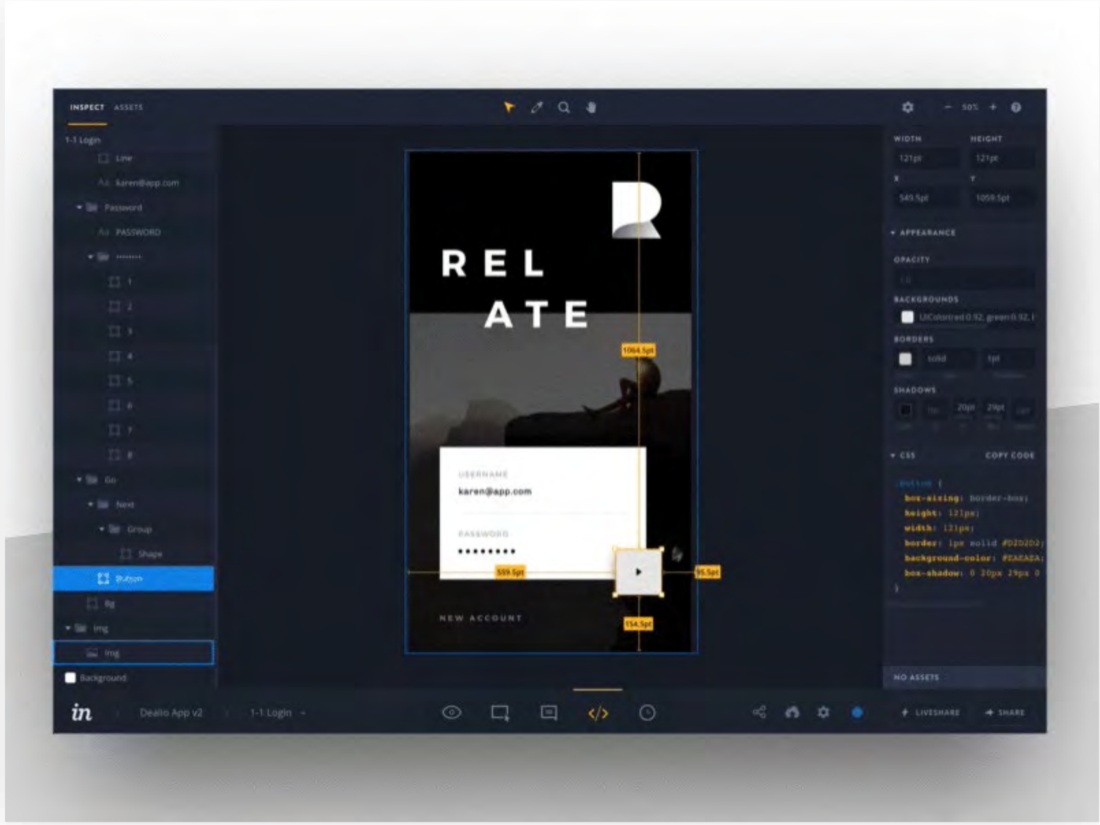
Get product prototypes into the hands of users and stakeholders in days, rather than months - without wasting precious developer time.

VMLY&R, a global agency with 7,000 employees, sped up product development by 40% with InVision!

invision Enterprise.

Inspect.

InVisionCloud



Give developers direct access to the specs, images and fonts required to build the working product faster.

Amazonians saved an average of 6 hrs per week per team on InVision!

InVision Enterprise.

Business benefits of InVision Enterprise

36 %

Faster product time-to-market with InVision Enterprise

99 %

Customers say InVision Enterprise helps them build better products

5 hrs/week

Time saved per engineer when developers join design peers in InVision Enterprise

inVision Enterprise.

PROTECTION

The most secure ecosystem for creativity

Total ownership of account data, built-in audit logs

Configurable security requirements that integrate with your IT & user access policies

SOC 2 Type II compliance, Multi-Factor Authentication, Encryption at rest and more

Developing AI

AN AWARENESS STORY (CHALLENGES AND SOLUTIONS) FOR ORGANIZATIONS ON THE AI JOURNEY

Agenda

AI/ML: AN INTRODUCTION

WHAT IS IT, WHY SHOULD YOU CARE, WHAT CAN IT DO FOR YOU, EXAMPLES

AI MATURITY LIFECYCLE

THE ORGANIZATIONAL AI LIFECYCLE JOURNEY

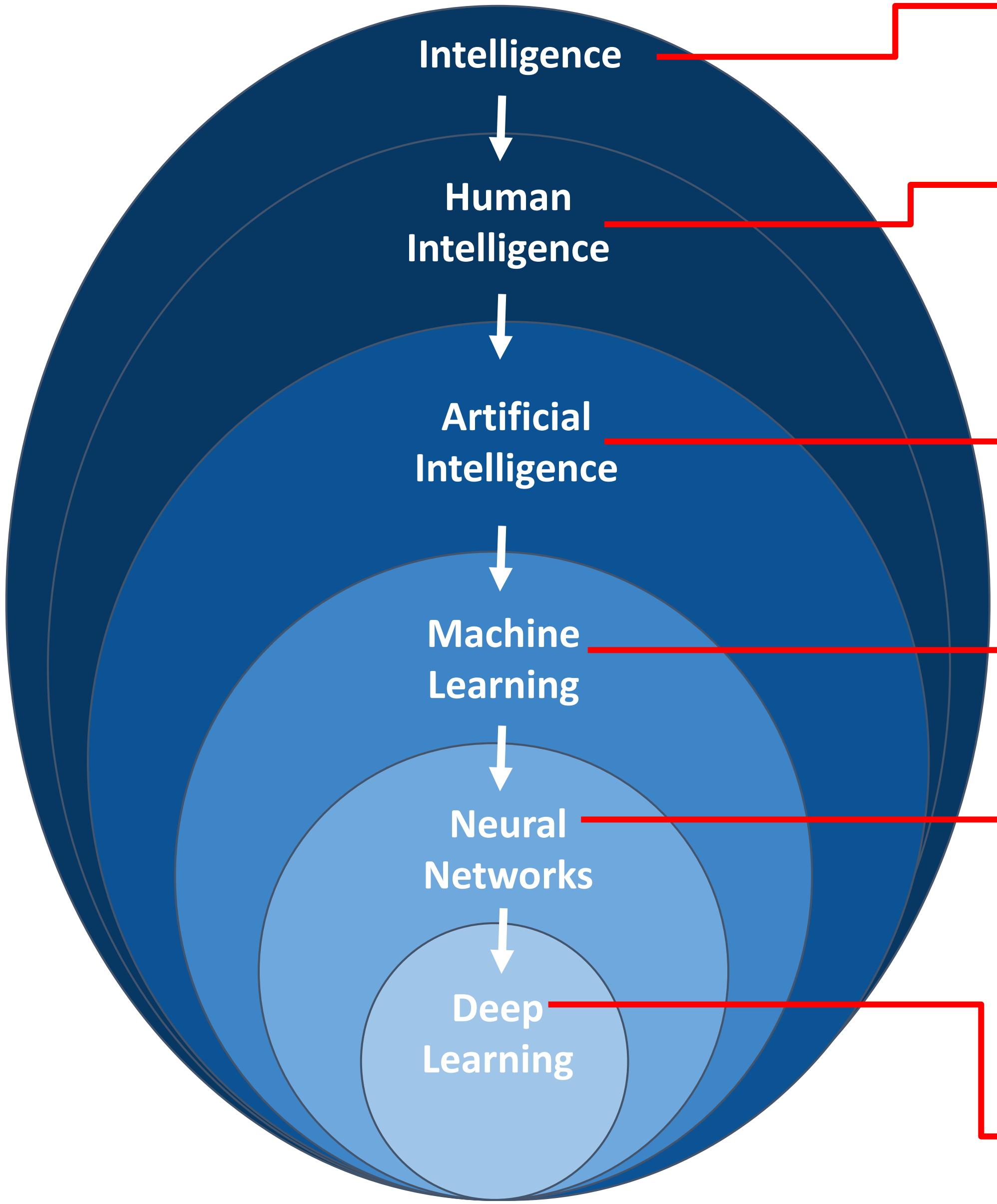
CHALLENGES

BUSINESS, DATA, BIAS, ALGORITHMS, ACCURACY AND DECISION MAKING, COMPLEXITY….

SOLUTIONS

SOLUTIONS AND RESOURCES

AS BEST AS WE CAN DESCRIBE IT TODAY



The capacity for **logic**, **understanding**, **self-awareness**, **learning**, **emotional knowledge**, **reasoning**, **planning**, **creativity**, **critical thinking**, and **problem-solving** - *Wikipedia*

Through Intelligence, the **cognitive abilities** to **learn**, **form concepts**, **understand**, **apply logic**, **reason**, **recognize patterns**, **plan**, **innovate**, **solve problems**, **make decisions**, **retain information**, **create and use language to communicate** across a **vast array of disparate problem spaces**- *Wikipedia*

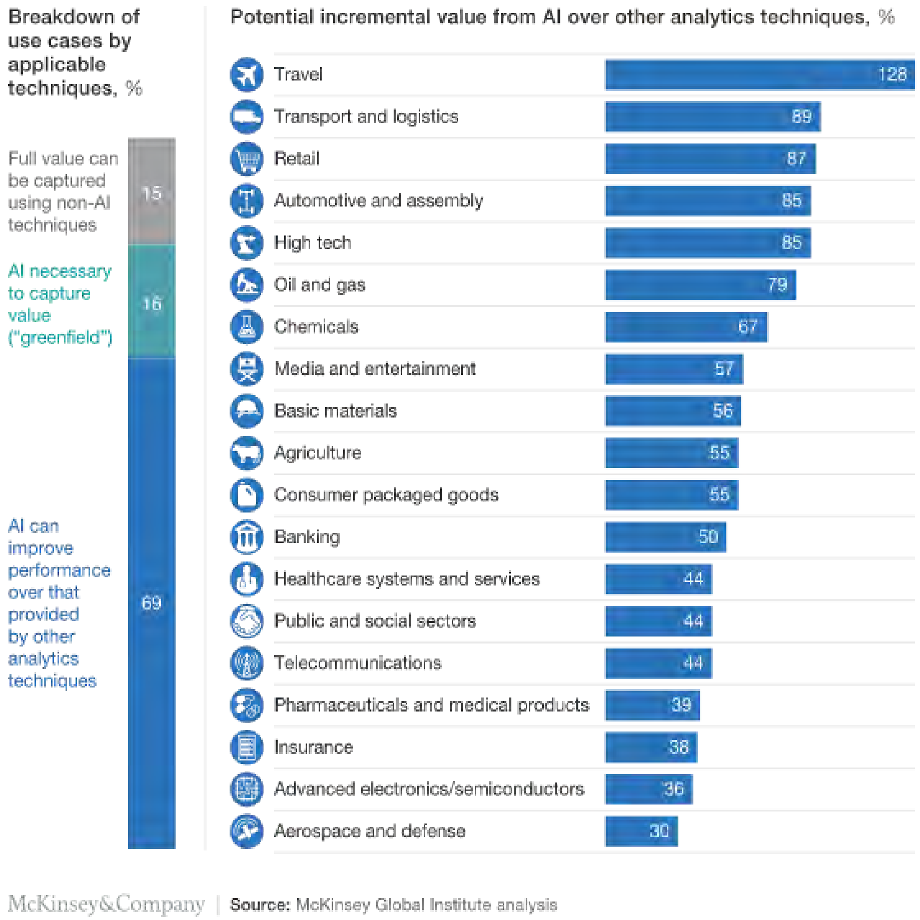
Intelligence demonstrated by machines programmed by humans (today) demonstrating abilities to **reason**, **problem solve**, have **computational form of Knowledge Representation and Knowledge**, process **natural language**, **plans and take actions**, **learn from data** (machine learning), demonstrate motion and manipulation (**robotics**), input from all kinds of sensors and deduce aspects of world (**computer vision, speech**), **be socially intelligent** (recognize, interpret, process, and simulate human effects), and one day, **demonstrate General Intelligence** (understand and learn what a human can) - *Wikipedia*

Subset of **AI** based on **statistical and probabilistic data inferential** techniques where human built **ML algorithms** construct a **mathematical model based on sample data** in order to **make predictions or decisions without being explicitly programmed**

Subset of **ML** that **model data** using **Graphs of Artificial Neurons** which attempt to **mimic** (very, very approximately) how **neuronal connections might work in the brain**

Subset of **Neural Networks** that have deep layers of Artificial Neural connections called “hidden layers” which distributes learning from data across the layers

You + Other People Interacting == Better and Smarter AI == Better Experiences



- Automates Repetitive Learning leveraging Data
- Make your stuff smarter: *digital experiences, automation*
  progressively learning through data & logic
- AI/ML adapts and improves through *usage & feedback*
  more data, feedback from success & failures
- AI/ML Analyzes Data and turns it into *structured knowledge* - deeper analysis and spreading its "understanding" across its computational fabric
- AI/ML creates *dynamic experiences* - based on you or collections of users

And all of that changes your daily life, your daily experiences, your job
And then one day, it might help save your life (if done right!)

Yes, might, but everything has a caveat..

Examples of what it can it do for you

- **Read & Summarize**
  - News, articles, books, email
- **Write**
  - News, Marketing media posts, novels
- **See**
  - Self Driving Cars, police work, payment portals, facial recognition
- **Hear and understand**
  - Digital voice assistants, meeting management, detect and alert
- **Speak**
  - Google Home, Alexa, Schedule appointments, Automated Voice systems
- **Smell**
  - Detect illnesses, gas leaks, develop perfumes
- **Touch**
  - Prosthetic arm, robot ankle
- **Understand emotions**
  - Track emotions (facial expressions, body), Sentiment analysis
- **Play games**
  - Chess, Go, Poker
- **Create**
  - Art, Poetry, Music, Photographs
- **Do on Your Behalf**
  - Trade, Buy
- **Read your mind!**
  - Neuralink, OpenBCI.com, Thought controlled medical devices

And so much more..Great article by Ed Newton-Rex - https://medium.com/on-coding/the-state-of-ai-9aae385c2038#.7yzbhq88m

AI MATURITY JOURNEY: WHAT STAGE ARE YOU IN?

Exploring | Experimenting | Formalizing | Optimizing | Transforming

- Element AI Maturity Model (www.elementai.com)
  - Founded by JF Gagné and A.M.Turing Award recipient Prof. Yoshua Bengio, PhD
  - Clear framework to evaluate **AI Maturity Model**
    - Assess **Dimensions** where you stand in terms of Business/Strategy/Communications, People, Data, Tech and Governance
    - With **experience phase markers** e.g.:
      - Novice, Beginner, Intermediate, Proficient, and Expert

- Understanding what Stage you're in across Dimensions
  - Is ESSENTIAL to understand the **nature** and **magnitude** of challenges
  - Apply **Stage appropriate Solutions**
  - Formulate **a plan to advance Stages**

- Some Papers to help with AI Maturity Assessment
  - Element.AI - https://s3.amazonaws.com/element-ai-website-bucket/AI-Maturity-Framework_White-Paper_EN.pdf
  - AMDocs - https://www.amdocs.com/sites/default/files/filefield_paths/ai-maturity-model-whitepaper.pdf
  - Sulaiman, Messom, Cheung - Towards an AI Maturity Model: From Science Fiction to Business Facts - http://www.pacis2019.org/wd/Submissions/PACIS2019_paper_146.pdf

Challenges

REGARDLESS OF WHAT STAGE YOU'RE IN

People Challenges

Lack of understanding of AI by non-technical employees

- Lack of knowledge leads to lack of understanding leads to *lack of proper business application and needs*

Lack of Organization and Effective Leadership

- Hierarchy without central coordination leads to redundant and even conflicting AI efforts
- Ineffective AI aware Leadership lead to suboptimal decision making
- Suboptimal decision making related to the adoption and effective usage of AI == ***Waste company resources***

Scarcity of field specialists

- Hard to find, harder to hire!

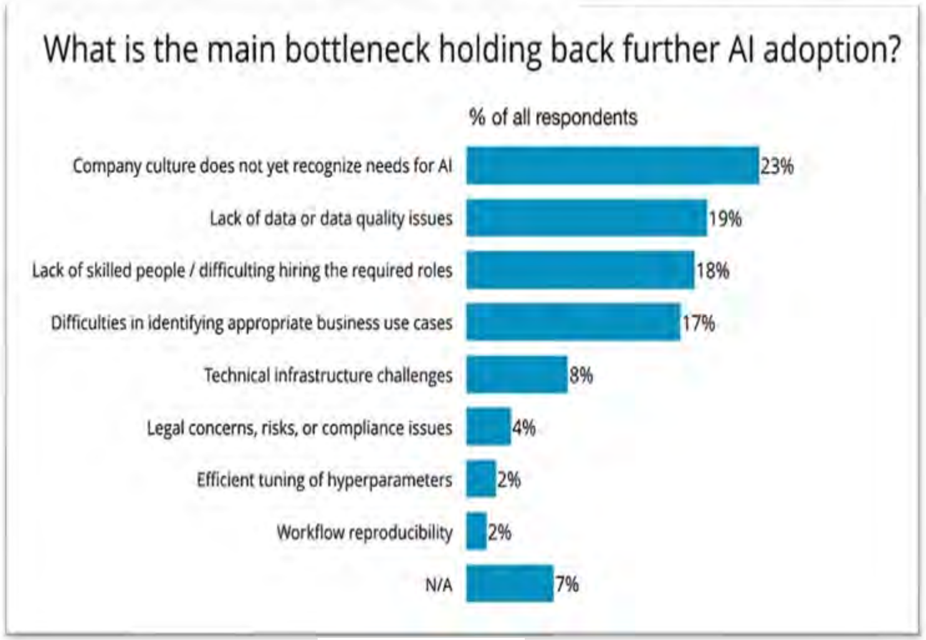
Specialized Education

- Built by few, for few, understood by fewer

Lack of Training and Mentorship Programs

Lack of Industry, Governmental or Academic Partnerships

- Leads to “compartmentalized” thinking



Source: O’Reilly

Data Challenges

Data quality and quantity

- Quality: Completeness, Accuracy, Consistency, Validity, Timeliness, Integrity
- Quantity: Dependent on Problem Domain, Model Complexity, Data Patterns needed, Attributes of the Model

Data labeling

- Specific to supervised or hybrid learning
- Across text, images, all kinds of labeling

Bias

- Collection, sample, generation of data

Discovery, Access and Processing

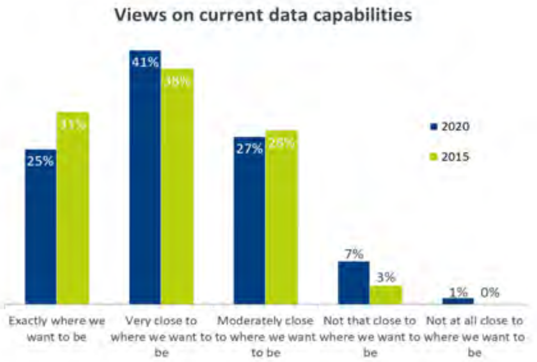
- Hidden in data lakes, no clear ontology, no clear ownership
- Expensive and complex Processing
- Data Access from 3rd Party Vendors expensive

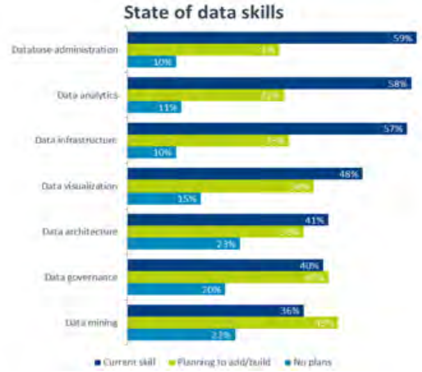
Governance

- No clear ownership and stewarding of data lifecycle
- Underdeveloped Data Security and Privacy Classification and management
- Unmanaged or Unclear usage of Real time vs batch streams with security and privacy sensitivity

Data Sets

- Unclear / Unmanaged training, testing, validation sets





Source: **Comptia.org**

Technology Challenges

Integration Challenges

- Systematic alignment of interfaces between you and system (or vendor)
- Data infrastructure (storage, labeling) needs for feedback and training are not simple - especially in today's world of GDPR
- Without feedback and constant improvement, AI becomes dumb (and out of date)
- Unclear ROI (for the money, did you get your worth?)

Not cheap

- Compute, storage, systems, scale, vendors - all cost money

Too many tools and frameworks

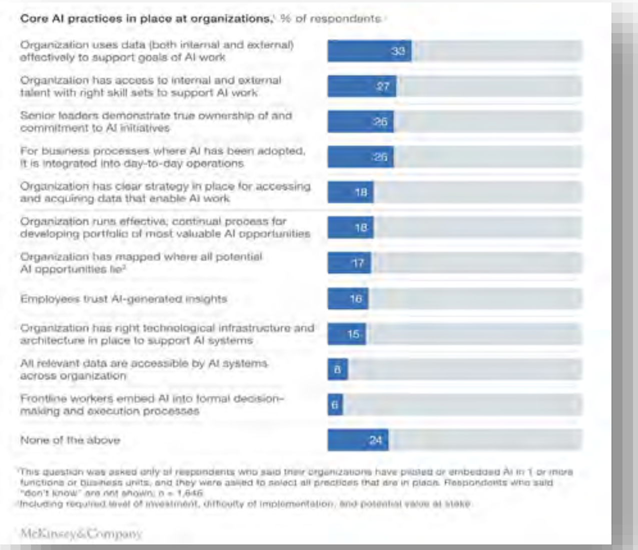
- Plethora of tools, systems, frameworks, languages

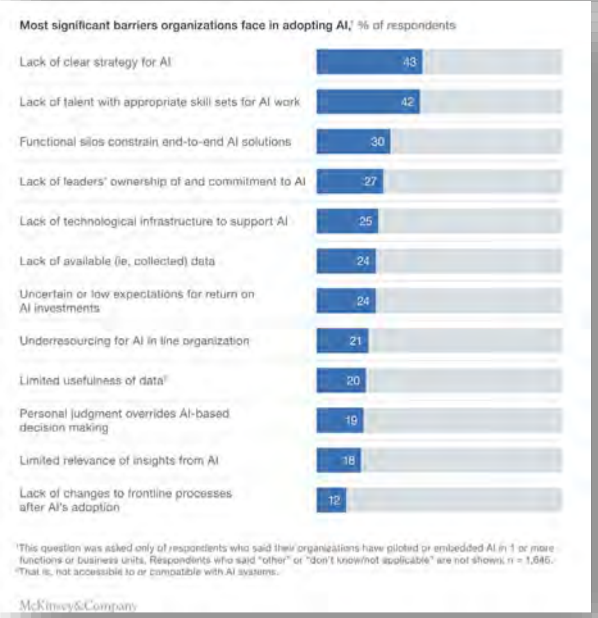
Complex Data and Infrastructure Demands

- Data Processing systems for Big Data
- Infrastructure for training and feedback

Model errors

- Complex models need detailed understanding to change model predictions
- Cost of model errors are not well understood until they hit you
- Models need retraining, retraining needs data + infrastructure





Source: McKinsey & Company

Governance Challenges

*Governance is the discipline of **managing regulatory requirements, roles and responsibilities, investments**, **organizational structure**, **risk management**, and **performance management (metrics)** to **achieve business outcomes, including business goals and strategy, effective operations, compliance, etc.***

Regulatory Requirements, Roles and Responsibilities

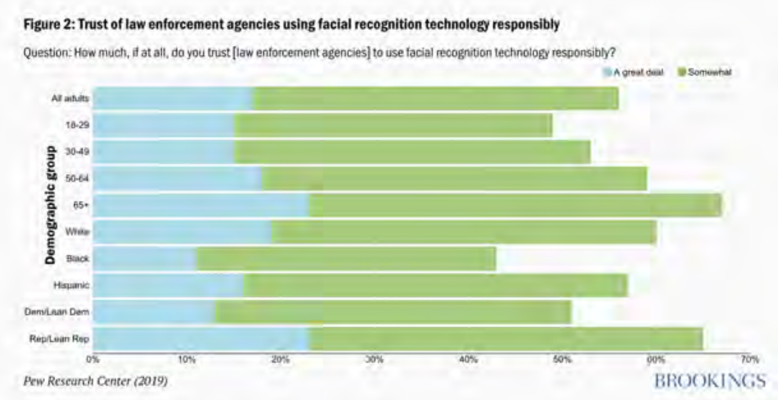
- We barely agree within national boundaries, across nations in a digital world is exponentially harder
- Regulations across industry are still in infancy
- Some Evolving Regulations Examples (with much debate and caution)
  - White House
    https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf
  - FDA on AI in Medical Devices
    https://www.fda.gov/files/medical%20devices/published/US-FDA-Artificial-Intelligence-and-Machine-Learning-Discussion-Paper.pdf
  - Europe
    https://ec.europa.eu/growth/tools-databases/dem/monitor/tags/regulatory-framework

Roles, Responsibilities

- Only very mature companies have some definition of the Chief Data Officer, Chief Risk Officer, Chief AI Officer, Chief Security Officer with varying levels of role and responsibility definitions dependent on industry

Compliance

- GDPR is now active, more coming, most scrambling
- Unclear Assessments, Audits and Compliance metrics for Governance given there are no clear standards (or standards exist but are moving targets)

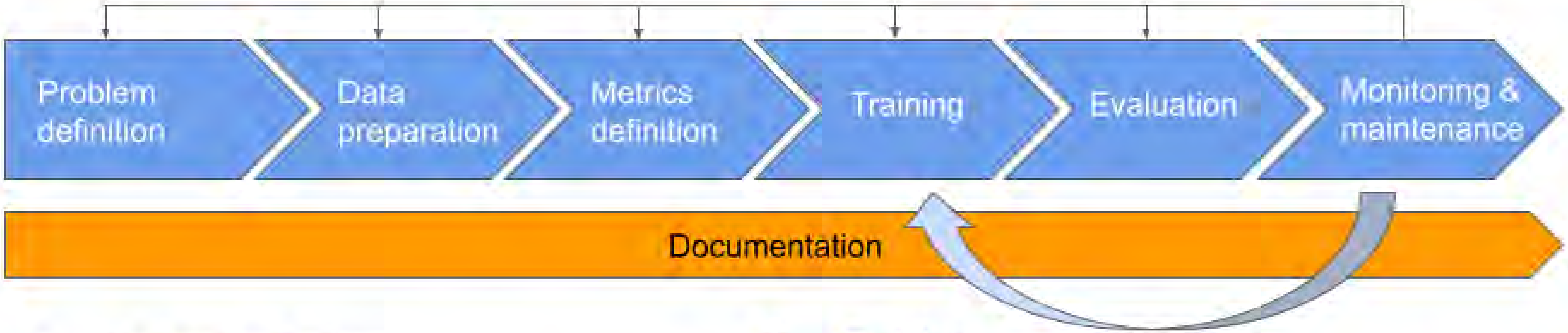


Source: Brookings.EDU

AI Development Basics

IMPORTANT TO UNDERSTAND DATA, TECH, & GOVERNANCE CHALLENGES

AI LIFECYCLE



1. **Problem Definition**
   - ❑ What problem are you solving?
   - ❑ What are your optimizing for?
   - ❑ What is your evaluation criterion?
   - ❑ What is your baseline?
2. **Data Preparation**
   - ❑ Does your training data represent your production data?
   - ❑ Is your training data clear of validation and test data?
3. **Metrics Definition**
   - ❑ Are you using industry standards?
   - ❑ Are your metric and your loss function aligned?
4. **Training**
   - ❑ How did you tune the hyperparameters?
5. **Evaluation**
   - ❑ Do you exceed your baseline?
   - ❑ Is it statistically significant?
   - ❑ Is your confidence score well calibrated?
   - ❑ Do you meet the operating constraints?
6. **Maintenance**
   - ❑ How will you monitor performances?
   - ❑ How often will you retrain the model?

People | Systems | Data

Categories of Bias

Cultural

Interpreting and Judging events by standards based on one's own culture.

Statistical

Feature of a statistical technique or of its results whereby the expected value of the results differs from the true underlying quantitative parameter being estimated.

Cognitive

Systematic pattern of deviation from norm or rationality in judgment

Confirmation

Tendency to search for, interpret, favor, and recall information in a way that confirms or supports one's prior beliefs or values

https://sanjeevkatariya.github.io/ai/machinelearning/chapter-4/section-4-21-index.html

Type of Bias Impacting AI in Digital Experiences

Activity Bias (Human Behavior Interactions)
- Do something vs nothing

Statistical(Data) Bias
- Expected vs true

Sampling Bias
- Sampling with uneven/abnormal low/high distributions

Algorithmic Bias
- Systematic and repeatable errors in a computer system that create unfair outcomes

Presentation (and Positional) Bias
- Where you put things on a screen matters.

Social Bias (Human Behavior Interactions)
- Too many to count! https://en.wikipedia.org/wiki/List_of_cognitive_biases#Social_biases

Interaction Bias (Human Behavior Interactions)
- Targeted Interacts with others exhibiting certain traits or behaviors

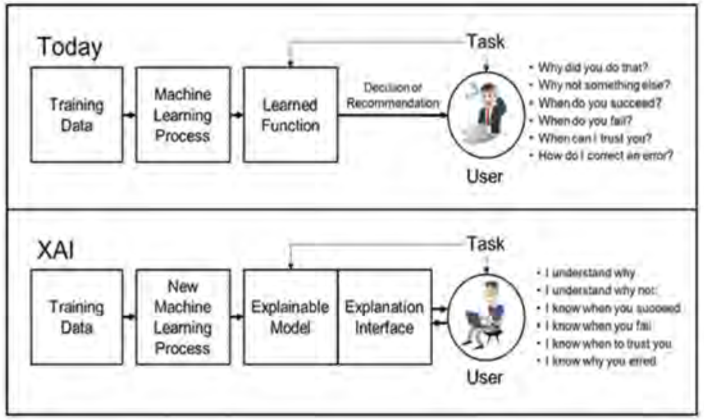
Latent Bias
- Text and Video labeling hidden or derivative bias

Self Selection Bias (Humans and Perceived Interests)
- Individuals select themselves into a group, causing a biased sample with nonprobability sampling.

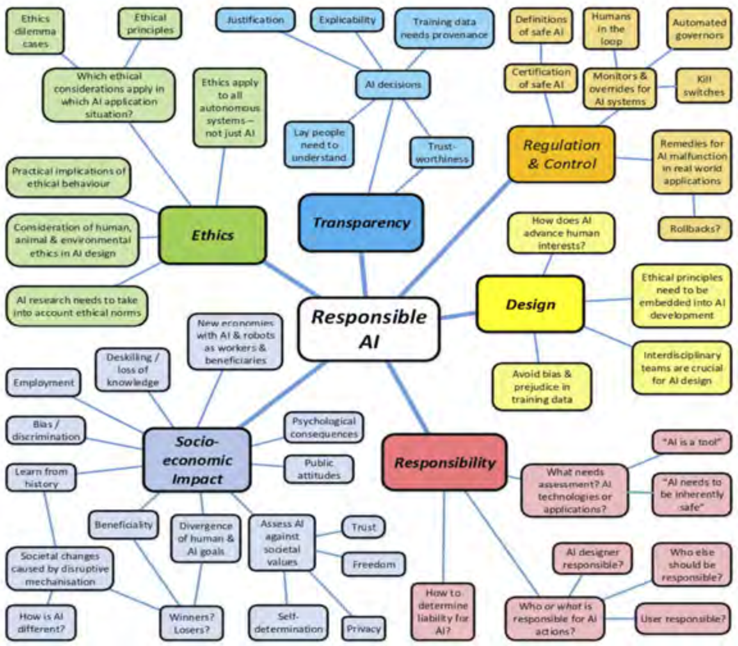
Order (First, Second..)
- Another statistical bias

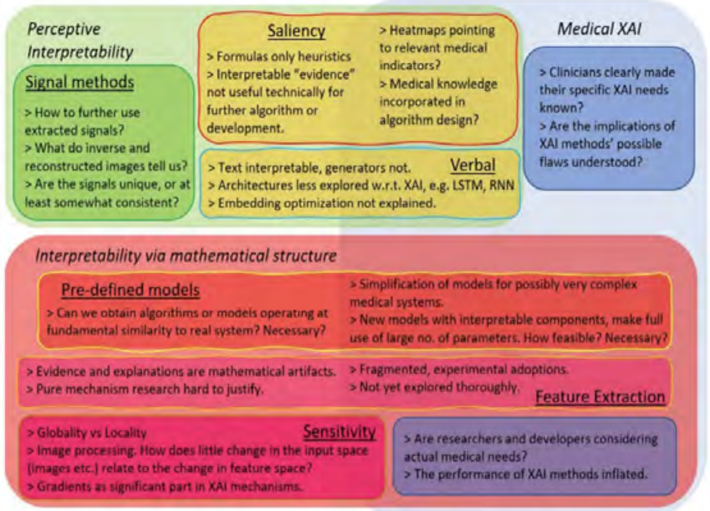
Explainable (X-AI) | Responsible | Accurate | Auditable | Ethical | Transparent | Fair

- Explainable (X-AI)
  - If humans must accept AI decisions, they must trust them. AI must explain itself in a defensible and understandable fashion
  - In ML, the scientific area is called “Interpretability”
  - E.g. IBM XAI Toolkit - https://github.com/Trusted-AI/AIX360



- Responsible
  - AI can potentially do a lot
    - Should it?
    - Who should decide?
    - Which values should be considered?
    - Whose values should be considered?
    - How do we deal with dilemmas?
    - How should values be prioritized?
  - Challenges
    - Chain of Responsibility
    - Levels of Autonomy
    - Open-ness
    - Human Like AI
  - Reports
    - NGU EU Commission https://www.ngi.eu/wp-content/uploads/sites/48/2018/07/Responsible-AI-Consultation-Public-Recommendations-V1.0.pdf





https://sanjeevkatariya.github.io/ai/machinelearning/chapter-4/section-4-21-index.html

Explainable (X-AI) | Responsible | Accurate | Auditable | Ethical | Transparent | Fair

- Accurate

  Considerations regarding accuracy
  - Models of areas where people predict well
  - Expert predictions are generally poor
  - Disparate predictions
  - Similarity of old and new predictions
  - Similarity of expert and lay opinions
  - Predictions are about different things and often misinterpreted
  - Impacted by Bias

- Auditable
  - Institute of Internal Audit

    https://na.theiia.org/periodicals/Public%20Documents/GPI-Artificial-Intelligence-Part-II.pdf
  - They define the Audit Framework over:
    - Three overarching components — AI Strategy, Governance, and the Human Factor
    - Seven elements: Cyber Resilience; AI Competencies; Data Quality; Data Architecture & Infrastructure; Measuring Performance; Ethics; and The Black Box

Good performance:	Poor performance:
Static stimuli	Dynamic (changeable) stimuli
Decisions about things	Decisions about behavior
Experts agree on stimuli	Experts disagree on stimuli
More predictable problems	Less predictable problems
Some errors expected	Few errors expected
Repetitive tasks	Unique tasks
Feedback available	Feedback unavailable
Objective analysis available	Subjective analysis only
Problem decomposable	Problem not decomposable
Decision aids common	Decision aids rare

The errors, insights and lessons of famous AI predictions – and what they mean for the future

Stuart Armstrong*, Kaj Sotala and Seán S. ÓhÉigeartaigh

May 20, 2014

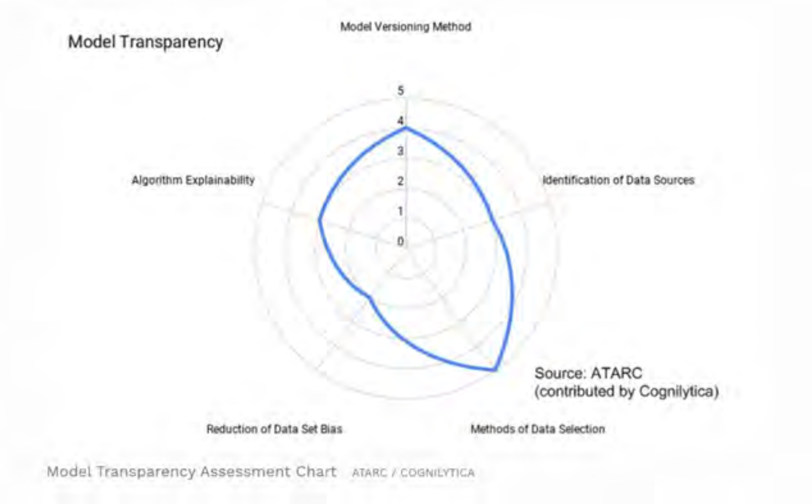
Abstract

Predicting the development of artificial intelligence (AI) is a difficult project – but a vital one, according to some analysts. AI predictions already abound: but are they reliable? This paper will start by proposing a decomposition schema for classifying them. Then it constructs a variety of theoretical tools for analysing, judging and improving them. These tools are demonstrated by careful analysis of five famous AI predictions: the initial Dartmouth conference, Dreyfus's criticism of AI, Searle's Chinese Room paper, Kurzweil's predictions in the 'Age of Spiritual Machines', and Omohundro's 'AI Drives' paper. These case studies illustrate several important principles, such as the general overconfidence of experts, the superiority of models over expert judgement, and the need for greater uncertainty in all types of predictions. The general reliability of expert judgement in AI timeline predictions is shown to be poor, a result that fits in with previous studies of expert competence.// *Keywords:*AI, predictions, experts, bias, case studies, expert judgement, falsification

Explainable (X-AI) | Responsible | Accurate | Auditable | Ethical | Transparent | Fair

Ethical

- Concern with the moral behavior of humans as they design, construct, use and treat artificially intelligent beings
- Machine ethics - moral behavior of artificial moral agents (AMAs)
  - Focus: AI control problem, Algorithms and training, Integration of Artificial General Intelligences with society, Machine learning bias
- Ethical Frameworks
  - Active Inclusion, Fairness, Right to Understanding, Access to Redress
  - World Economic Forum and Global Future Council on Human Rights - http://www3.weforum.org/docs/WEF_40065_White_Paper_How_to_Prevent_Discriminatory_Outcomes_in_Machine_Learning.pdf



Transparent == Trustworthy

- Tools available for Creators of ML Models
  - Data, Hyperparameters, tools, frameworks, algorithms
- Questions Users have
  - Why did the model perform the way it did? (Decisions)
  - How was it trained? Did that matter? (Education)
  - Did the scientist/engineer select and develop poorly? Did they consider diversity in their approach?
- Problems
  - Unexplainable Algorithms
  - Lack of visibility into training and data and developed understanding
  - No accounting for a plethora of bias or understanding how it was dealt with
  - What was the ML model built for? For whom? Why?
- Advancements
  - AI Standards - NIST https://www.nist.gov/news-events/events/2019/05/federal-engagement-artificial-intelligence-standards-workshop
  - ATARC AI Ethics and Responsible AI https://atarc.org/working-groups/ai-working-group/
  - 3rd Party Assessments

Explainable (X-AI) | Responsible | Accurate | Auditable | Ethical | Transparent | Fair

- **Fair**
  - How do you define Fair? At what levels - individuals, groups? What kinds of groups? In that form so that the machine understands the "goal of being fair"?
  - One potential modified definition
    " In fair AI, the objective is to provide systems that both quantify bias and mitigate discrimination against individuals and subgroups" (*Feuerriegel, S., Dolata, M. & Schwabe, G. Fair AI. Bus Inf Syst Eng 62, 379–384 (2020). https://doi.org/10.1007/s12599-020-00650-3*)
  - Need for a mathematical definition of fairness for algorithms to operate
    - Group: Fair on [sensitive attributes/metrics] that does not lead to [discrimination] where prediction is "fair" across groups
    - Individual: Similarly situated individuals treated similarly - where similarly balances equality and equity
  - IBM AI Fairness Framework - https://github.com/Trusted-AI/AIF360

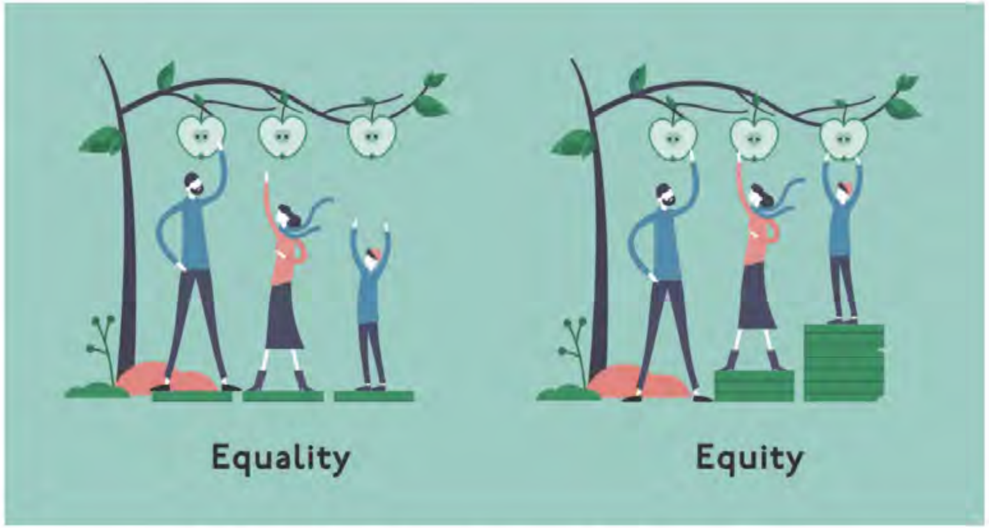


Fig. 1: Equality means, that everybody is treated the same.
Equity means, that everybody gets what they need to be successful.

Potential Solutions

IMPORTANT TO UNDERSTAND DATA, TECH, & GOVERNANCE CHALLENGES

People | Data | Technology | Governance | Business | Strategy | Comm

Leverage Common AI Education Avenues

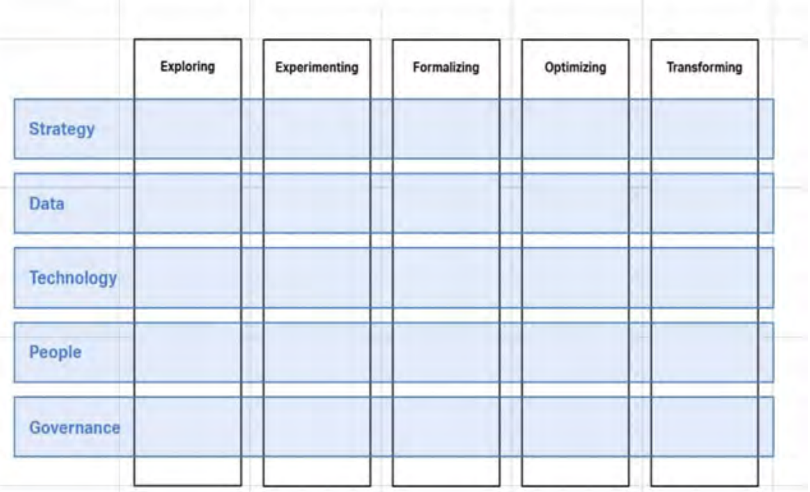
- Coursera, EDX, AI Conferences (https://www.unite.ai/conferences/)
- Open Source
- AI for Business Leaders (e.g. Microsoft, eDX etc)
- AI for Product Leaders (e.g. Udacity, Medium)

Get Hiring Help!

- Standard Hiring practices, AI Boutique Companies (If you are in your early stages, don't assume you know how to hire)

Build an effective AI and Leadership Organization

- Build a Hub-Spoke Leadership model for AI (Hub for strategic coordination and initiatives, spoke fc
- Build an AI Business and Customer Advocacy Team with Product to get maximal alignment
- Build an AI Virtual Tech Organization from Departments to coordinate on tech and reduce redunda
- Build an AI central tech team for vetting partnerships, technologies and more
- Build Incentive and Reward programs to build up the right AI teams and behaviors



Courtesy: Element.AI Maturity Framework

Develop Training and Mentorship Programs

- Develop in house internal open source sharing practices
- Rotate people through teams with AI expertise to learn and up level skills
- Involve teams in Conferences to be exposed, learn and grow
- Build in- house training and mentorship programs with internal and external help on a regular basis

Develop Industry, Governmental or Academic Partnerships

- Use Hub-Spoke teams to coordinate and engage in targeted business case / initiative centric cases for Business / Product and Tech Advancement

People | **Data** | Technology | Governance | Business | Strategy | Comm

Address Data quality and quantity

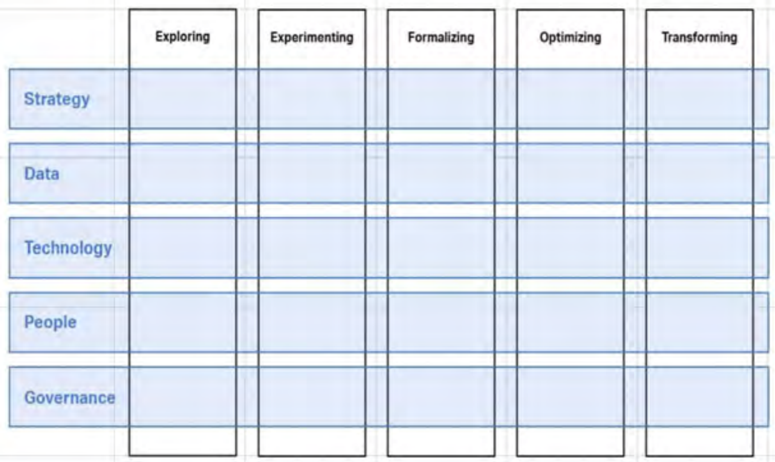
- Approach: List the types of data and categories of data you have and/or you need
- Public Cloud offerings + Tons of Vendors in Data Management space == Makes things easier
- Open Source Offerings (if you like doing things yourself)
- Data Vendors to help with “more data, more complex data” - if you can afford
- Data Generative techniques to “artificially generate data”

Address Data labeling

- Lots of Data Vendors with a diverse set of labeling techniques across all kinds of assets (text, images, videos)
- Adopt-an-approach (or set of): Internal Labeling, External Team, Outsource, Program, Explicit Experience Feedback

Develop Strategies and Stance to handle Bias

- Detection: Open Source (e.g. FairML(https://github.com/adebayoj/fairml), IBM (http://aif360.mybluemix.net/)
- Sampling Bias reduction through standard statistical sampling techniques and through oversampling
- Collection Diversity (Don’t rely on one data source)



Courtesy: Element.AI Maturity Framework

Develop Ease Around Discovery, Access and Processing

- Hidden in data lakes, no clear ontology, no clear ownership
- Expensive and complex Processing
- Data Access from 3rd Party Vendors expensive

Invest in Governance

- Approach: Be deliberate. Develop “data” (much like code) ownership and stewarding of data lifecycle
- Develop clear lifecycle Data Security and Privacy Classification and management
- Develop an approach to managing Real time vs batch streams with security and privacy sensitivity
- And if you don’t know how to, hire consultants and people who do! And if you don’t know how to hire (or where to start), go attend conferences where this is all people talk about!

Develop Data Sets

- Develop systematic approaches around training, testing, validation sets

S O L U T I O N S

People | Data | **Technology** | Governance | Business | Strategy | Comm

Build Deliberate Integration Solutions

- Build appropriate vendor shims to plug in / take out vendors
- Build feedback loops and updates as a first class citizen in all engineering work
- Be metric based and Use telemetry to track usage and ROI

Be Cost Aware

- Build cost modeling from day 1 into your solutions
- Track usage on a regular cadence to refine and improve
- Always look for the bigger and better deal as part of ROI cadence with vendors

Standardize Tools and Frameworks

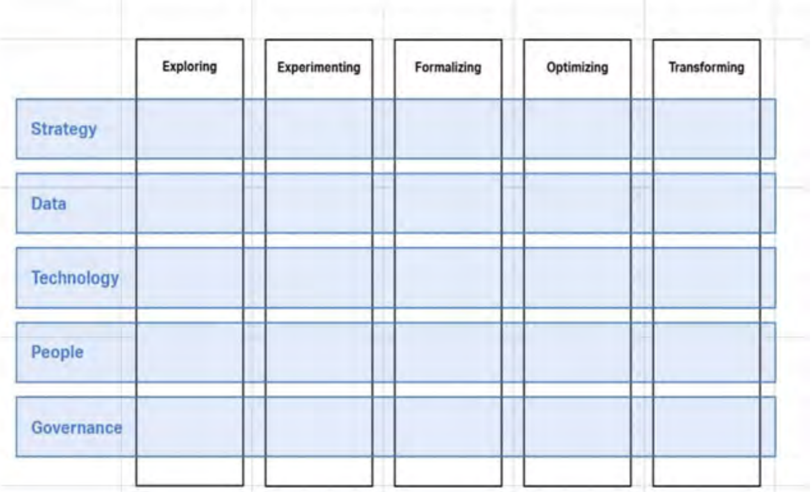
- Standardize! Don't think you can do it all!
- Have a planned "M&A" strategy which builds on and augments and aligns to your tech offerings

Deal with Complex Data and Infrastructure Demands

- Hire "Data" centric teams (Chief Data Officer) who manage Data Lifecycle and Governance
- Model and grow slowly with cost awareness
- Leverage public offerings (Cloud, Data, Systems, Vendors) where it makes sense - sensibly

Manage Model Error Solutions

- Hire the right People, create the right org and leadership



Courtesy: Element.AI Maturity Framework

Clarify Regulatory Requirements, Roles and Responsibilities

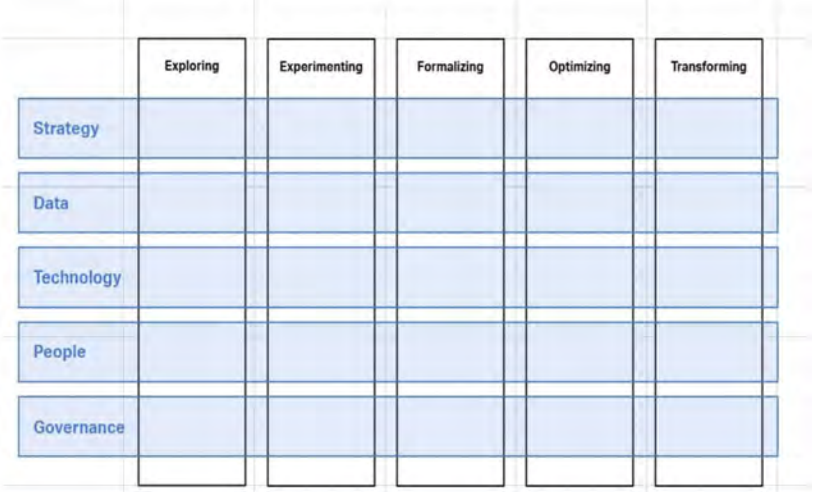
- Legal and Government relations groups have to be intrinsically involved from the start to develop an internal and external stance

Develop Clear Roles & Responsibilities

- Hiring the right people with the right skills leads to the right results:
  - Chief **Risk** Officer
  - Chief **Trust** officer
  - Chief **Data** Officer
  - Chief **Privacy** Officer
  - Chief **Security** Officer
  - Chief **Compliance** Officer..

Develop a Clear Stance around Compliance

- Develop an Assessments, Audits and Compliance stance internally with clear metrics around insights to clear actions
- Work in parallel with 3rd party companies on AI compliance and Government(s) to evolve your stance



Courtesy: Element.AI Maturity Framework

People | Data | Technology | Governance | Business | Strategy | Comm

Develop a Coordinated AI Strategy

- Don't think it will come together - be deliberate. Define key initiatives, business cases, customer experiences. Build an AI Experience customer panel of business, product and tech. Set a clear strategic approach with Problem Statements, OKRs, ROI using the Hub-Spoke Leadership structure

Develop business alignment

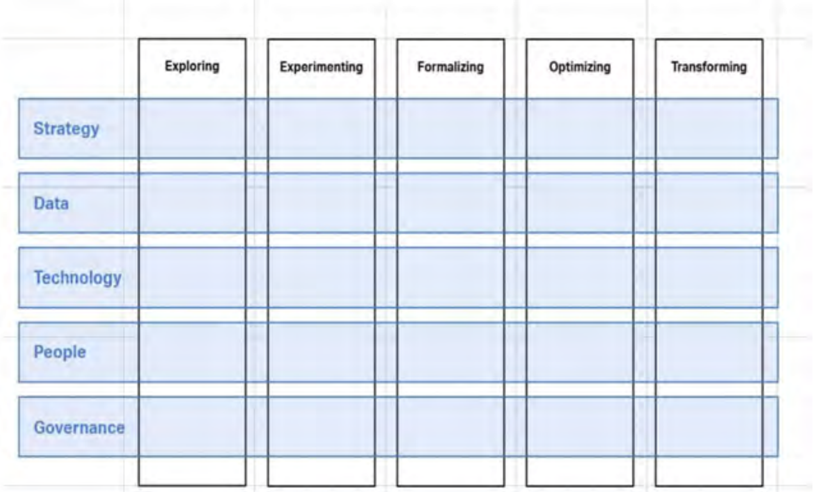
- Look to Industry leaders, Startups on a regular basis in your relevant space
- Map the quadrants of AI business use cases relevant to your business stage

Get Help Assessing vendors

- Get help (if you're earlier in your journey) - it's money worth spent
- POC with vendors and build abstractions around their solutions to "plug them in or take them out"

Work with Legal (Based on your stage)

- Work with Legal to outline clear risk and liability even if you can't address it
- Build up a clear GDPR program to address data lifecycle and data governance issues
- Build (or demand from vendors) Clear AI Accountability measures - don't leave this to chance



Courtesy: Element.AI Maturity Framework

Questions & Answers

THANK YOU FOR YOUR TIME