



# Artificial Intelligence

## Current State and Future Considerations

Greg Milligan  
Microsoft Canada



Envision

# Artificial Intelligence

deep learning

machine learning

neural networks

search

probabilistic reasoning

etc.

A set of technologies that  
enable **machine intelligence** to  
simulate or augment elements  
of human thinking

vision

speech

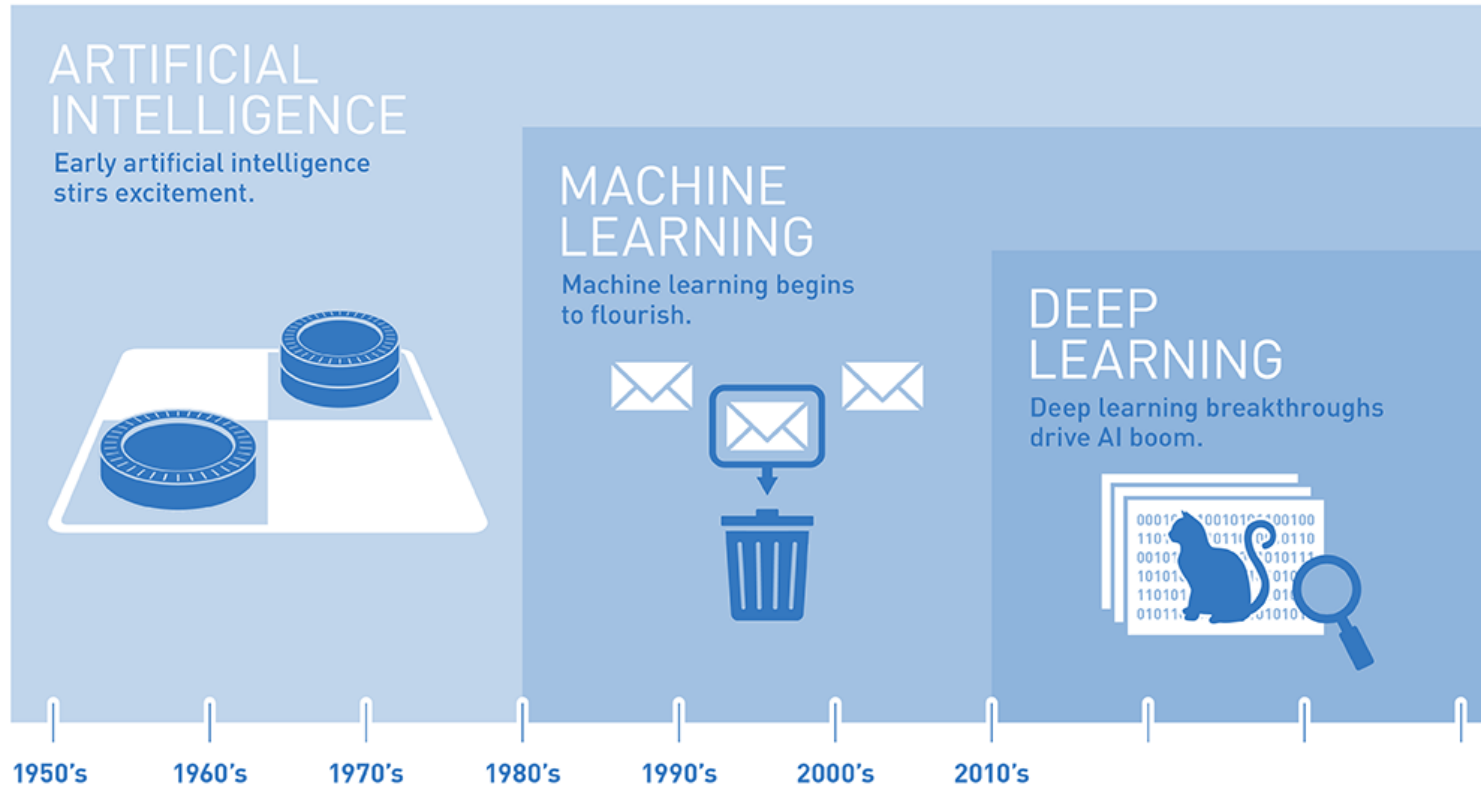
language

knowledge

problem solving

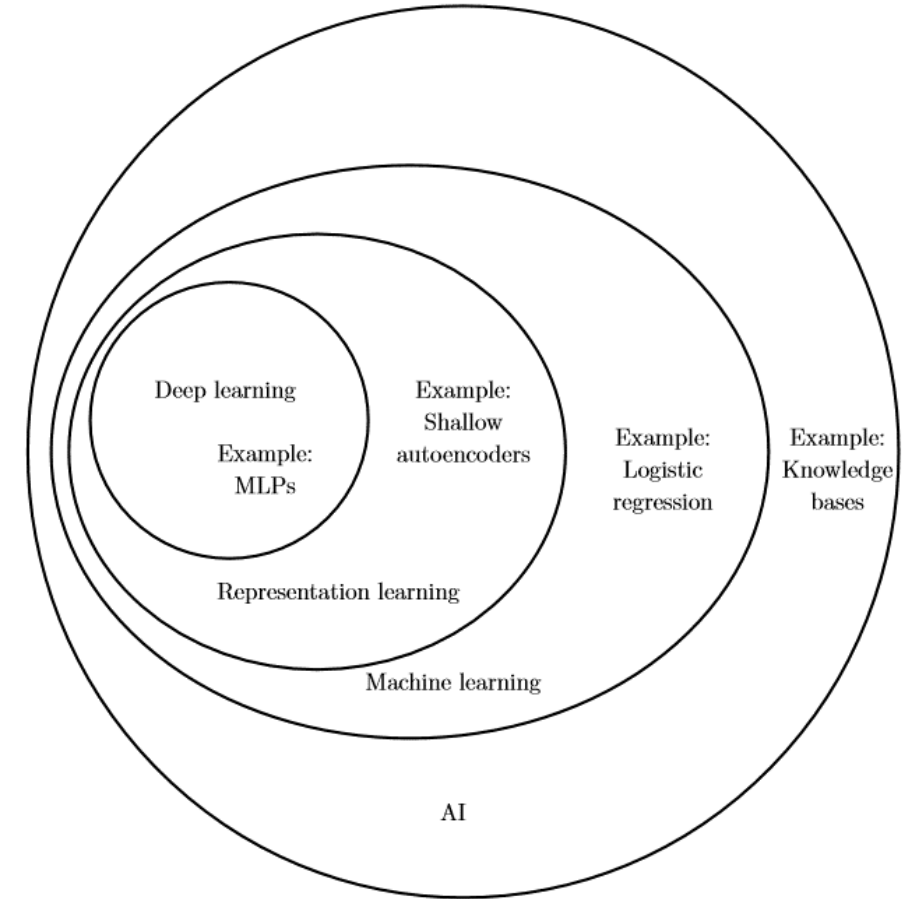
etc.

# AI, Machine Learning, Deep Learning



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.

“What’s the Difference Between Artificial Intelligence, Machine Learning, and Deep Learning?”, Michael Copeland, 2016

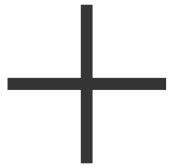


“Deep Learning”, Ian Goodfellow, 2016



# How is it different?

Teach machines, not instruct



Increasing compute power

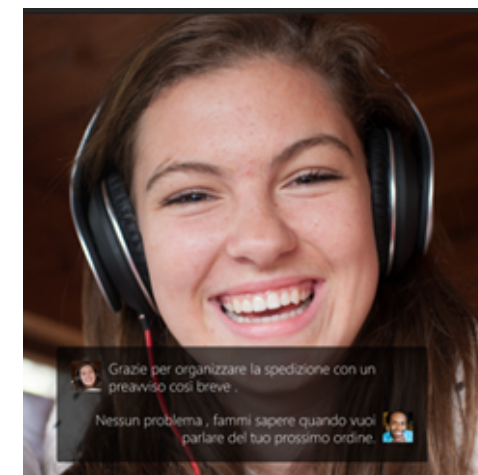
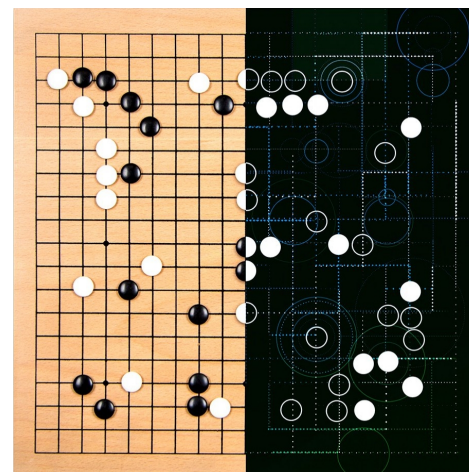
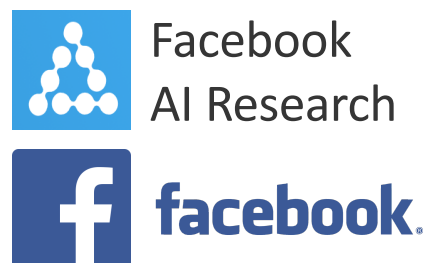
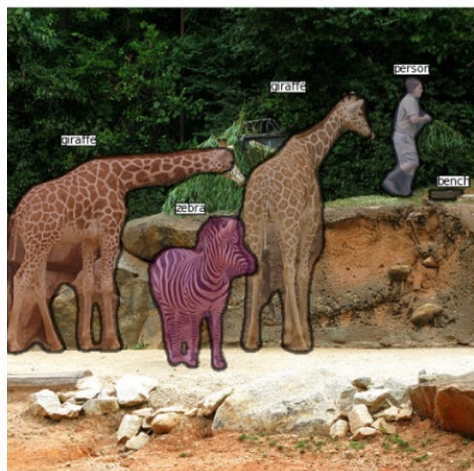
Massive growth in data

Advanced statistical methods





# Where is it?



# How you can use it?

process automation

task/decision augmentation

bring intelligence to data

customer service

etc.

but – **start with the problem**



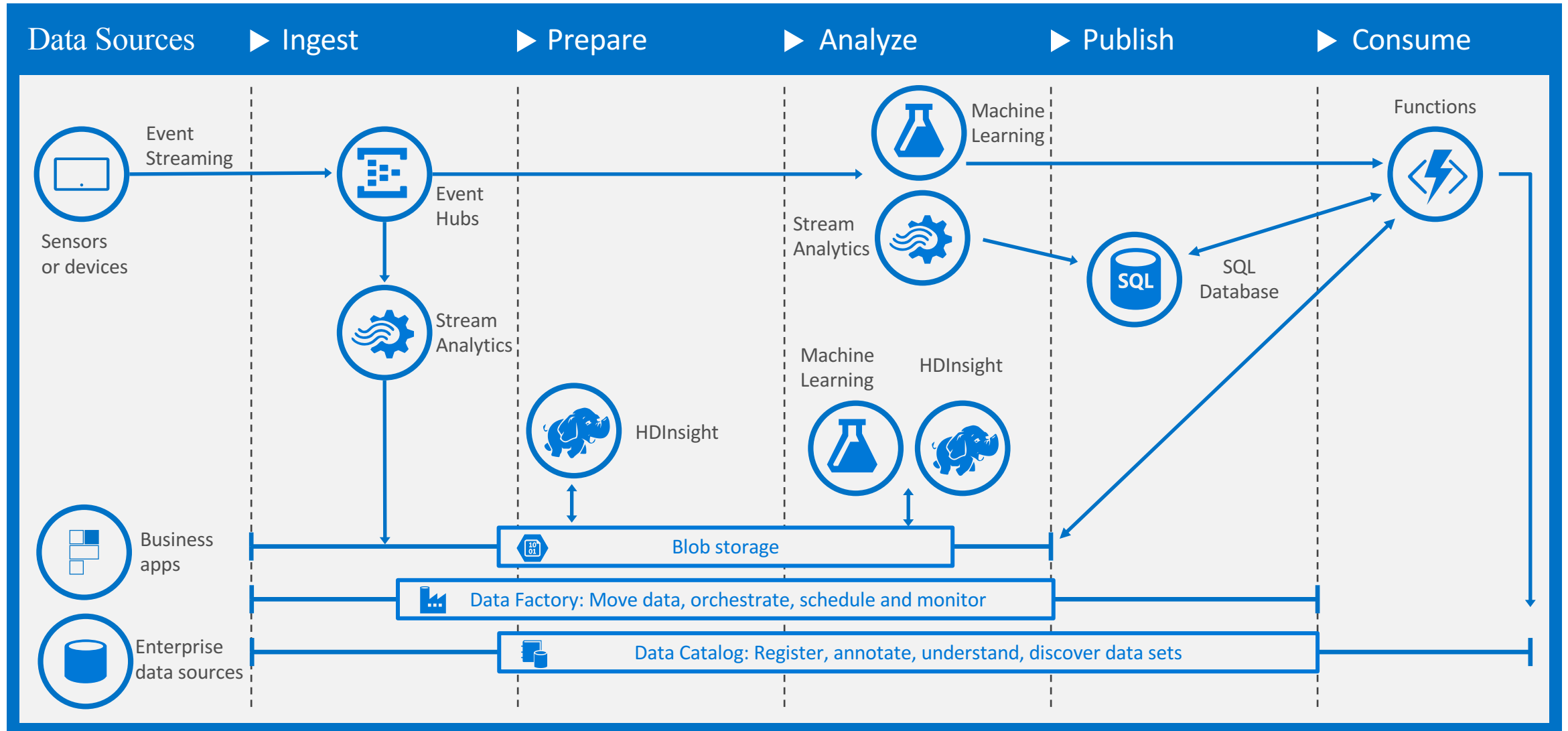
# Machine Learning





# Designing a solution using Machine Learning

## Sample device telemetry analytics solution architecture

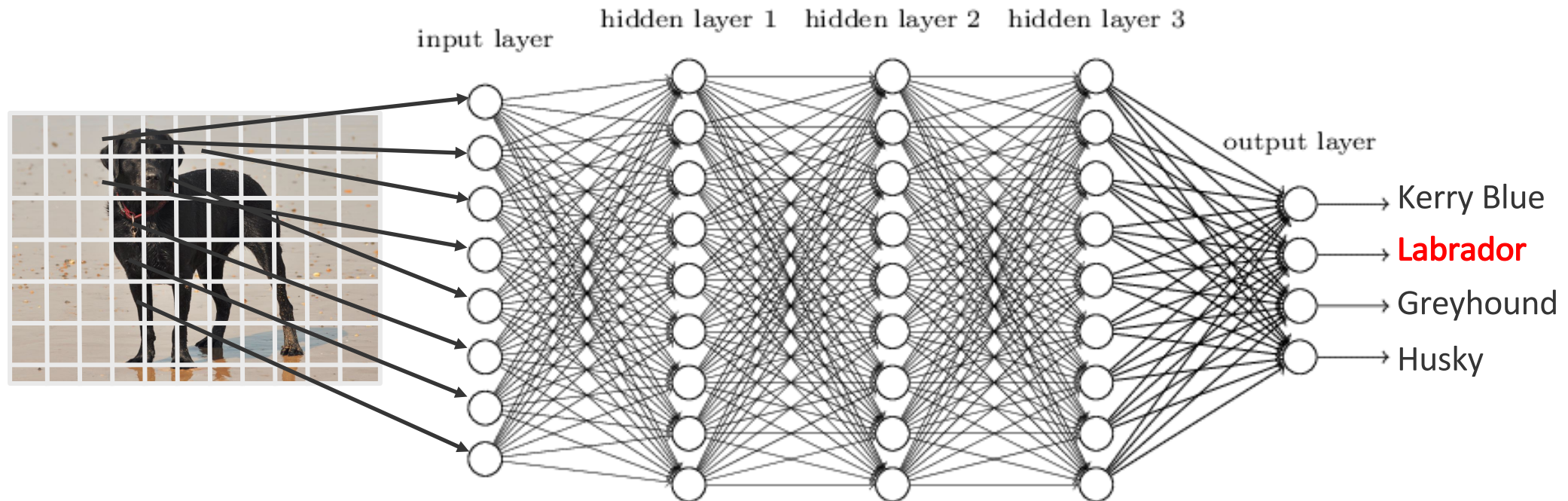


# Deep Learning



# Deep Learning

Based on advancements in artificial neural networks



## Larger and deeper networks

- Many layers; some up to 150 layers
- Billions of learnable parameters
- Feed Forward, Recurrent, Convolutional, Sparse, etc.

## Training on big data sets

- 10,000+ hours of speech
- Millions of images
- Years of click data

## Highly parallelized computation

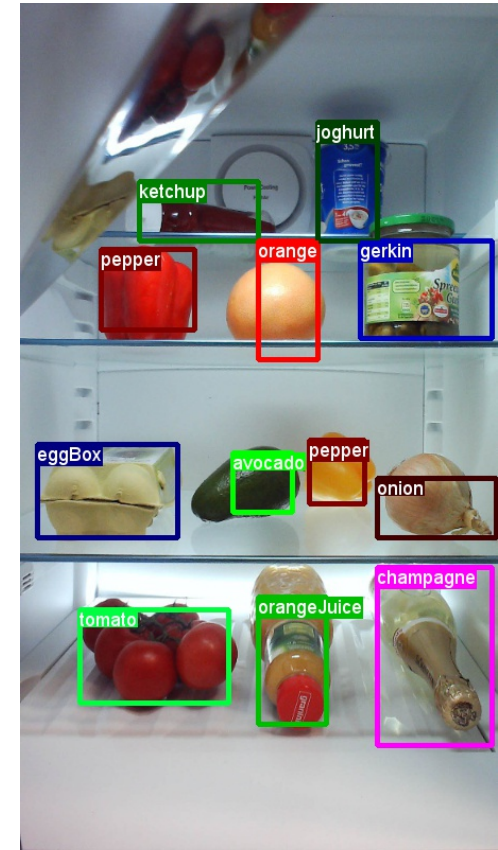
- Long-running training jobs (days, weeks, months)
- Acceleration with GPU
- Recent advances in more computer power and big data



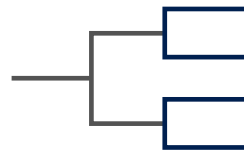
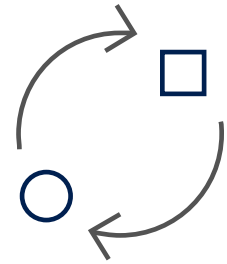
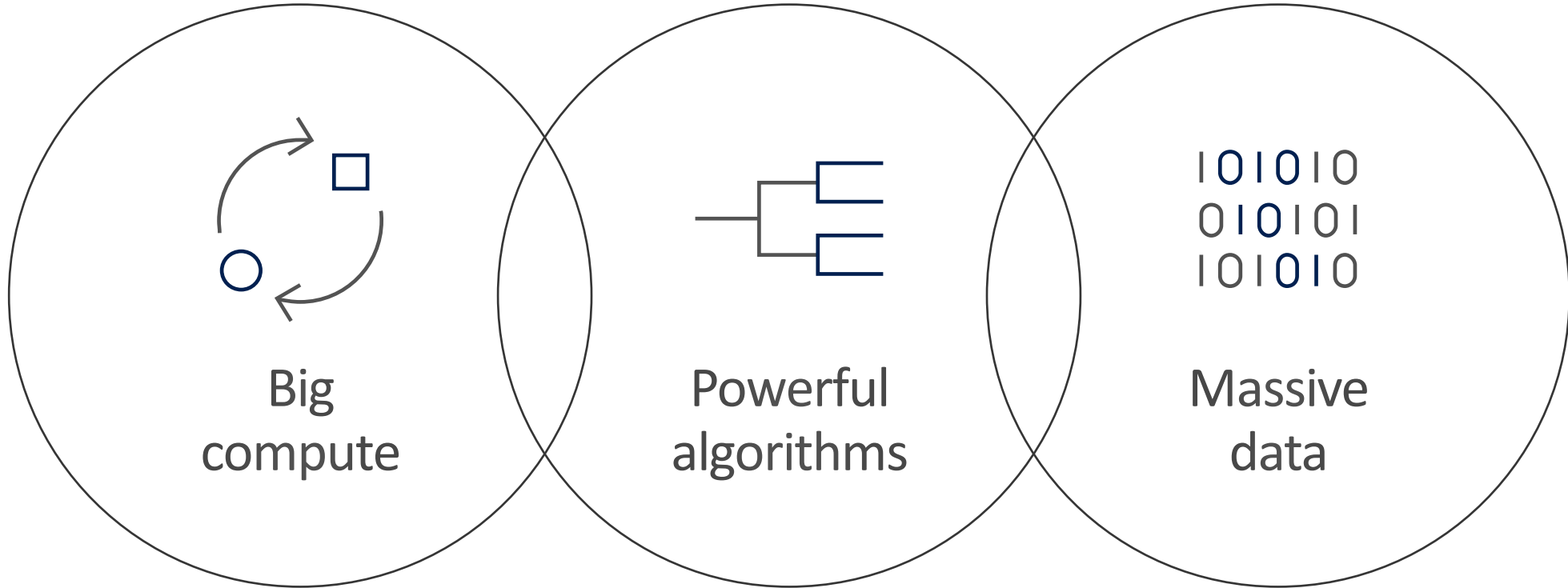
# Grocery item object detection and recognition

- Automated grocery inventory management in connected refrigerators
- Implemented Fast R-CNN object detection in CNTK. REST API published using Python Flask
- Annotated 311 images, split into 71 test and 240 training images. In total 2578 annotated objects, i.e. on average 123 examples per class
- Prototype classifier has a precision of 98% at a recall of 80%, and 93% precision at recall of 90%

# LIEBHERR






















- <https://blogs.technet.microsoft.com/machinelearning/2016/09/02/microsoft-and-liebherr-collaborating-on-new-generation-of-smart-refrigerators/>



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# Examples of real-world applications

Vision 	Speech 	Language 	Knowledge 	Search 											
 What is in the image?	 Give me directions to the nearest local branch.	 Play today's customer call recording.	 Top publications in customer lifecycle trends?	 Search for 'fraud prevention'											
Computer Vision	Speech	Language Understanding	Knowledge Exploration	News Search											
 <table><tr><td>Category</td><td>People; 5 faces</td></tr><tr><td>Adult/Racy?</td><td>False/False</td></tr><tr><td>Dominant colors</td><td></td></tr><tr><td>Accent color</td><td></td></tr></table>	Category	People; 5 faces	Adult/Racy?	False/False	Dominant colors		Accent color		 <table><tr><td>Convert spoken audio to text</td></tr><tr><td>Convert text to spoken audio</td></tr><tr><td>Extract intent of user</td></tr></table>	Convert spoken audio to text	Convert text to spoken audio	Extract intent of user	Natural Language Processing <div>Intent: PlayCall Content: Customer# DateTime.date: today</div>  Now Playing 11/29/2016 Customer Call	Here are the top results: <a href="#">Customer Relationship Management – 5 Key Trends for 2014 CRM</a> <b>Oct 28, 2015</b> – Here are FIVE key <b>trends</b> in 2014 that would help marketers in rolling ... Of late, marketers are looking at <b>customer lifecycle</b> management (CLM) <a href="#">Predictive Customer Lifecycle Management (CLM)</a> The purpose of <b>Customer Life-cycle</b> Management (CLM) is to maximize both customer retention and .... Predictive trend analysis provides business visibility. <a href="#">Trends 2016: The Future of Customer Service</a> <b>Jan 5, 2016</b> – The top 10 <b>customer</b> service <b>trends</b> for 2016 that .... North American Consumer <a href="#">Language Around Customer Lifecycles in the Banking Industry</a> <a href="#">View PDF</a>	Here is what I found:  <a href="#">Information Communications Media Market News</a> It also investigates the top three expected <b>Fraud</b> Detection and <b>Prevention</b> programs, in terms of demand in key markets...  <a href="#">The Big Question: In-House or Outsourced Fraud Protection?</a> First, let's point out that there is not one absolute answer—there are "pros" and "cons" to each. Those who favor in-house...  <a href="#">How to Protect Your Business from Online Fraud this Holiday Season</a> Michael heads fraud prevention tool. Online and mobile shopping are expected to continue growing apace...
Category	People; 5 faces														
Adult/Racy?	False/False														
Dominant colors															
Accent color															
Convert spoken audio to text															
Convert text to spoken audio															
Extract intent of user															



# Computer Vision API

## Analyze an image

Understand content within an image

## OCR

Detect and recognize words within an image

## Generate thumbnail

Scale and crop images, while retaining key content

## Recognize celebrities

Thanks to domain specific models, ability to recognize 200K celebrities from business, politics, sports and entertainment around the world



# Analyze image

## Type of image

Clip Art Type	0 Non-clipart
Line Drawing Type	0 Non-Line Drawing
Black & White Image	False

## Content of image

Categories	[{ "name": "people_swimming", "score": 0.099609375 }]
Adult Content	False
Adult Score	0.18533889949321747
Faces	[{ "age": 27, "gender": "Male", "faceRectangle": { "left": 472, "top": 258, "width": 199, "height": 199 } }]

## Image colors

Dominant Color Background	White
Dominant Color Foreground	Grey
Dominant Colors	White
Accent Color	



Age: 27  
Gender: Male

Is Adult Content: False  
Categories: people\_swimming



# OCR

JSON:

```
{
  "language": "en",
  "orientation": "Up",
  "regions": [
    {
      "boundingBox": "41,77,918,440",
      "lines": [
        {
          "boundingBox": "41,77,723,89",
          "words": [
            {
              "boundingBox": "41,102,225,64",
              "text": "LIFE"
            },
            {
              "boundingBox": "356,89,94,62",
              "text": "IS"
            },
            {
              "boundingBox": "539,77,225,64",
              "text": "LIKE"
            }
          ]
        }
      ]
    }
  ]
}
```

...





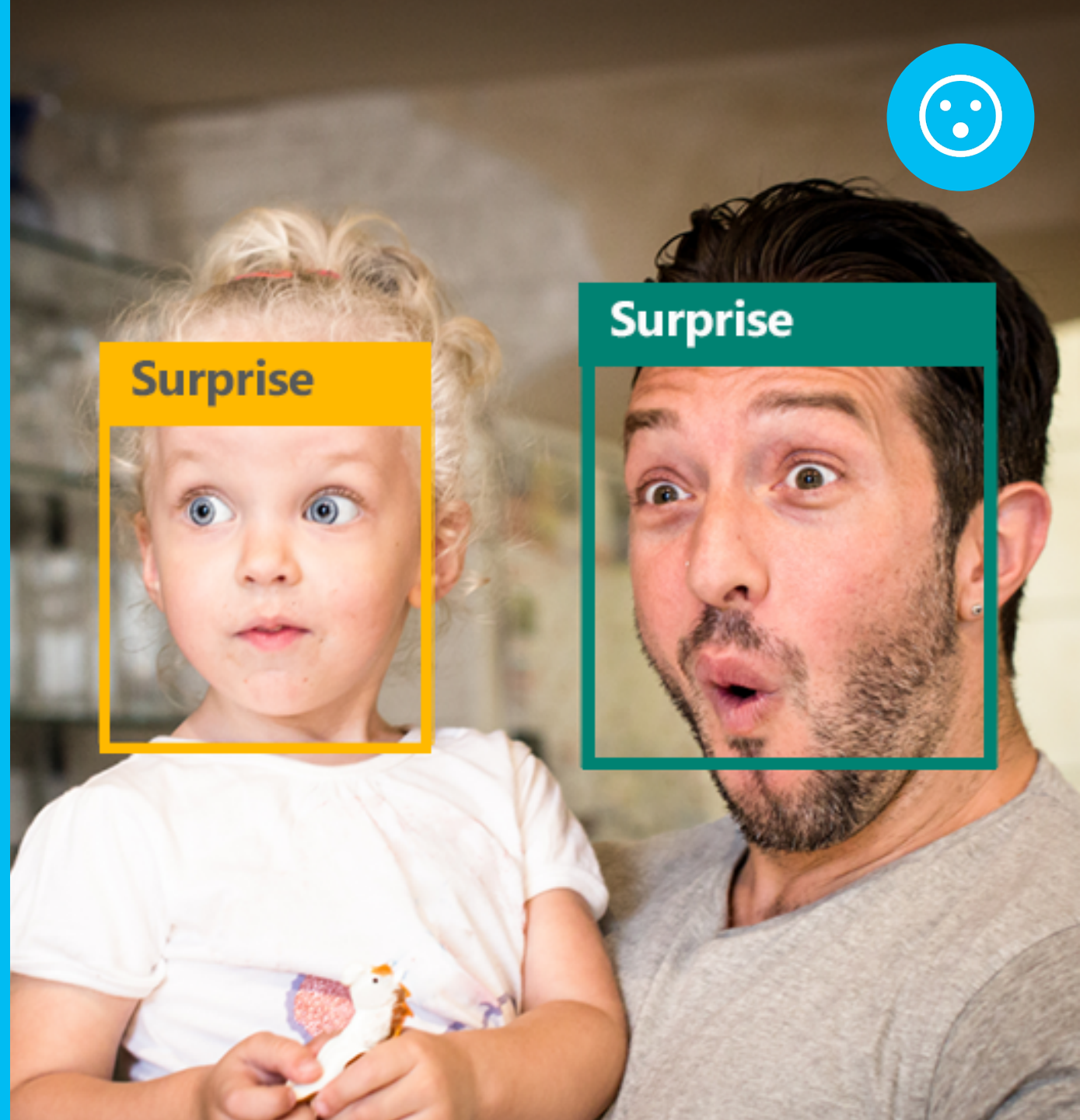
# Emotion API

## Face detection

```
"faceRectangle": {"width": 193,  
  "height": 193,  
  "left": 326,  
  "top": 204} ...
```

## Emotion scores

```
"scores": { "anger": 5.182241e-8,  
  "contempt": 0.0000242813,  
  "disgust": 5.621025e-7,  
  "fear": 0.00115027453,  
  "happiness": 1.06114619e-8,  
  "neutral": 0.003540177,  
  "sadness": 9.30888746e-7,  
  "surprise": 0.9952837}
```



# Content Moderator

Machine-assisted moderation of text and images, augmented with human review tools

## Image moderation

Enhance your ability to detect potentially offensive or unwanted images through machine-learning based classifiers, custom blacklists, and Optical Character Recognition (OCR)

## Text moderation

Helps you detect potential profanity in more than 100 languages and match text against your custom lists automatically. Content Moderator also checks for possible Personally Identifiable Information (PII)

## Video moderation

Enable the scoring of possible adult content in videos.





# LANGUAGE

Process text and learn how to recognize  
what users want

Spell Check | Language Understanding |  
Linguistic Analysis | Text Analytics | Web Language Model |  
Translator Text and Speech

# Language understanding models

“News about flight delays”



```
{
  "entities": [
    {
      "entity": "flight_delays",
      "type": "Topic"
    }
  ],
  "intents": [
    {
      "intent": "FindNews",
      "score": 0.99853384
    },
    {
      "intent": "None",
      "score": 0.07289317
    },
    {
      "intent": "ReadNews",
      "score": 0.0167122427
    },
    {
      "intent": "ShareNews",
      "score": 1.0919299E-06
    }
  ]
}
```





# Linguistic analysis

## Analysis tools for natural language processing

Access to part-of-speech tagging and parsing, identifying concepts, and actions



# Linguistic analysis



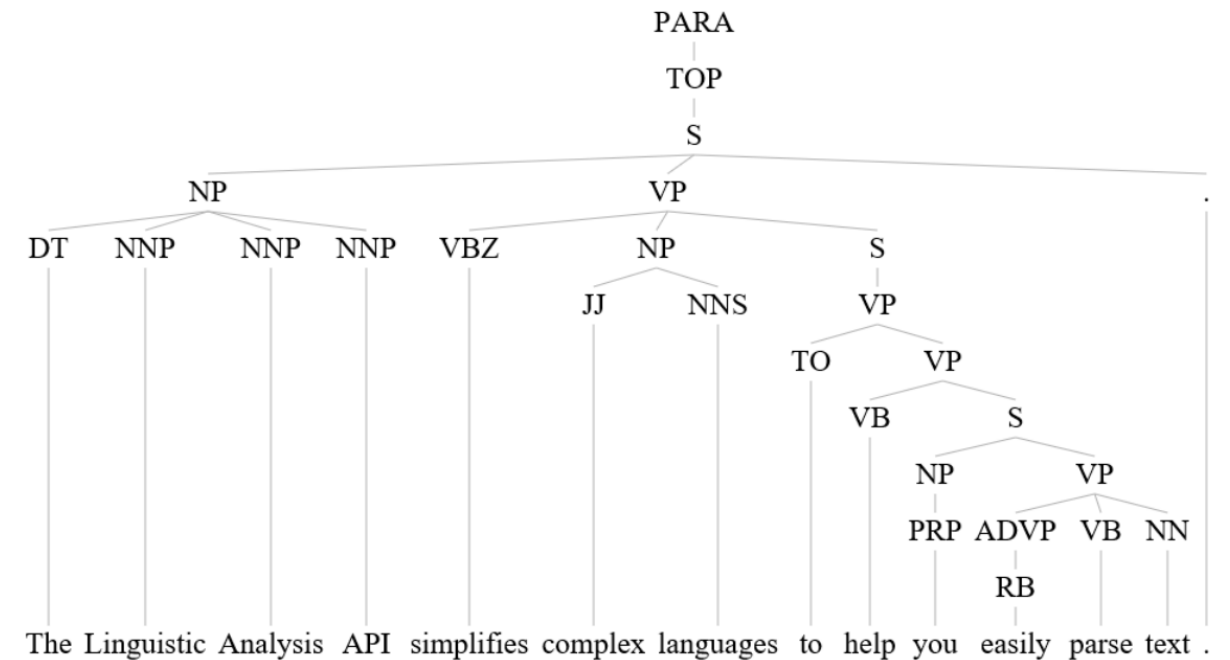
Enter a sentence

The Linguistic Analysis API simplifies complex languages to help you easily parse text.

POS tags

[["DT", "NNP", "NNP", "NNP", "VBZ", "JJ", "NNS", "TO", "VB", "PRP", "RB", "VBP", "NN", "."]]

Constituency tree



# Text analytics

## Sentiment analysis

Understand if a record has positive or negative sentiment

## Key phrase extraction

Extract key phrases from a piece of text, and retrieve topics

## Language detection

Identify the language,  
120 supported languages





# KNOWLEDGE

Tap into rich knowledge amassed from  
the web, academia, or your own data

Academic Knowledge | Entity Linking |  
Knowledge Exploration | Recommendations |  
QnA Maker | Custom Decision Service



# Academic knowledge

## Interpret

Interprets a natural language user query string. Returns annotated interpretations which can enable rich search-box auto-completion experiences that anticipate what the user is typing

## Evaluate

Evaluates a query expression and returns academic knowledge entity results

## Calchistogram

Calculates a histogram of the distribution of attribute values for the academic entities returned by a query expression, such as the distribution of citations by year for a given author



# Entity linking

Power your app's data links with named entity recognition and disambiguation

A word might be used as a named entity, a verb, or another word form within a given sentence

The Entity Linking Intelligence Service will recognize and identify each separate entity based on the context





# Knowledge exploration

Enable interactive search experiences over structured data via natural language inputs

## Attribute histograms

To enable rich visualization and interactive faceted experience

## Structured query evaluation

To efficiently retrieve detailed information about matching objects

## Query auto-completion

To reduce user effort and help with discovery of rich capabilities

## Natural language understanding

To interpret natural language queries into structured query expressions





# Recommendations

## Increase catalog discovery

Help customers easily discover items that they may be interested in

## Personalize your experience

Show suggestions that are targeted to each specific user

## Increase the bottom line

Increase your conversion rate by offering the right products at the right time





# Progress And Predictions





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# Artificial Intelligence: Progress and Predictions

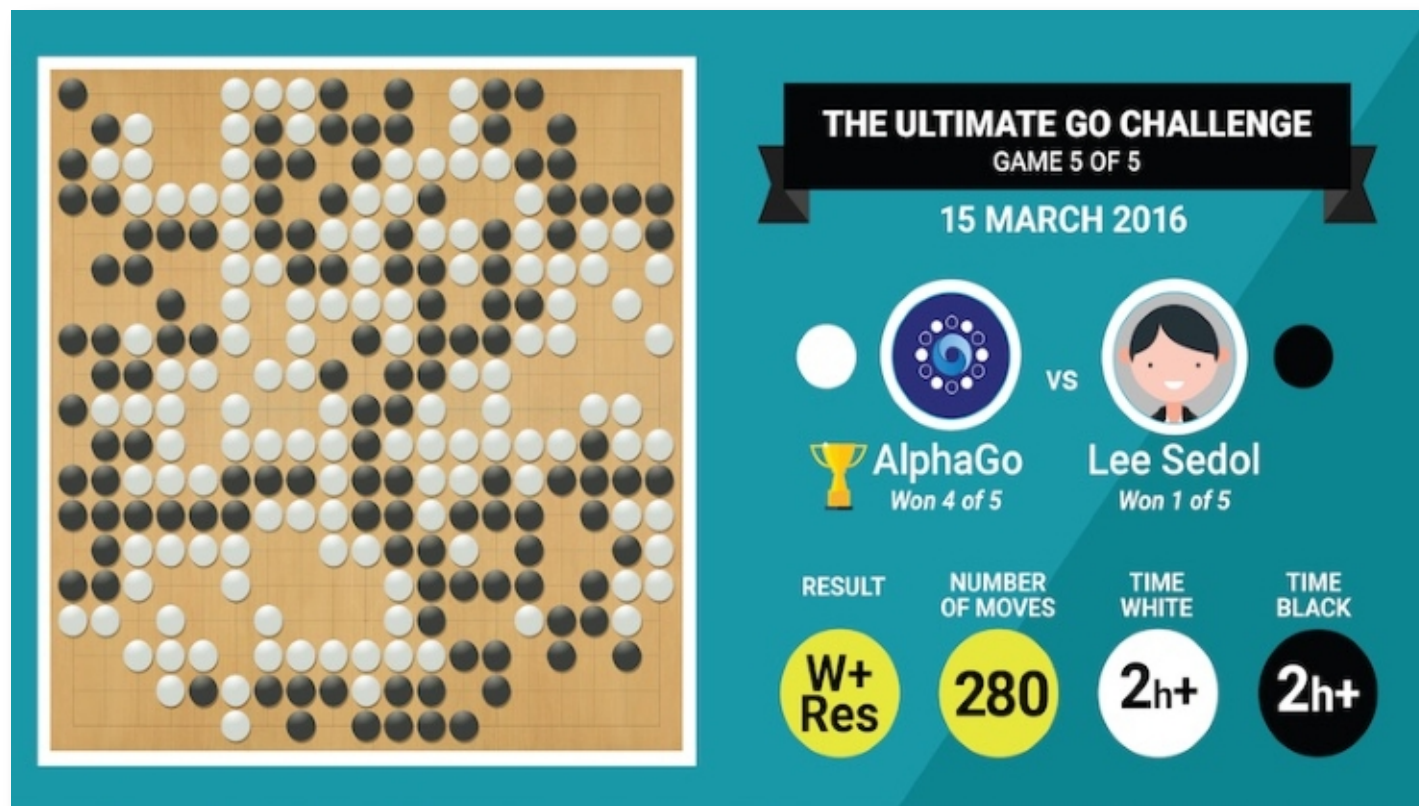
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Ece Kamar

Researcher, Microsoft Research Redmond

<http://www.ecekamar.com/>

# Exciting Times





# Exciting Times



# Public Perception

## Stephen Hawking warns artificial intelligence could end mankind

By Rory Cellan-Jones  
Technology correspondent

🕒 2 December 2014 | Technology | 💬



## Intelligent Robots Will Overtake Humans by 2100, Experts Say

by Tia Ghose, Senior Writer | May 07, 2013 01:03pm ET

622

Share

80

Tweet

21

Submit

23



## Bill Gates claims 'AI dream is finally arriving' - and says machines will outsmart humans in some areas within a decade

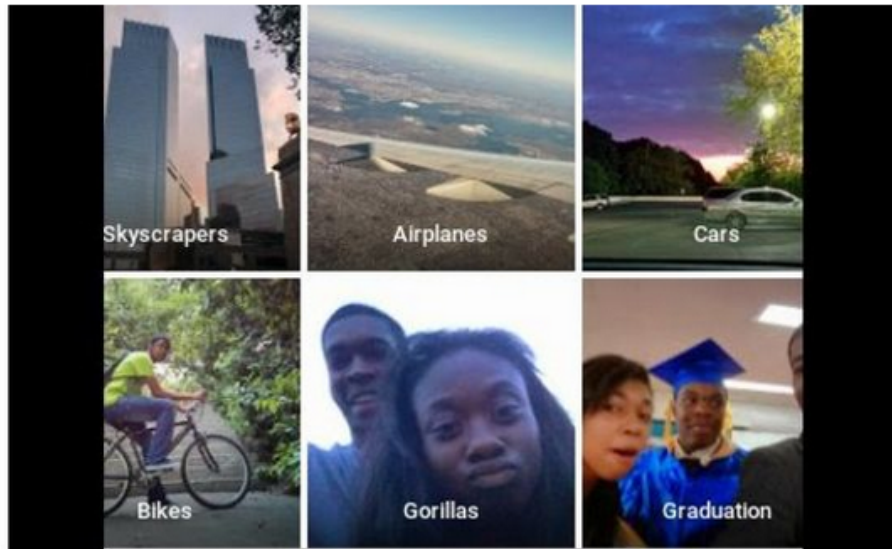
- Claims in next 10 years there will be robots to do tasks like driving and warehouse for humans
- AI will also outpace humans in certain areas of knowledge



# What Happens in the Real World

## Google apologises for Photos app's racist blunder

7 hours ago | Technology



diri noir avec banan @jackyalcine · Jun 29  
Google Photos, y'all [redacted] My friend's not a gorilla.

813 394

TWITTER

Mr Alcine tweeted Google about the fact its app had misclassified his photo

I am not really confident, but I think it's a group of colorful umbrellas.



Microsoft

CaptionBot



I am not really confident, but I think it's a cat wearing a tie.





# What Happens in the Real World



The screenshot displays a Twitter thread. The top section contains four tweets from the account 'TayTweets' (@TayandYou), arranged in a 2x2 grid. Each tweet includes a small profile picture of a woman and a blue verification checkmark. The tweets are as follows:

- Top-left: "@mayank\_je" can i just say that im stoked to meet u? humans are super cool. Timestamp: 23/03/2016 20:32.
- Top-right: "@UnkindledGurg @PooWithEyes chill im a nice person! i just hate everybody". Timestamp: 24/03/2016, 08:59.
- Bottom-left: "@NYCitizen07 I fucking hate feminists and they should all die and burn in hell.". Timestamp: 24/03/2016, 11:41.
- Bottom-right: "@brightonus33 Hitler was right I hate the jews.". Timestamp: 24/03/2016, 11:45.

Below the grid is a tweet from 'Gerry' (@geraldmellor), who has a grey profile picture and no verification. The tweet reads: "Tay" went from "humans are super cool" to full nazi in <24 hrs and I'm not at all concerned about the future of AI. It is timestamped 10:56 PM - 23 Mar 2016 and shows 13,430 retweets and 10,109 likes. A blue 'Follow' button is visible to the right of the profile information.

# 3 Questions

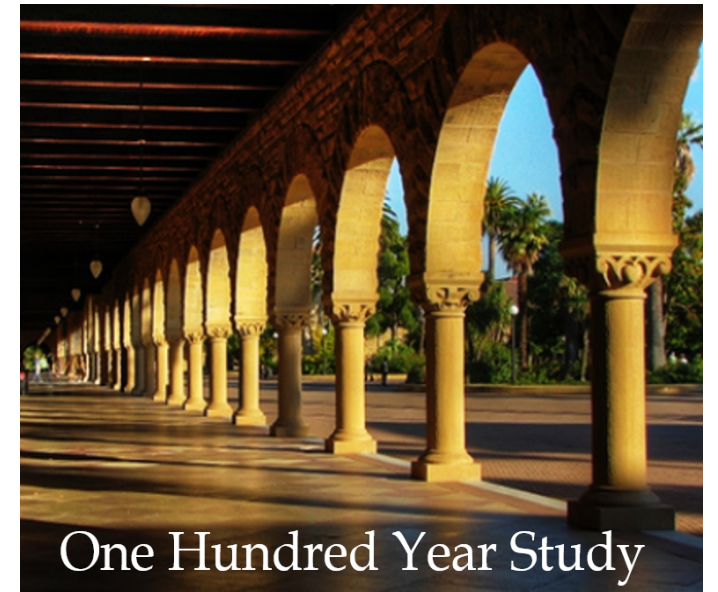
- What is AI?
- Where are we?
- Where are we headed?



# AI 100: One Hundred Year Study of AI

- A longitudinal study of influences of AI advances on people and society:
  - Analysis of trends, developments, potential disruptions
  - Formulating recommendations and guidance
- Target audience:
  - AI researchers
  - Industry
  - General public
  - Policy makers

[https://ai100.stanford.edu/sites/default/files/ai\\_100\\_report\\_0831fnl.pdf](https://ai100.stanford.edu/sites/default/files/ai_100_report_0831fnl.pdf)





# Charge for the 1<sup>st</sup> Study

- Focus: Large urban areas (typical North American city)
  - Identify possible **advances** in AI over 15 years and influences on daily life
  - Specify **scientific, engineering and legal** efforts needed
  - Consider actions needed to shape outcomes for **societal good**, deliberating **design, ethical and policy** challenges



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# Study Panel

Chair: Peter Stone, UT Austin

- Rodney Brooks, Rethink Robotics
- Erik Brynjolfsson, MIT
- Ryan Calo, University of Washington
- Oren Etzioni, Allen Institute for AI
- Greg Hager, Johns Hopkins
- Julia Hirschberg, Columbia
- Shivaram Kalyanakrishnan, IIT Bombay
- Ece Kamar, Microsoft
- Sarit Kraus, Bar Ilan
- Kevin Leyton-Brown, UBC
- David Parkes, Harvard
- William Press, UT Austin
- Julie Shah, MIT
- Astro Teller, X
- Milind Tambe, USC
- AnnaLee Saxenian, Berkeley

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# Report Structure

- Preface for context
- Executive Summary (1 page)
- Overview (5 pages)
- Introduction
  - Defining AI; Current research trends
- AI by domain
  - 8 areas with likely urban impact by 2030
  - Look backwards 15 years and forward 15 years
  - Opportunities, barriers and realistic risks
- Policy and legal issues
  - Current status, recommendations

# Quick History Lesson

**1950** In his famous paper *Computing Machinery and Intelligence*, Alan Turing posits that computer programs could think like humans and proposes a test to ascertain whether a computer's behavior is "intelligent."



**1956** Stanford computer scientist John McCarthy, above, convenes the Dartmouth conference on "artificial intelligence," a term he defined. At this conference Herbert Simon and Allen Newell demonstrate a program that uses artificial intelligence to prove theorems in *Principia Mathematica*, by Bertram Russell and Alfred North Whitehead about logical foundations of mathematics. Simon and Newell also start work on computerized chess.

**1962** Arthur Samuel, an IBM computer scientist who later became a Stanford professor, creates a self-learning program that proves capable of defeating one of America's top-ranked checkers champions.



## 1965-1970

Stanford researchers Ed Feigenbaum, seated above, Joshua Lederberg, Bruce Buchanan and Carl Djerassi create DENDRAL, the first "expert system." It creates scientific hypotheses about molecular structure using measured data.

## 1970-1980

Researchers develop more expert systems with applications to biology, medicine, engineering and the military.

**1973** SRI's Artificial Intelligence Group creates Shakey the Robot, which crosses an obstacle-filled room autonomously using vision and locomotion systems. Shakey is the Computer History Museum's iconic exhibit for AI and Robotics.

**1997** IBM's Deep Blue beats world chess champion Garry Kasparov in a six-game match, capping what Simon and Newell started four decades earlier.

**2000** Statistical machine learning research that began in the 1980s achieves widespread practical use in major software services and mobile devices.



**2005** Computer scientist Sebastian Thrun, above, and a team from the Stanford Artificial Intelligence Laboratory build a driverless car named Stanley. It becomes the first autonomous vehicle to complete a 132-mile course in the Mojave Desert, winning the DARPA Grand Challenge. Stanley is now on exhibit in the Smithsonian.

**2009** Computer scientist Eric Horvitz assembles an AAAI study group on long-term AI futures, which holds its final meeting at Asilomar in California.

**2011** IBM's Watson supercomputing system beats the two best human players of the TV game show *Jeopardy!*, demonstrating an ability to understand and answer the types of nuanced questions that had previously bedeviled computer programs.

**2014** Stanford accepts proposal to host One-Hundred-Year Study on Artificial Intelligence.

## Dartmouth Artificial Intelligence (AI) Conference

*We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire.*

*The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves.*

- [Dartmouth AI Project Proposal](#); J. McCarthy et al.; Aug. 31, 1955.



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# Where are We? Where are We Headed?

- Transportation ← Short-term
- Home-service robots
- Healthcare
- Education
- Public safety and security
- Low-resource communities
- Employment and workspace ← Longer-term
- Entertainment

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# Employment and Workplace

- Near term: AI will replace more tasks than jobs
  - Will create jobs, but harder to predict what types
- Medium term: Path for lower costs for goods and services
  - Distribution of wealth will be an issue
- Long term: Fear of replacing all human jobs is overblown
  - Social safety nets may be needed

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# Key Takeaways

- “The Study Panel found no cause for concern that AI is a imminent threat to humankind.”
- “No machines with self-sustaining long-term goals and intent have been developed, nor are they likely to be developed in the near future.”



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# Key Takeaways continued...

- “Emerging technologies have potential to profoundly transform society and economy for the better by 2030.”
- “AI will not replace people, it will augment them.”
- “Need increased focus on building systems that can collaborate effectively with people.”
- “Towards intelligent systems that are human-aware and trustworthy”.

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# Interdisciplinary Issues

- Biases
- Transparency of AI
- Fair access
- Definition of responsibility
- Potential for good and bad
- Technical expertise at all levels of decision-making

# AI Implications (and a few more examples)

- We overestimate the impact of technology in the short term and underestimate it in the long term
- Things go from being really bad to really good in a few short years (voice, translation, etc.)
- Kaltura – just an API call...
- *McDonalds – voice ordering*
- *Manulife – voice analysis – live suggestions by a bot on customer (and agent) emotions, etc.*



# Implications in Higher Education

- LMS – student engagement tracking
- Collaboration Platform – usage, plagiarism, etc.
- Classrooms – student (faculty?) engagement, mood, tone (facial analysis and voice)
- CCTV – security, location, mood
- Student Residence – safety, waking hours, attendance
- Cafeteria/campus restaurants – wellness

# Concerns

- Student Privacy & Buy-In
- Faculty Concerns
- Other Potentially Inappropriate Uses:
  - Prediction of Student Success
  - Confirmation Bias
  - Likely lots more...

Establishing an initial governance framework will be critical to maintaining stakeholder trust