Smart Cities Tech

Piero Scaruffi

www.scaruffi.com

City Planning,
Los Angeles 1950

Summary

There is a difference between "smart" and "intelligent". Smart cities are popping up everywhere, but they are not necessarily cities where i personally would like to live. Artificial Intelligence can help them get "smarter" but hopefully it can also help them get "intelligent", i.e. hubs of creativity. Silicon Valley is never listed in the top smart cities of the world, but every country would like a Silicon Valley. For example, the Stanford Peace Innovation Lab works on creating intelligent, creative cities, not just smart cities.

Piero's 4 Challenges

Smart
vs
Intelligent

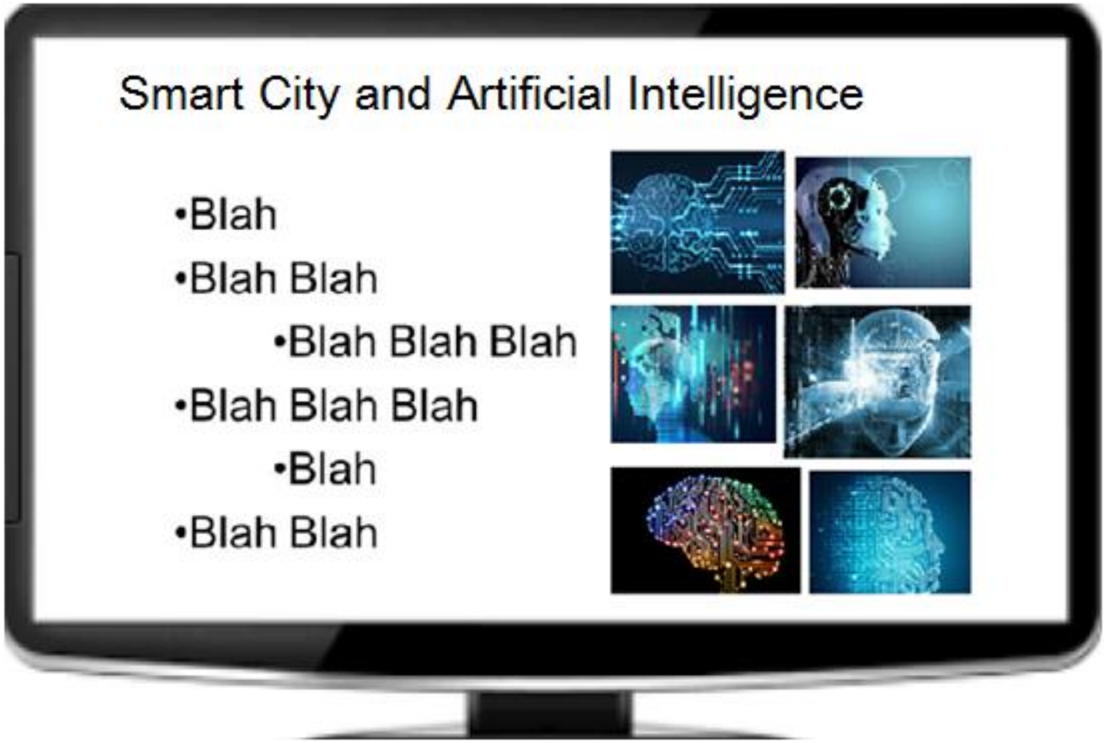
Silicon
Valley is
not smart

YC2016
Question

Smart
Cities are
not cities

Piero’s Challenge #1

Most presentations on “A.I. for Smart City” have 19 slides on Smart Cities and 1 slide on A.I. (which is probably just a picture of the brain)



Piero’s Challenge #2

IESE
Business School
University of Navarra

Silicon Valley is not a smart city…

TOP 10 SMART CITIES

	CITY	INDEX
1.	Tokyo	100%
2.	London	84%
3.	New York	81%
4.	Zurich	80%
5.	Paris	79%
6.	Geneva	76%
7.	Basel	71%
8.	Osaka	69%
9.	Seoul	68.3%
10.	Oslo	68%

Piero's Challenge #3

Answer the YC2016 question:

What should a city optimize for?

How can we measure its effectiveness?

What values to embed in its culture?

How can cities make their residents happy?

How should citizens guide government?

How can we make sure a city is constantly evolving and always open to change?

New Cities

By Adora Cheung

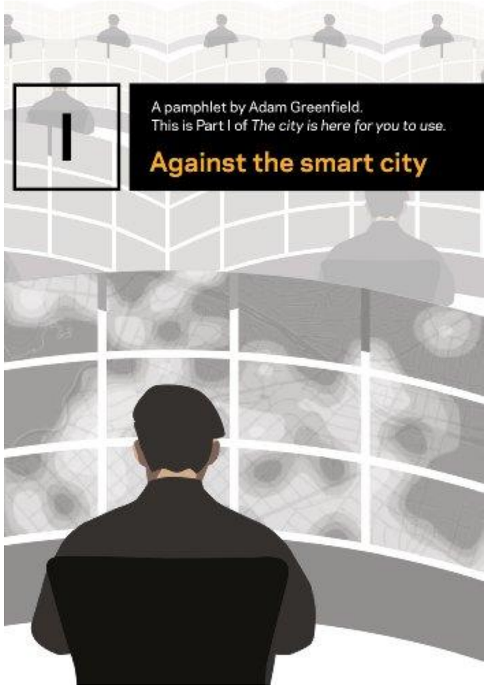
June 27, 2016

We want to study building new, better cities.

Piero’s Challenge #4

(I’m not sure I like smart cities!)

- Adam Greenfield’s book *“Against the Smart City”*: cities are products of specific geographies and economies (2013)
- Michael Batty: *"The image of the smart city which comes from the corporate world betrays a level of ignorance about how cities function that is woeful and dangerous"* (2014)



Michael Batty, Director of the Centre for Advanced Spatial Analysis at University College London s, author of "The New Science of Cities“

Piero's Challenge #4

(I'm not sure I like smart cities!)

Edward Glaser: "Technology lets us hold virtual meetings, and the Internet keeps us in touch 24/7, but neither can be a substitute for the social cues" (2011)

Shannon Mattern: "A city is not a computer" (2017)

Edward Glaeser
(Harvard University)

Engines of Innovation

Most of humanity now lives in a metropolis. That simple fact helps to fuel our continued success as a species

(Scientific American, 2011)

By Edward Glaeser

Shannon Mattern,
(The New School

Piero’s Challenge #4

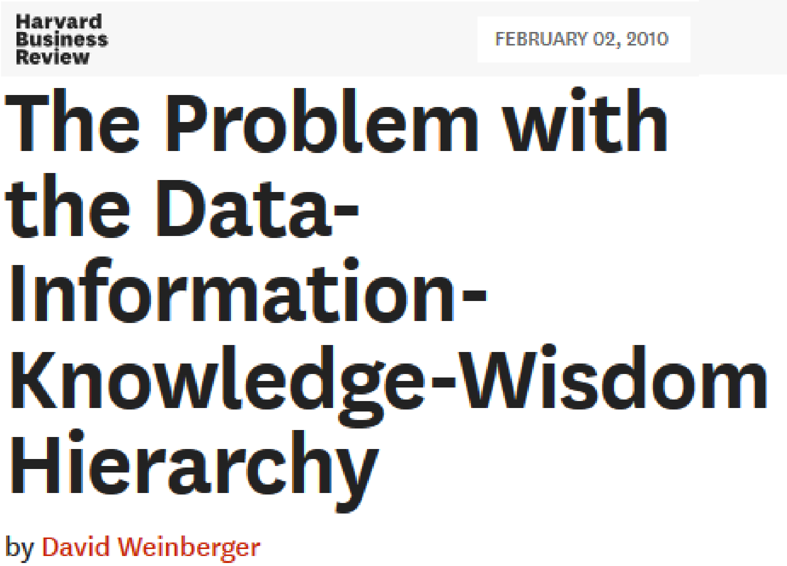
(I’m not sure I like smart cities!)

David Weinberger: “Knowledge is not a result merely of filtering or algorithms - knowledge is more creative, messier, harder won, and far more discontinuous” (2010)

Christine Rosen: “You cannot ‘co-shape’ an environment that was designed by others to prevent you from influencing it” (2012)

Christine Rosen
(New Republic)

David Weinberger
(Harvard University)


Harvard Business Review

FEBRUARY 02, 2010

The Problem with the Data-Information-Knowledge-Wisdom Hierarchy

by David Weinberger

Definitions!

"Smart" does not mean "intelligent"

- Your "smartphone" is NOT "intelligent"
- Your navigator is smart
- Your dish-washer is smart
- Many traffic lights are smart
- Apps for real-time bus locations and route options are smart
- They are NOT intelligent
- You ARE intelligent but not always smart!

Smart

Smart = efficient

How do you make a phone "smart"?

phone + camera + GPS + computer + apps

How do you make a city "smart"?

city + sensors + data + cloud + apps

Smart city: ***a unified digital platform that aggregates all data from a network of sensors into a single source, coordinates all operations across agencies, provides useful services to residents, all in real-time***

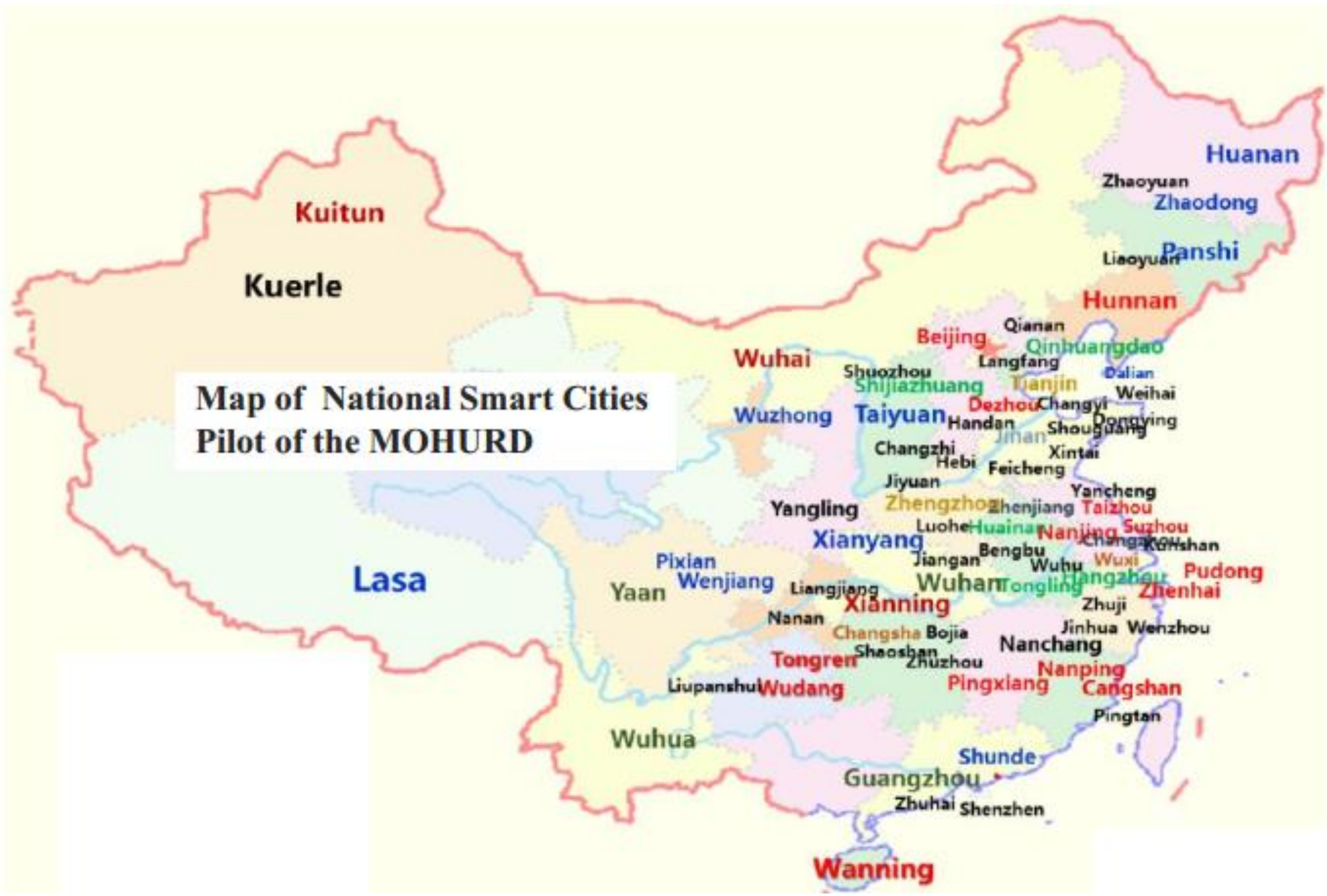
Smart City

How do you make a city “smart”?

An optimization problem

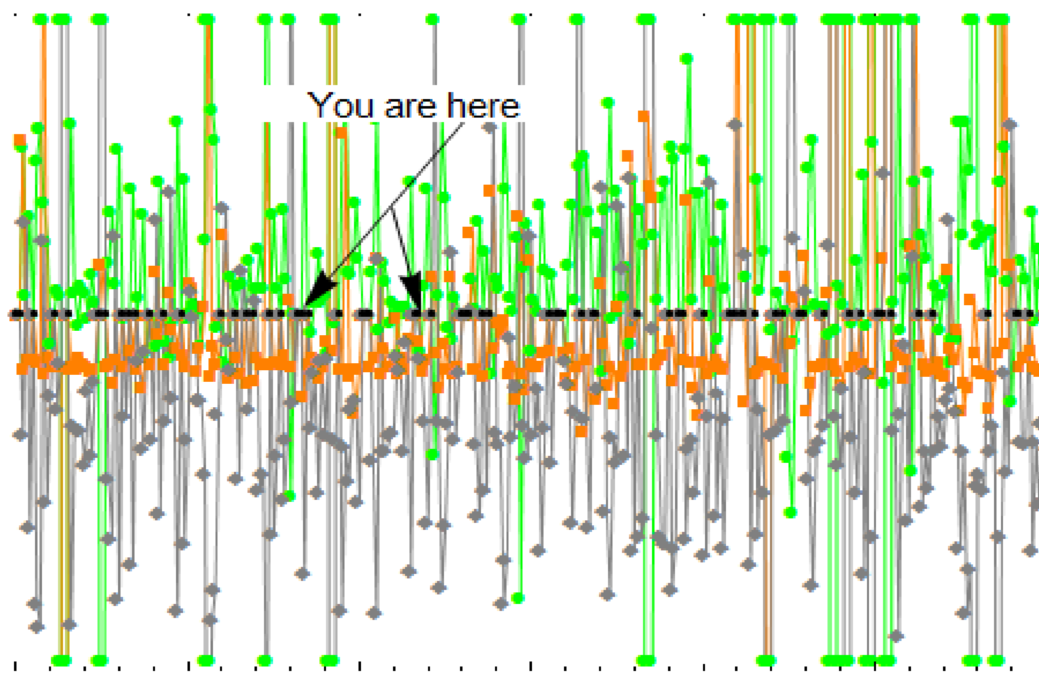
- Britain – OpenADR reduced peak electricity usage by 45%
- Dallas - Smart Cities Living Lab - measures pollutants
- Atlanta - Smart Corridor - adaptive traffic control system
- New York - Hudson Yards, “the first quantified community”
- Toronto & Sidewalk Labs

Smart Cities in China



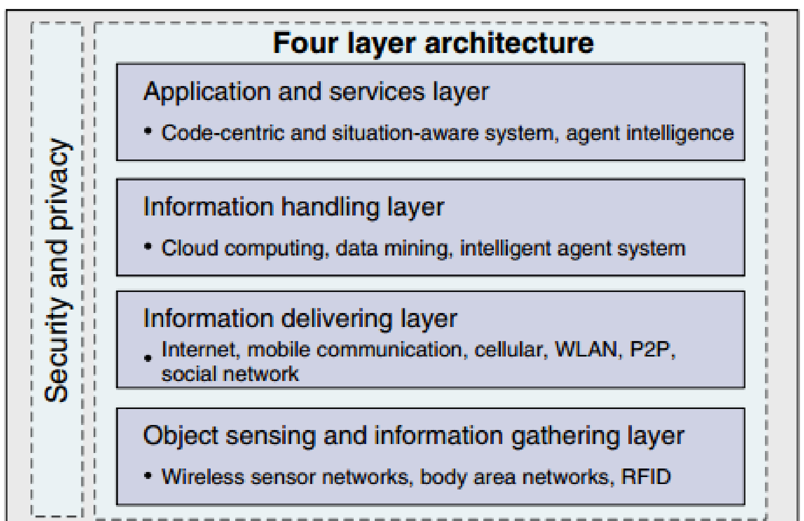
Smart City

A smart city is a heterogeneous system comprised of many interconnected subsystems, i.e. a nonlinear system



Smart City

- Four-layers model of the smart city
  - sensor layer
  - network layer
  - platform layer
  - application layer



Min Chen. 2012

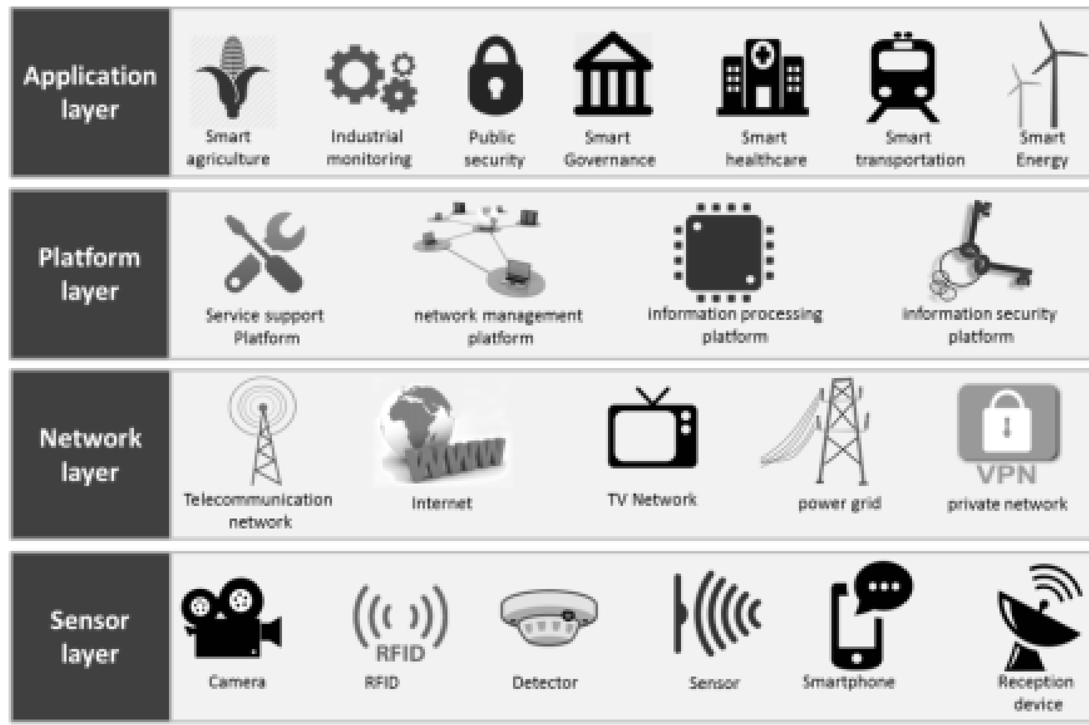
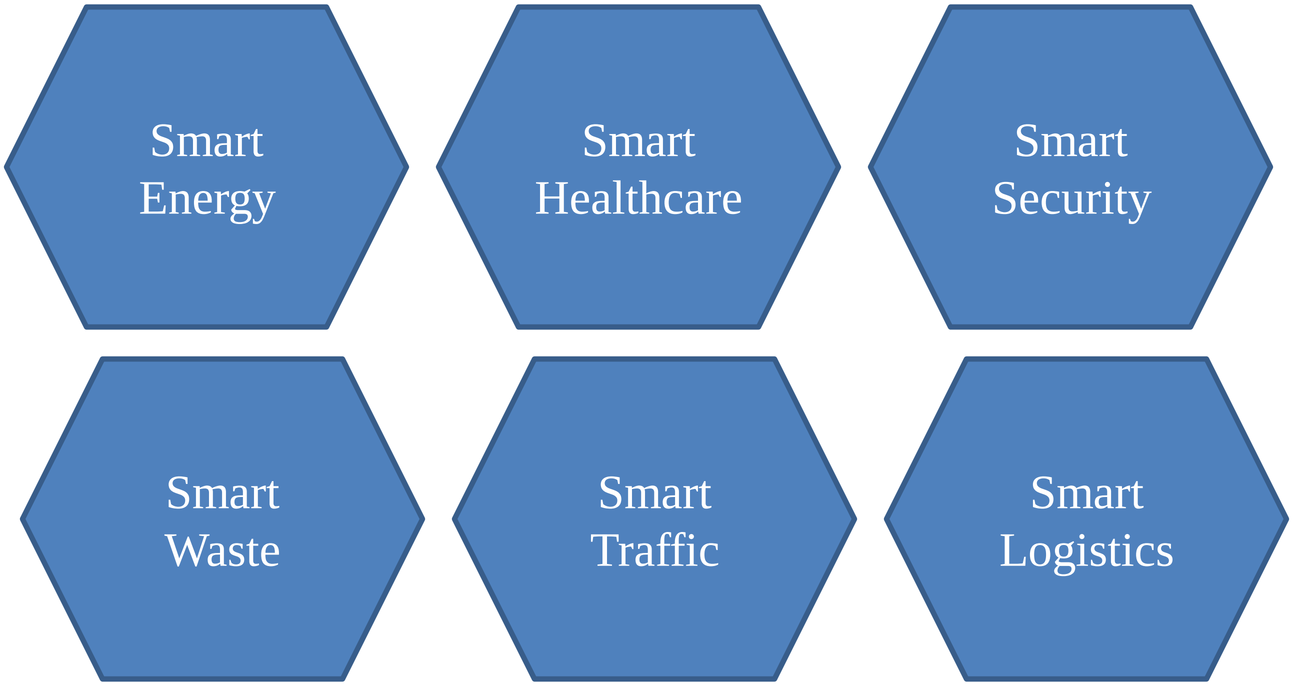
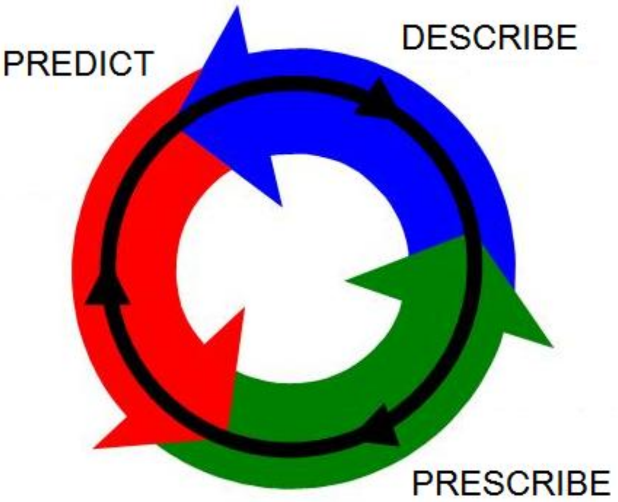


Figure 2. Four layers of smart city Yongling Li, Yanliu Lin and Stan Geertman

Smart Apps


Smart Energy
Smart Healthcare
Smart Security
Smart Waste
Smart Traffic
Smart Logistics

Tools for Smart Planners



- Planners need:
  - Descriptive tools
  - Predictive tools
  - Prescriptive tools
- Descriptive models approximate current behavior
- Predictive algorithms forecast future human behavior
- Prescriptive models enforce changes in human behavior

The “City-as-computer" Metaphor

"The city is a computer, the streetscape is the interface, you are the cursor, and your smartphone is the input device” (Paul McFedries, 2014)

Smart Apps

- Rubicon Global (Kentucky): the 'Uber for Trash'
- Rubicon's app for smart cities: to track and optimize fleets of garbage trucks, in turn feeding data back into their city's IT systems

Forbes December 2016

The City Of Atlanta Will Now Pick Up Its Trash Using An App From Tech Startup Rubicon Global

Smart Apps

- Swiftly (Bay Area) develops enterprise software to help transit agencies and cities improve urban mobility

Rationale for Shared Mobility

- Cars are people's second most expensive household expenditure…
- … but they sit unused 20+ hours a day
- When they are used, they also need to find parking

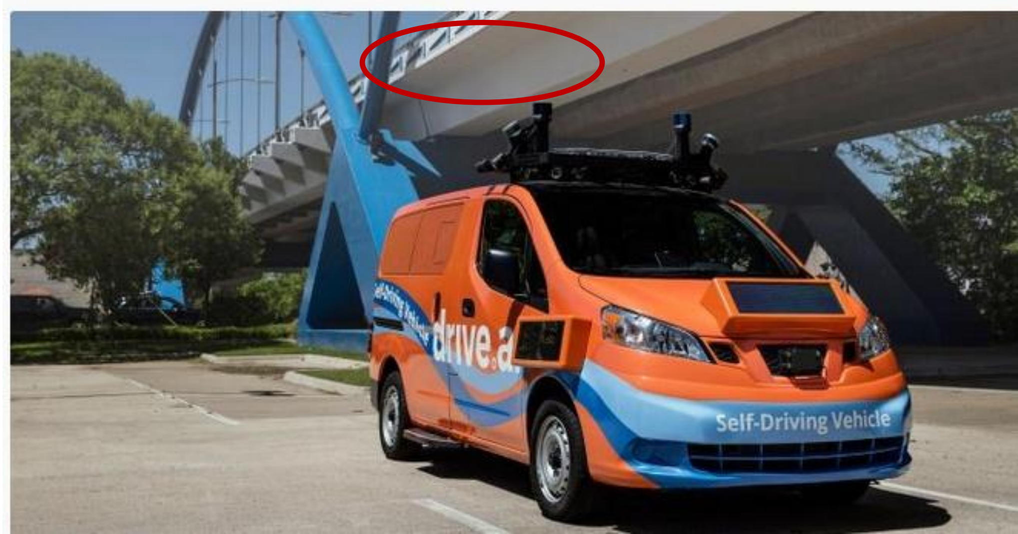
Shared Autonomous Mobility

- Mercedes (2016)
- NTU (2017)
- Drive.ai (Mountain View, 2018)


Interior of the Mercedes Benz autonomous concept car at the 86th International Geneva Motor Show in Palexpo, Geneva, March 1, 2016

Driverless car startup Drive.ai is launching a ride-hailing service in Texas

By Alison Griswold • May 7, 2018



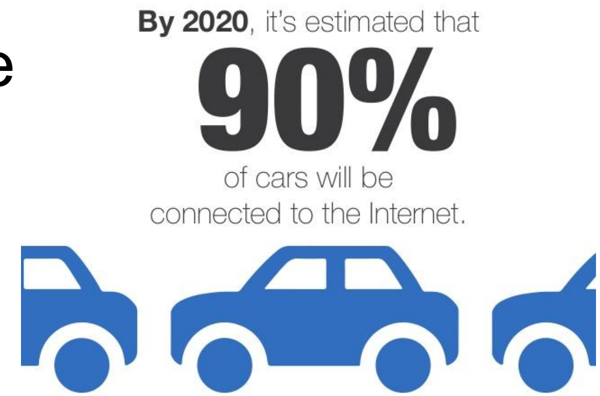

Nanyang Technological University (NTU),

Ride-sharing Problem

- Schaller Consulting (2018): Ride-sharing increased traffic by 160% *(“cities are likely to be overwhelmed with more automobility, more traffic and less transit”)*

Connected Mobility

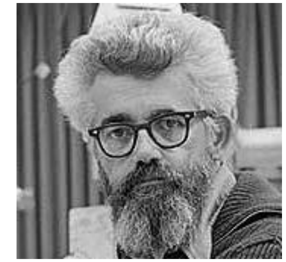
- An "internet of cars“: a system to share real-time data from vehicles, roads, traffic signals, etc
  - Infotainment
  - Diagnostics
  - Parking
  - Ride sharing
  - Driver behavior
  - …



What next?

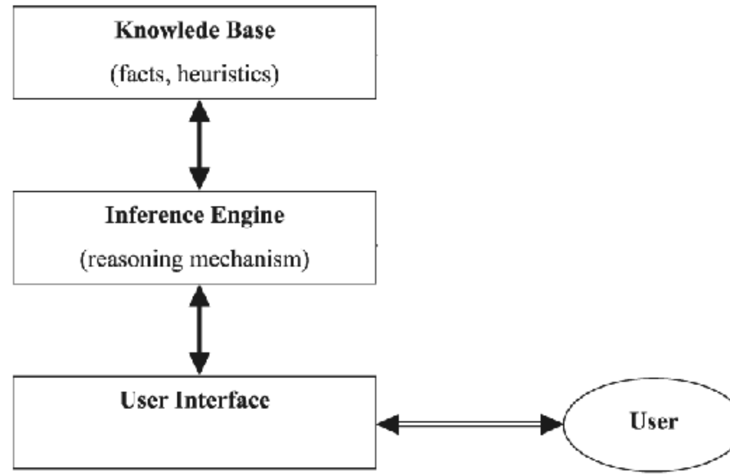
“Smart” does not mean “intelligent”

The two schools of A.I.

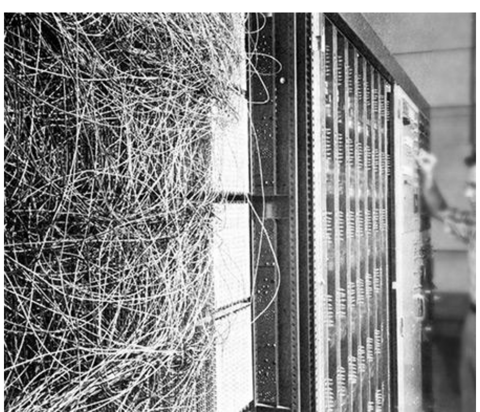


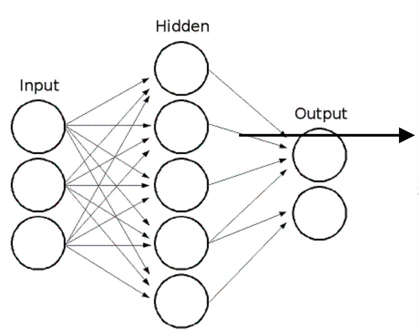
Artificial Intelligence (1956)

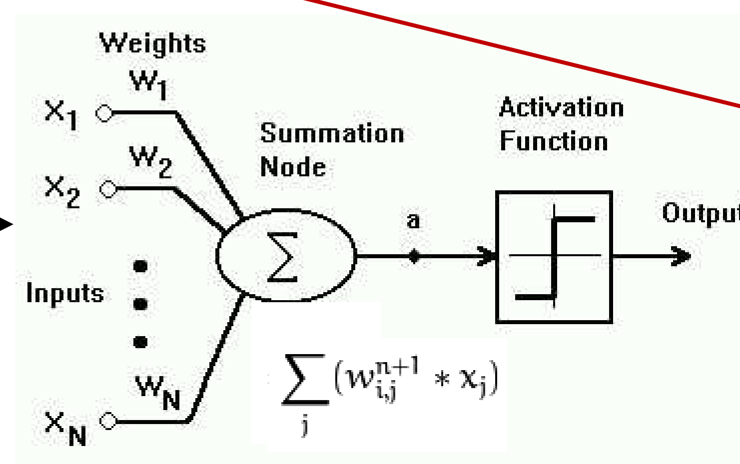
- Knowledge-based approach uses mathematical logic to simulate the human mind



- Neural-net approach simulates the structure of the brain

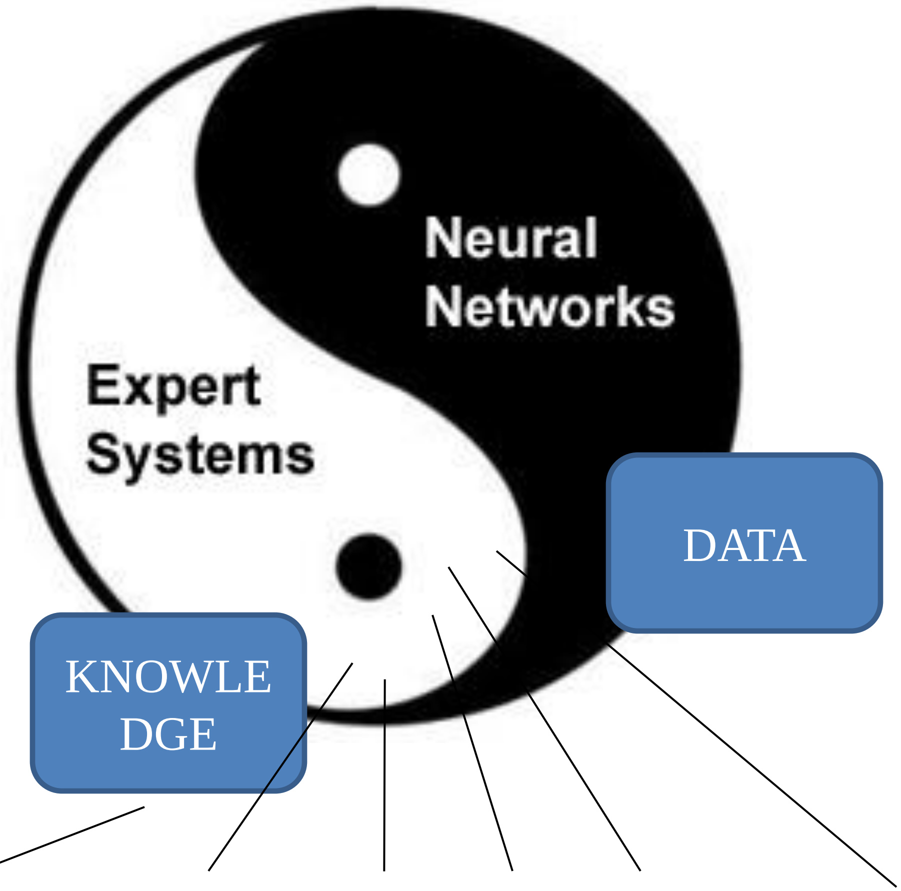






The two schools of AI

1956: Allen Newell and Herbert Simon’s "Logic Theorist“
1959: John McCarthy's "Programs with Common Sense"
1965: Ed Feigenbaum's Dendral
1965: Lofti Zadeh’s Fuzzy Logic
1966: Ross Quillian's Semantic Networks
1969: SRI's Shakey the Robot
1969: Roger Schank’s Conceptual Dependency Theory
1972: Bruce Buchanan's MYCIN
1972: Terry Winograd's SHRDLU
1974: Marvin Minsky's Frame



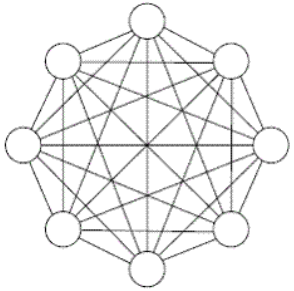
Knowledge-based A.I. failed

1957: Herbert Simon: *"there are now in the world machines that think, that learn, and that create"*

1970: Marvin Minsky: *“In from three to eight years we will have a machine with the general intelligence of an average human being”*

The Rise of Neural Networks

1982: John Hopfield's recurrent neural network



$$E(v) = -\frac{1}{2}\sum_{i \neq j}\sum_{i,j} w_{ij} v_i v_j - \sum_i I_i v_i + \sum_i \frac{1}{R_i}\int_0^{v_i} f_i^{-1}(z)dz$$

$$\nabla_v E(v) = Wv + I - u / R$$

1983: Terry Sejnowski's and Geoffrey Hinton's Boltzmann machine

$$\boldsymbol{P(x)} = \frac{\exp(-\boldsymbol{E(x)})}{\boldsymbol{Z}}$$

> E(x): Energy function

> Z: partition function where $\sum_x P(x) = 1$

1985: Judea Pearl's "Bayesian Networks"

$P(C,S,R,W,F) = P(C)\,P(S|C)\,P(R|C)\,P(W|R,S)\,P(F|R)$

$P(C,F) = \sum_S \sum_R \sum_W P(C,S,R,W,F)$

$P(F|C) = P(C,F) / P(C)$

Neural Networks

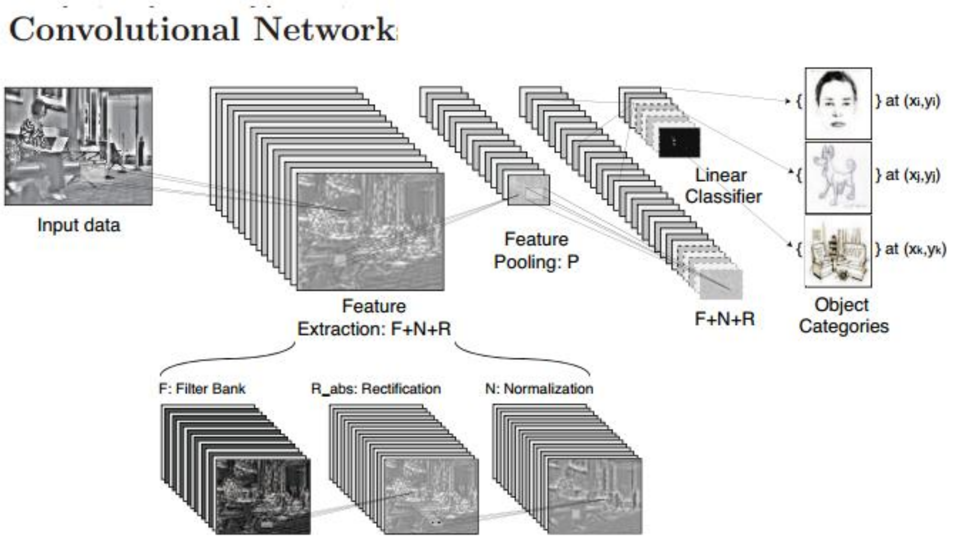
1990s: Yann LeCun's convolutional networks

Given functions $x(t)$ and $w(t)$, their convolution is a function $s(t)$

$$s(t) = \int x(a)w(t-a)da$$

Written as

$$s = (x * w) \quad \text{or} \quad s(t) = (x * w)(t)$$

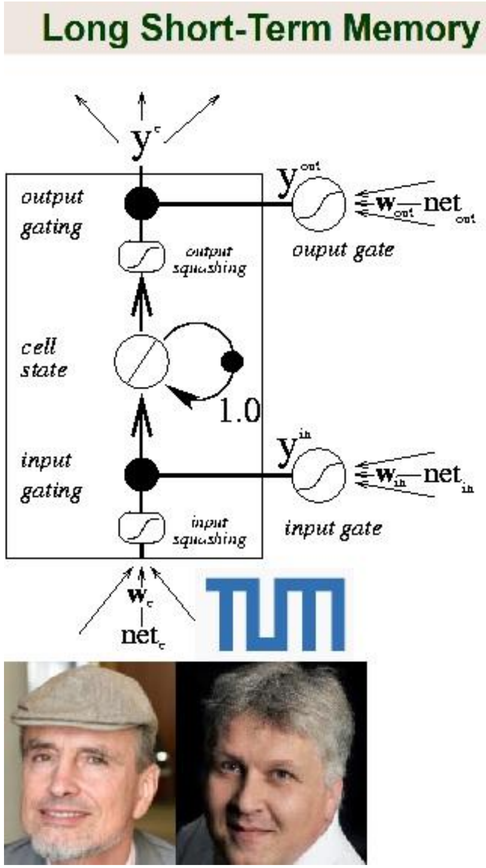


Architecture of a typical convolutional network for object recognition

From a paper by Yann LeCun

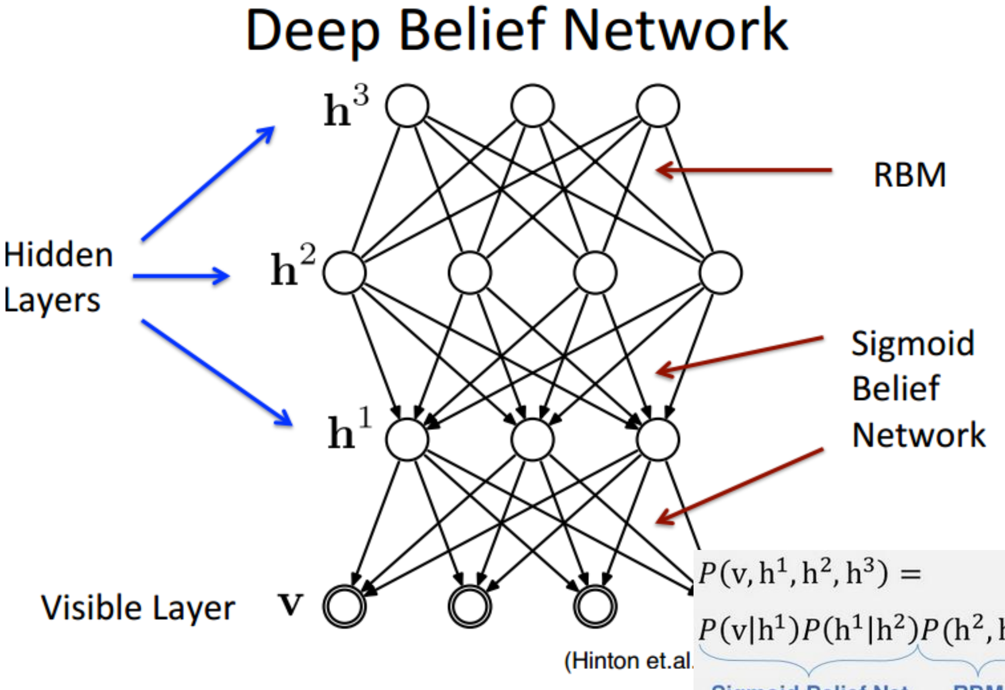
Neural Networks

1997: Sepp Hochreiter's and Jeurgen Schmidhuber's Long Short Term Memory (LSTM) model



Deep Learning

2006: Geoffrey Hinton's Deep Belief Networks

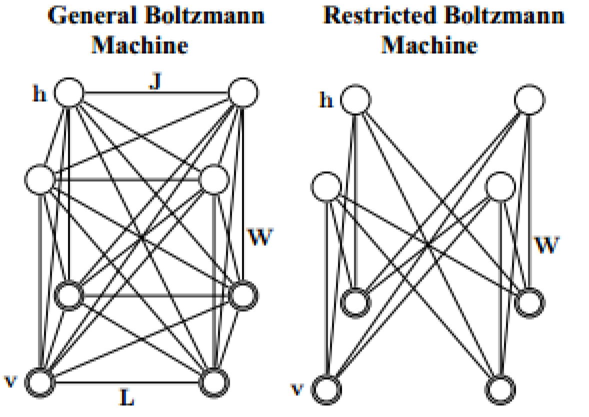


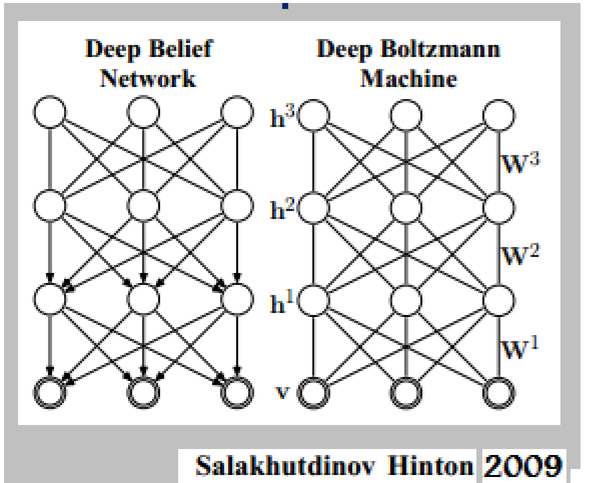
$$P(\mathrm{v},\mathrm{h}^1,\mathrm{h}^2,\mathrm{h}^3) = \underbrace{P(\mathrm{v}|\mathrm{h}^1)P(\mathrm{h}^1|\mathrm{h}^2)}_{\text{Sigmoid Belief Net}}\underbrace{P(\mathrm{h}^2,\mathrm{h}^3)}_{\text{RBM}}$$

$$P(\mathrm{v}|\mathrm{h}^1) = \prod_i P(v_i|\mathrm{h}^1)$$

$$P(\mathrm{h}^1|\mathrm{h}^2) = \prod_j P(h_j^1|\mathrm{h}^2)$$

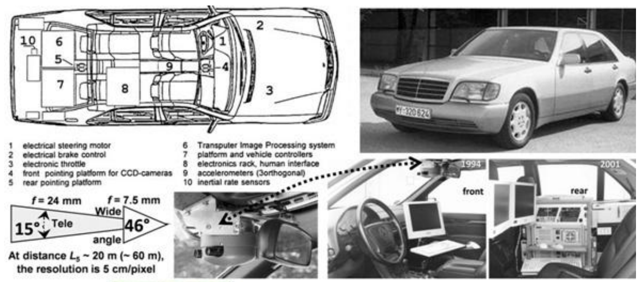
$$P(\mathrm{h}^2,\mathrm{h}^3) = \frac{1}{Z(W^3)}\exp(\mathrm{h}^{2T}W^3\mathrm{h}^3)$$





No need for Neural Nets

1994: Ernst Dickmanns' self-driving car drives more than 1,000 kms near the airport Charles-de-Gaulle in Paris



The "VAmP" Mercedes 500 SEL

1997: IBM's "Deep Blue" chess machine beats the world's chess champion, Garry Kasparov

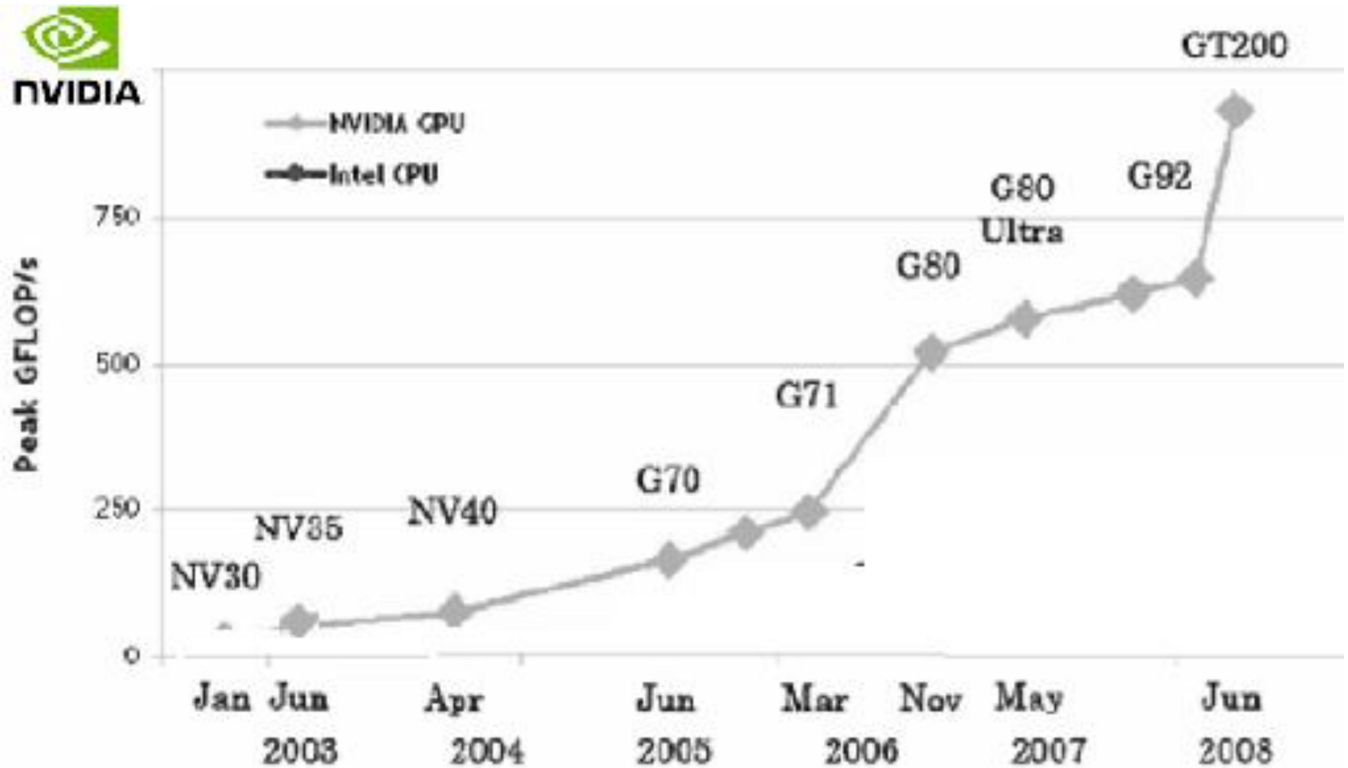
No need for Neural Nets

2011: IBM's Watson debuts on a tv show

2011: Apple Siri (2011)

The real heroes of Deep Learning

Nvidia's GPUs



Deep Learning is born

Nvidia Tesla P100 for deep learning

Evolution of Neural Networks

Reinforcement Learning

1950s

Recurrent Neural Networks

1980s

Convolutional Neural Networks

1990s

…

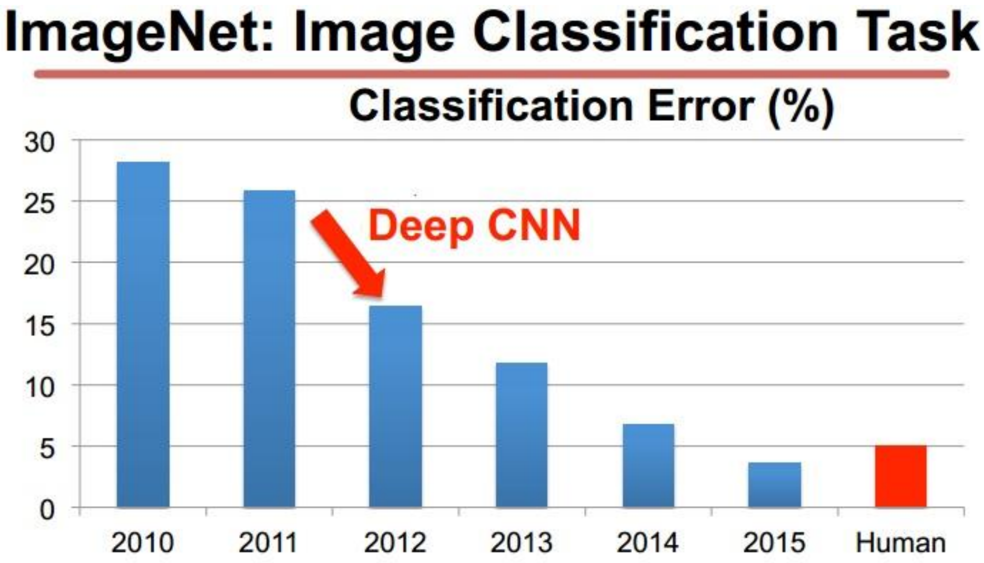
Generative Adversarial Networks

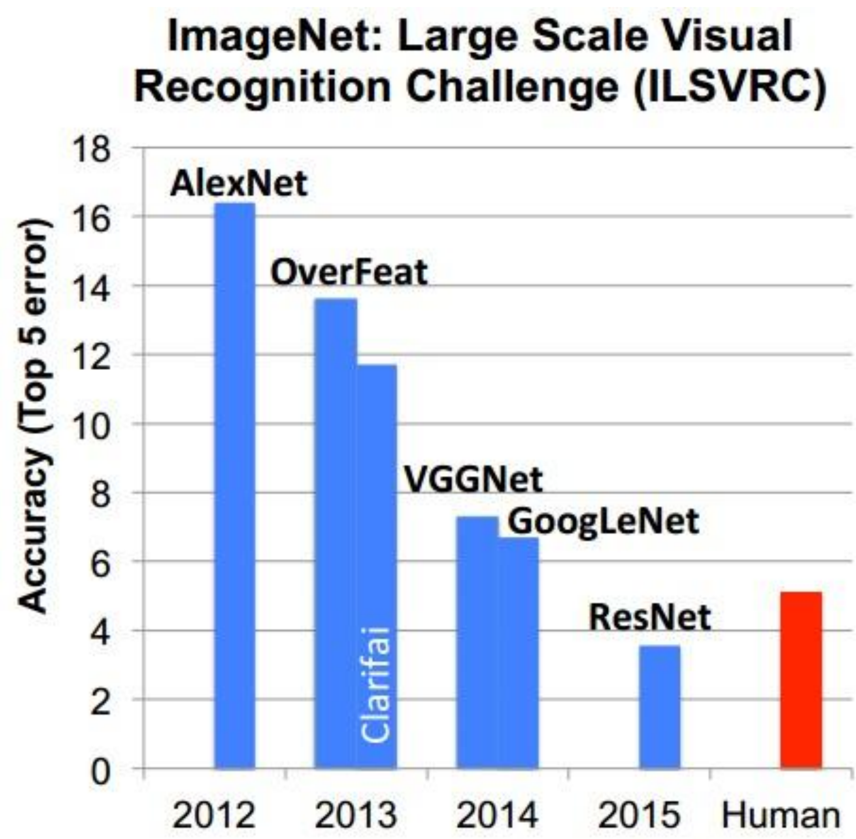
2010s

Reinforcement Learning

Google/DeepMind’s AlphaGo beats weichi champions

Convolutional Nets





Recurrent Neural Nets

- Using RNNs to guess the next word
- Using RNNs for machine translation
- Using RNNs for scene analysis

Recurrent Neural Nets

https://research.googleblog.com/2014/11/a-picture-is-worth-thousand-coherent.html

Generative Adversarial Networks

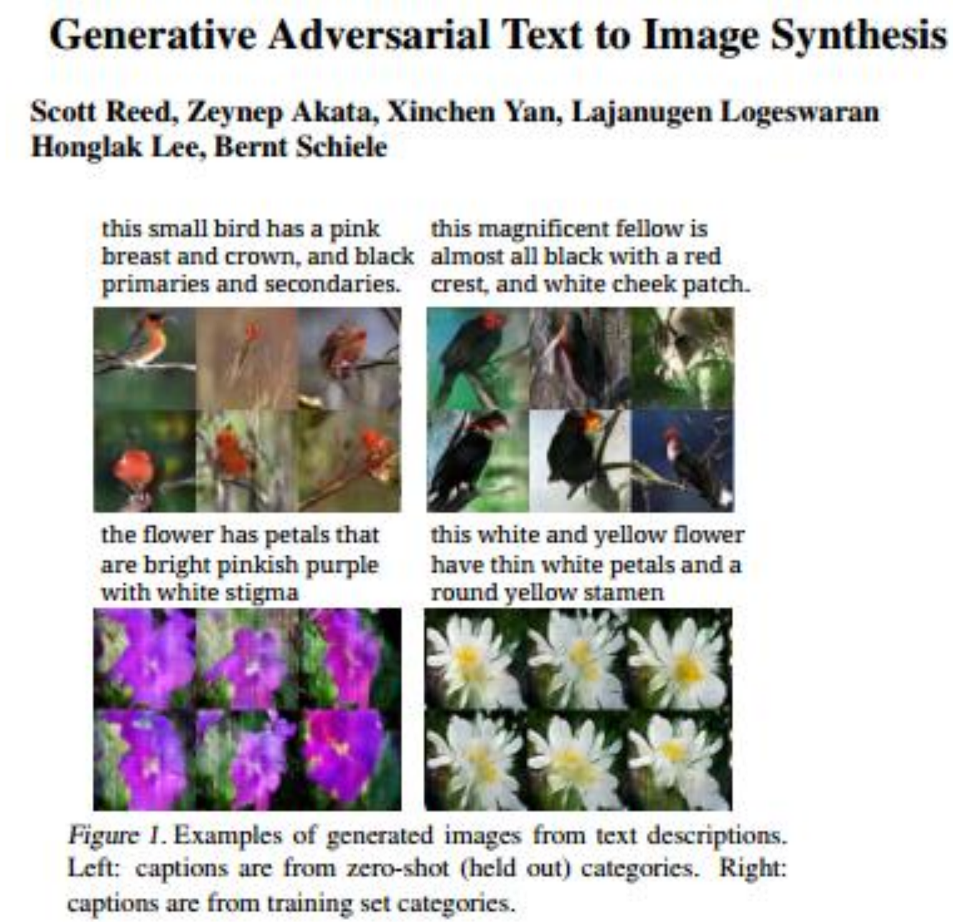
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks

Alec Radford, Luke Metz, Soumith Chintala

All images in this paper are generated by a neural network. They are NOT REAL.

Generative Adversarial Networks

- Text to image synthesis



Generative Adversarial Text to Image Synthesis

Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran
Honglak Lee, Bernt Schiele

this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.

the flower has petals that are bright pinkish purple with white stigma

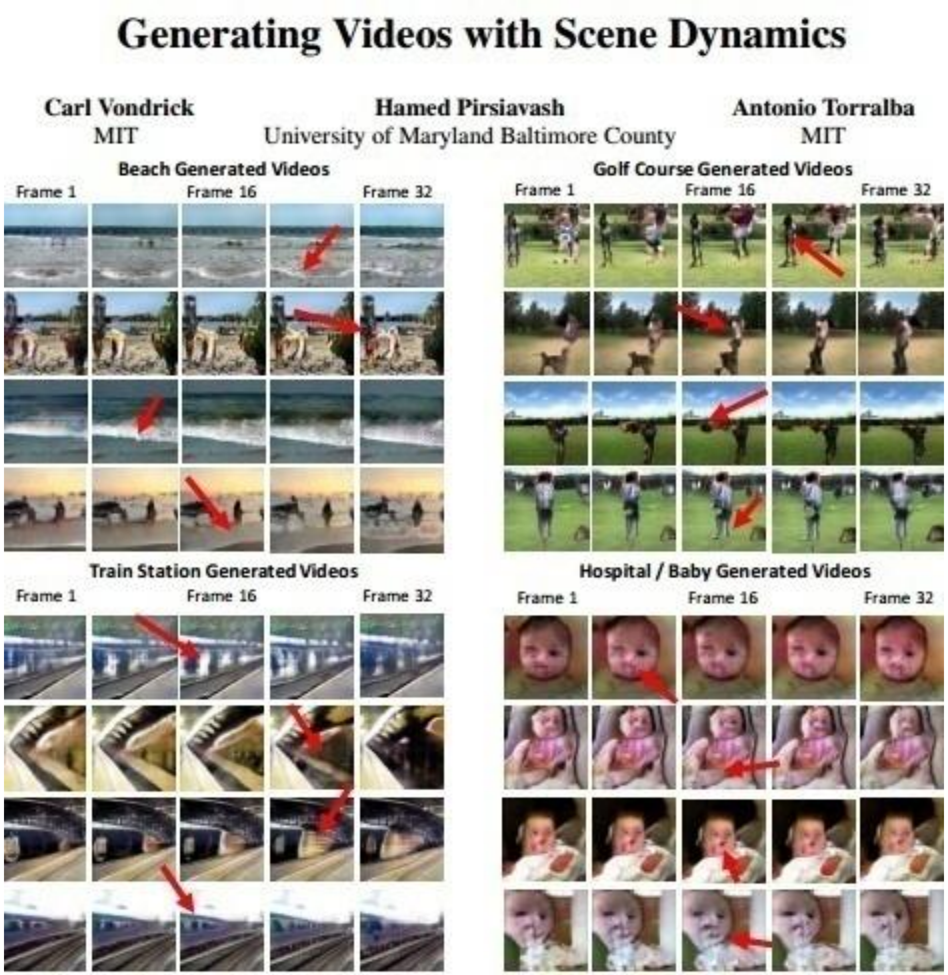
this white and yellow flower have thin white petals and a round yellow stamen

Figure 1. Examples of generated images from text descriptions. Left: captions are from zero-shot (held out) categories. Right: captions are from training set categories.

Generative Adversarial Networks

- Video generation

Vondrik   Torralba



Pattern Recognition

Classifies data into known categories

Uncovers information that was unknown before

Implicitly builds an approximate model of a nonlinear system

Implicitly discovers possible optimizations

Advises decision makers where perfect solutions don’t exist

Can it help?

Smart City

- Four-layers model of the smart city
  - sensor layer
  - network layer
  - platform layer
  - application layer

Pattern Recognition

- Classifies data
- Uncovers information
- Builds a model
- Discovers optimizations
- Decision making

Sensor layer: A new generation of “intelligent” sensors that can recognize situations

Network layer: A new generation of network optimization algorithms

Platform layer: A new generation of integrated platforms for situation analysis

Pattern Recognition

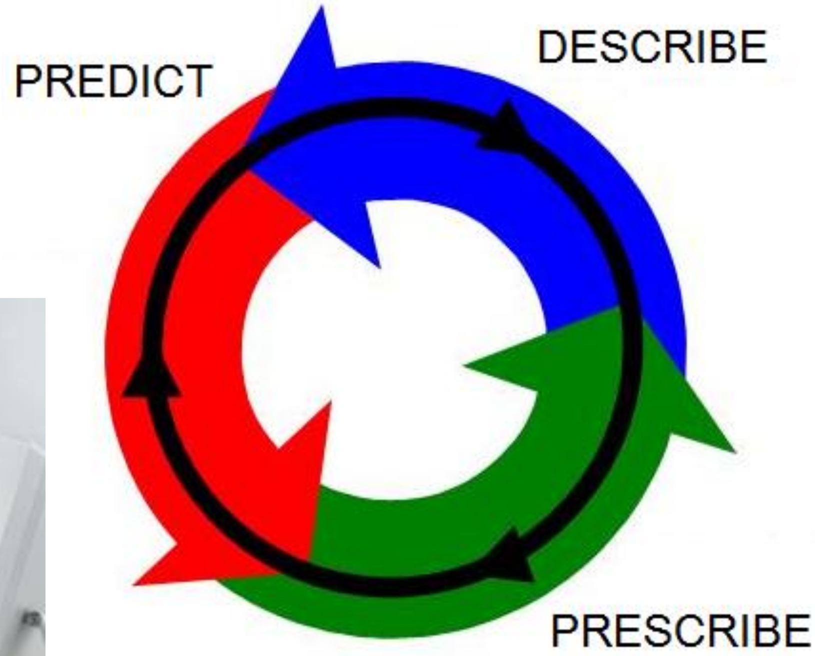
Application layer:

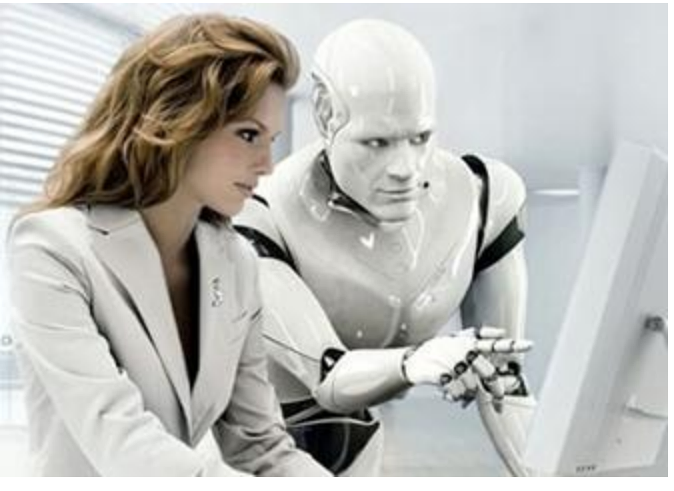
A new generation of situation-based applications (e.g. emergencies)

A new generation of citizen-city interaction (each citizen can have a digital personal assistant)

Pattern Recognition

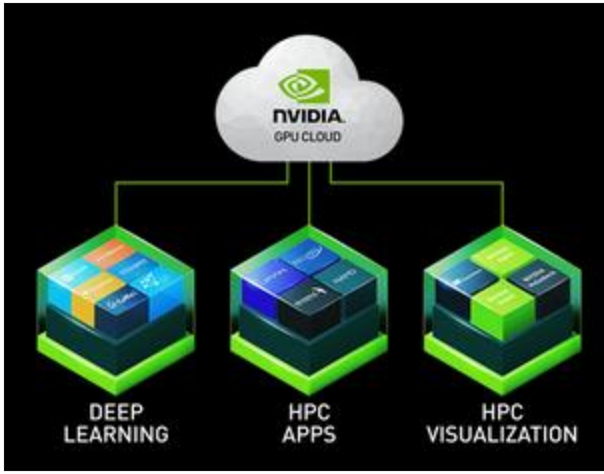
Can it help city planners?





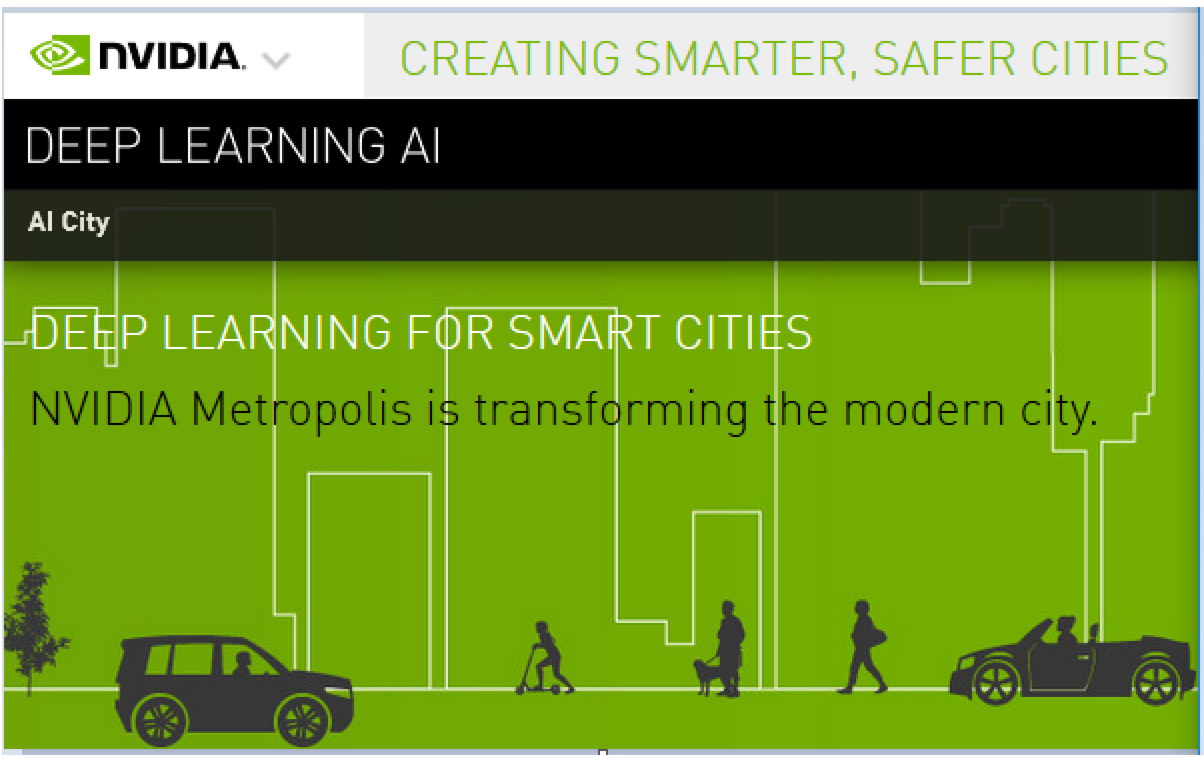
Case Studies

- NVIDIA Metropolis (May 2017)
- Cloud-based video analytics platform
  - Learn from video data collected by the city's security and traffic cameras
  - Monitor video in real-time and view video recordings 30 times faster than humans
  - Help to manage traffic, parking, law enforcement, and other city services.
  - Metropolis = Tesla GPU accelerators + deep learning software + DGX-1 cloud-based supercomputers



Case Studies

- NVIDIA Metropolis (May 2017)
  – Sep 2017: Nvidia partners with Alibaba and Huawei



Alibaba, Huawei Adopt NVIDIA's Metropolis AI Smart Cities Platform

Case Studies

- IBM Smarter Planet (2009)

Cognitive government

The next generation of buildings

Case Studies

- Microsoft Smart Cities for All (May 2017)
  - Smart cities that are friendly towards people with disabilities.
  - In collaboration with G3ict and World Enabled
- Virtual assistant named Chip (Los Angeles)
- A prototype police vehicle

Microsoft

TechRepublic

INNOVATION

Smart Cities NYC '17: Microsoft's deep dive into smart city tech

Microsoft made several announcements at Smart Cities NYC '17, including a new
for building accessible and inclusive cities. Also featured was an AI virtual assist
Los Angeles.

By Teena Maddox | May 5, 2017, 11:53 AM PST

Case Studies

- AT&T Smart Cities framework (2015)
  - Alliances with Cisco, Deloitte, Ericsson, GE, IBM, Intel, and Qualcomm
  - Exclusive reseller of GE Current's intelligent sensor nodes for connecting cities
  - GE will provide San Diego with largest smart city IoT sensor platform
  - Acumos: open-sourced AI project with Linux Foundation

Case Studies

- SMILE (Synchronized Multi-sensory Integrated Learning Environment) at CMU (2019)
- A smart city is a system of systems
- Integration of heterogeneous and non-compatible (separately-built, separately-owned, and separately-controlled) sensing and learning sub-systems

Case Studies

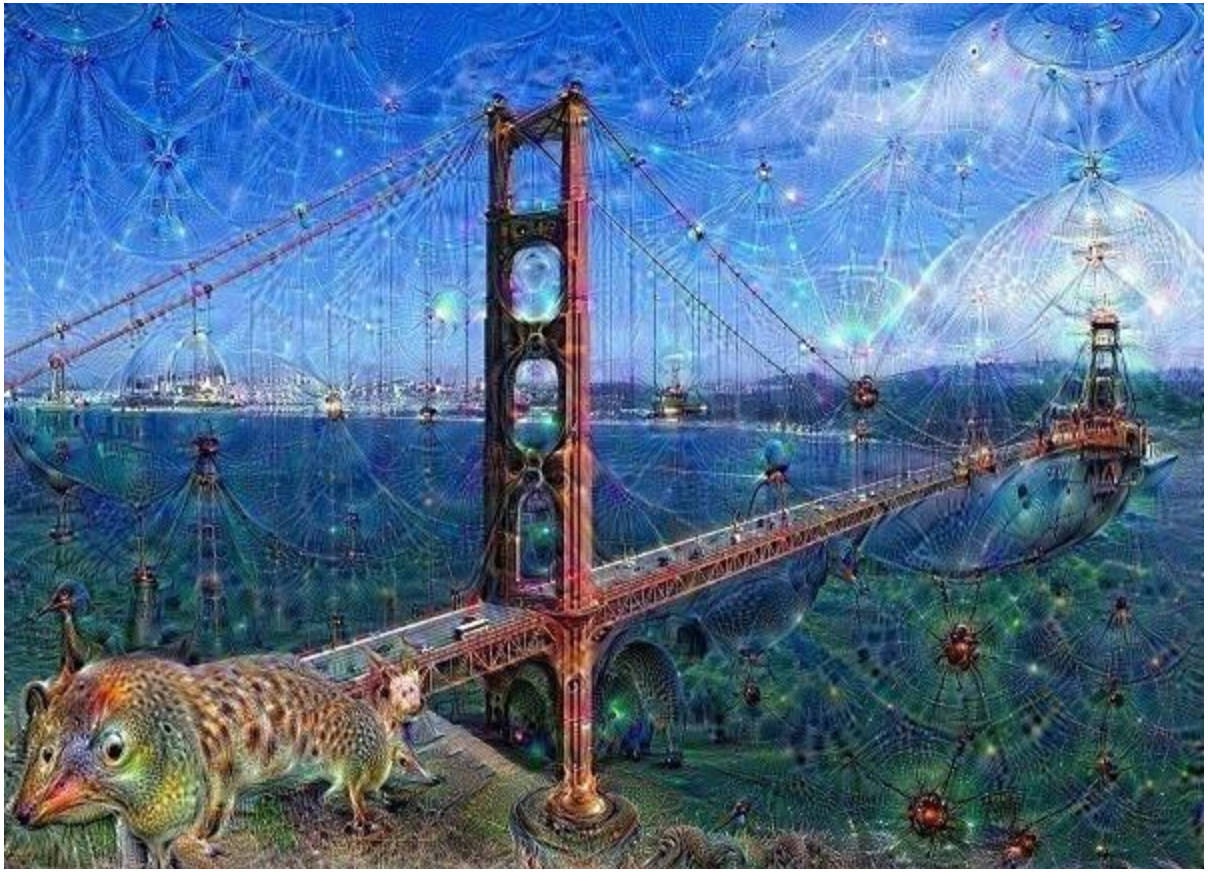
- Synchronized Multi-sensory Integrated Learning Environment, (SMILE)
- Clusters of drones + on-board deep learning + ground-based deep learning + air-to-ground video link
- High-performance, low-power processors and real-time sensory data processing
- Dynamic enrollment of drones into the cluster and transfer learning

Piero's 4 Challenges

- Smart vs Intelligent
- Silicon Valley is not smart
- YC2016 Question
- Smart Cities are not cities

Making smart cities attractive

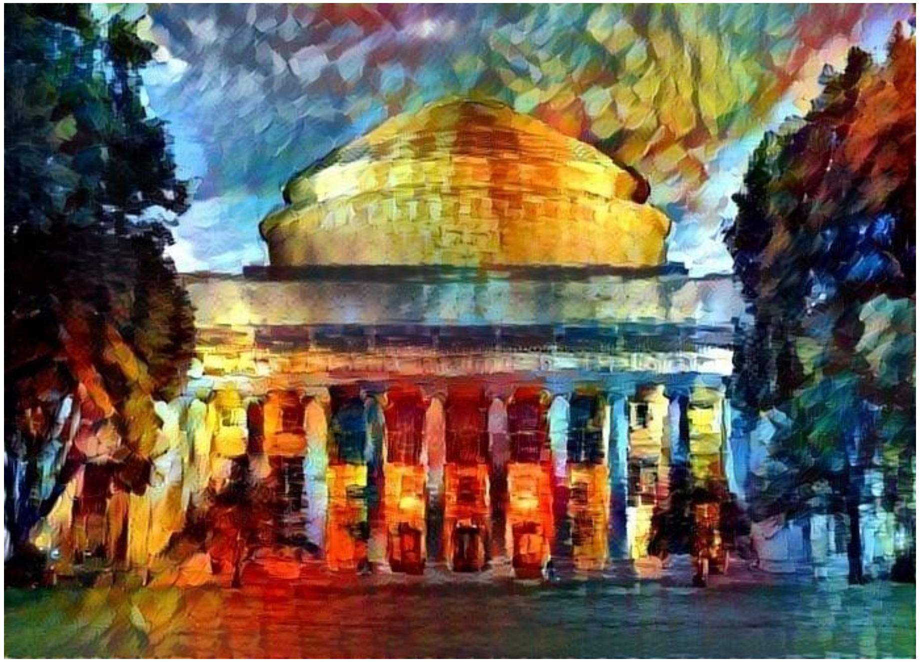
Alexander Mordvintsev's "Inceptionism“ (2015)



Making smart cities attractive

Leon Gatys and Alexander Ecker’s "A Neural Algorithm of Artistic Style“ (2015)

Leonid Afremov



Neural Network

Making smart cities friendly

Smart citizenship should be about *"exercising rights and responsibilities" and "advancing democratic engagement through dialogue and debate"* (Hannah Arendt, 1958)

"People want to co-*create with the whole process- the challenge is bringing them inside the process as a massive stakeholder"* (Renato de Castro, global advisory board of Leading Cities)

Making smart cities friendly

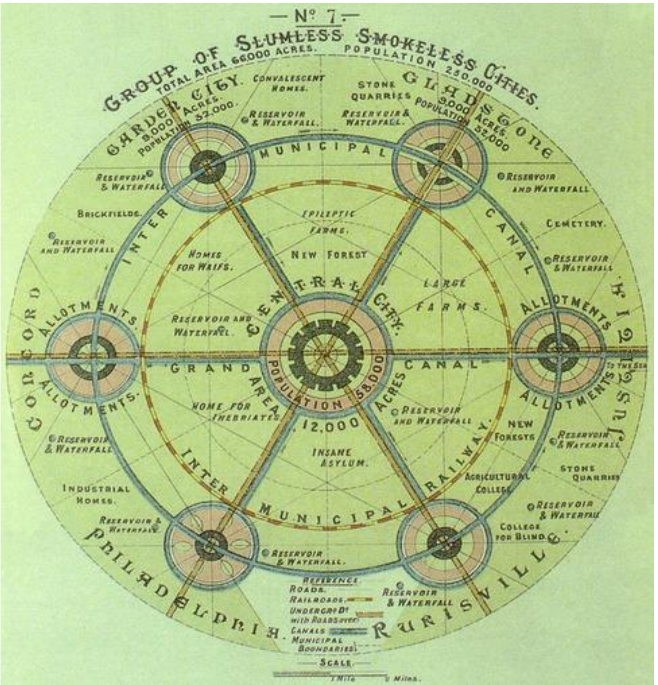
Enable citizen innovation

Citizen-generated data (not only sensor-generated data), e.g. Civicus DataShift

DATASHIFT

Making smart cities creative

- Smart city or creative city?
- Avoid the “cyburgs”
  - Ebenezer Howard: Garden City (1898)
  - LeCorbusier’s Plan Voisin (1924)



Making smart cities creative

- Smart city or creative city?
- The modern cyburgs?
  - Songdo (South Korea)
  - Masdar (UAE)

Smart City or Creative City?

IESE
Business School
University of Navarra

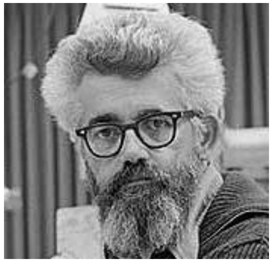
TOP 10 SMART CITIES

	CITY	INDEX
1.	Tokyo	100%
2.	London	84%
3.	New York	81%
4.	Zurich	80%
5.	Paris	79%
6.	Geneva	76%
7.	Basel	71%
8.	Osaka	69%
9.	Seoul	68.3%
10.	Oslo	68%

Making smart cities creative

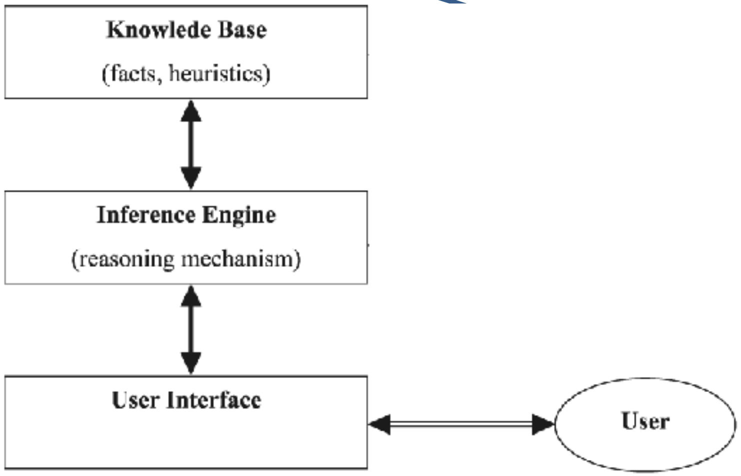
A Smart City is a city that gives inspiration, that motivates its inhabitants to create, an incubator of constant ubiquitous innovation.

The two schools of A.I.

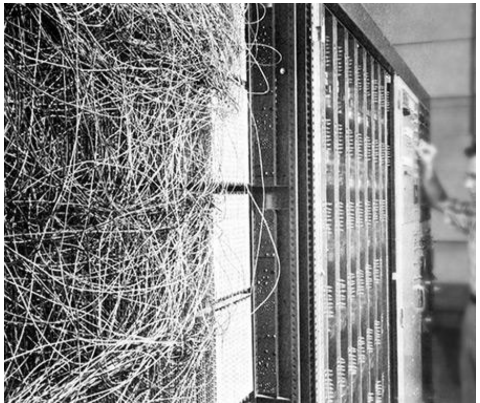


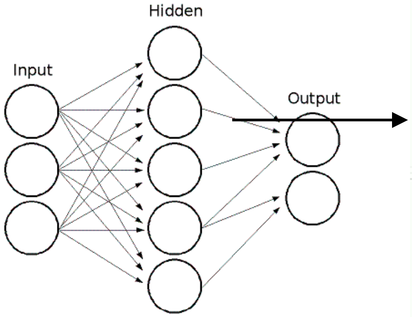
Artificial Intelligence (1956)

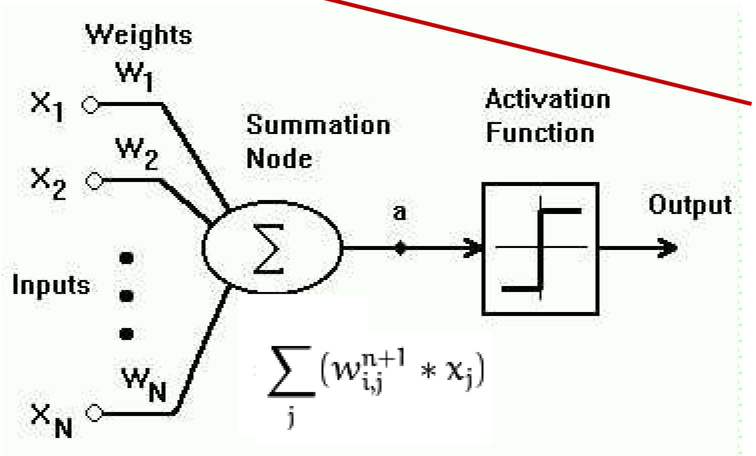
- Knowledge-based approach uses mathematical logic to simulate the human mind



- Neural-net approach simulates the structure of the brain







Peace Innovation Lab

PEACE INNOVATION LAB
Stanford University

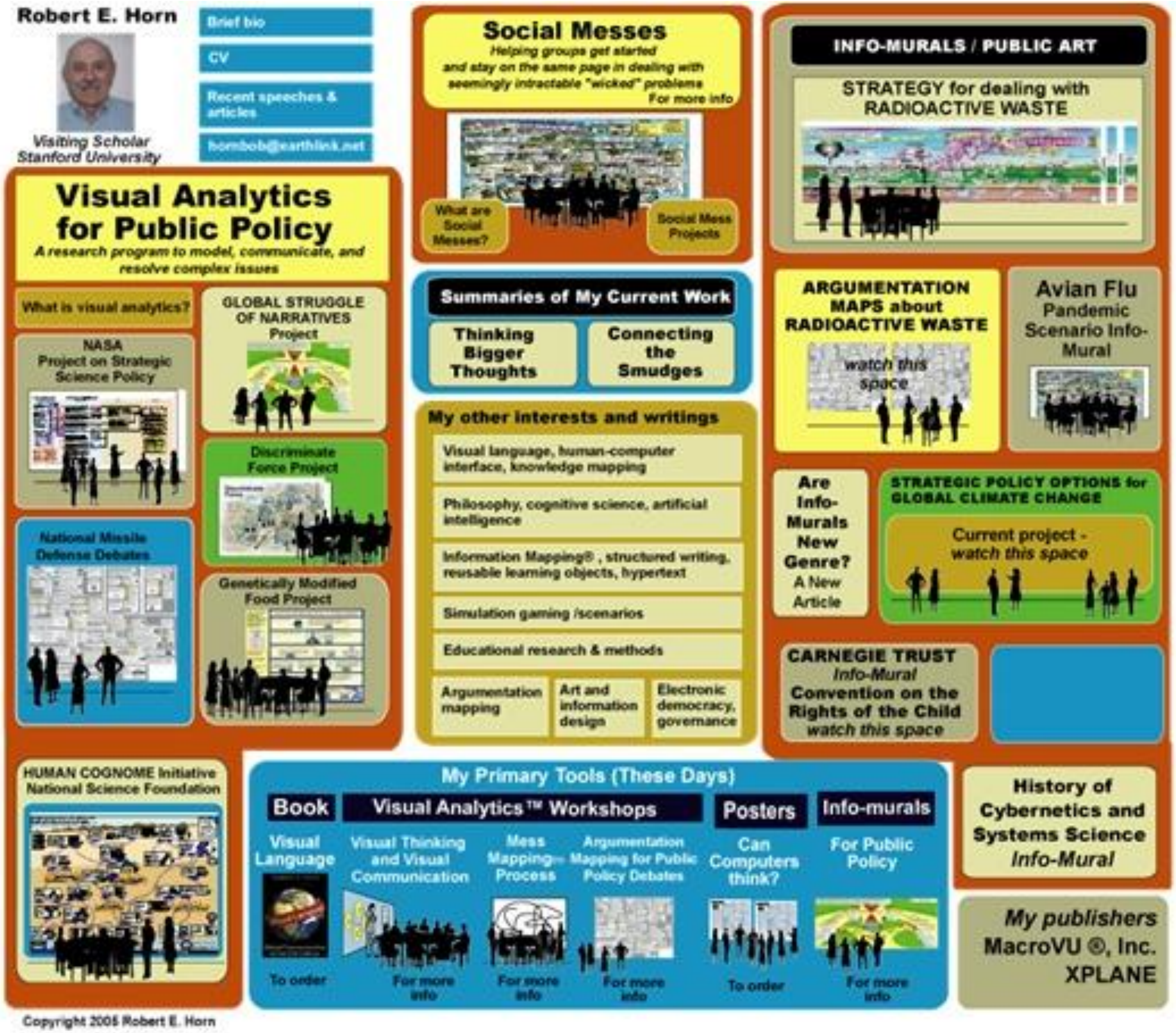
German chancellor Angela Merkel visiting the Berlin Peace Innovation Lab (2016)

Positive Engagement

- Improving the existing “positive engagement” (“peace”) generates new wealth for the city
- People’s ability to create new wealth directly depends on how “good” they can be to each other
- Cities are engines of positive engagement

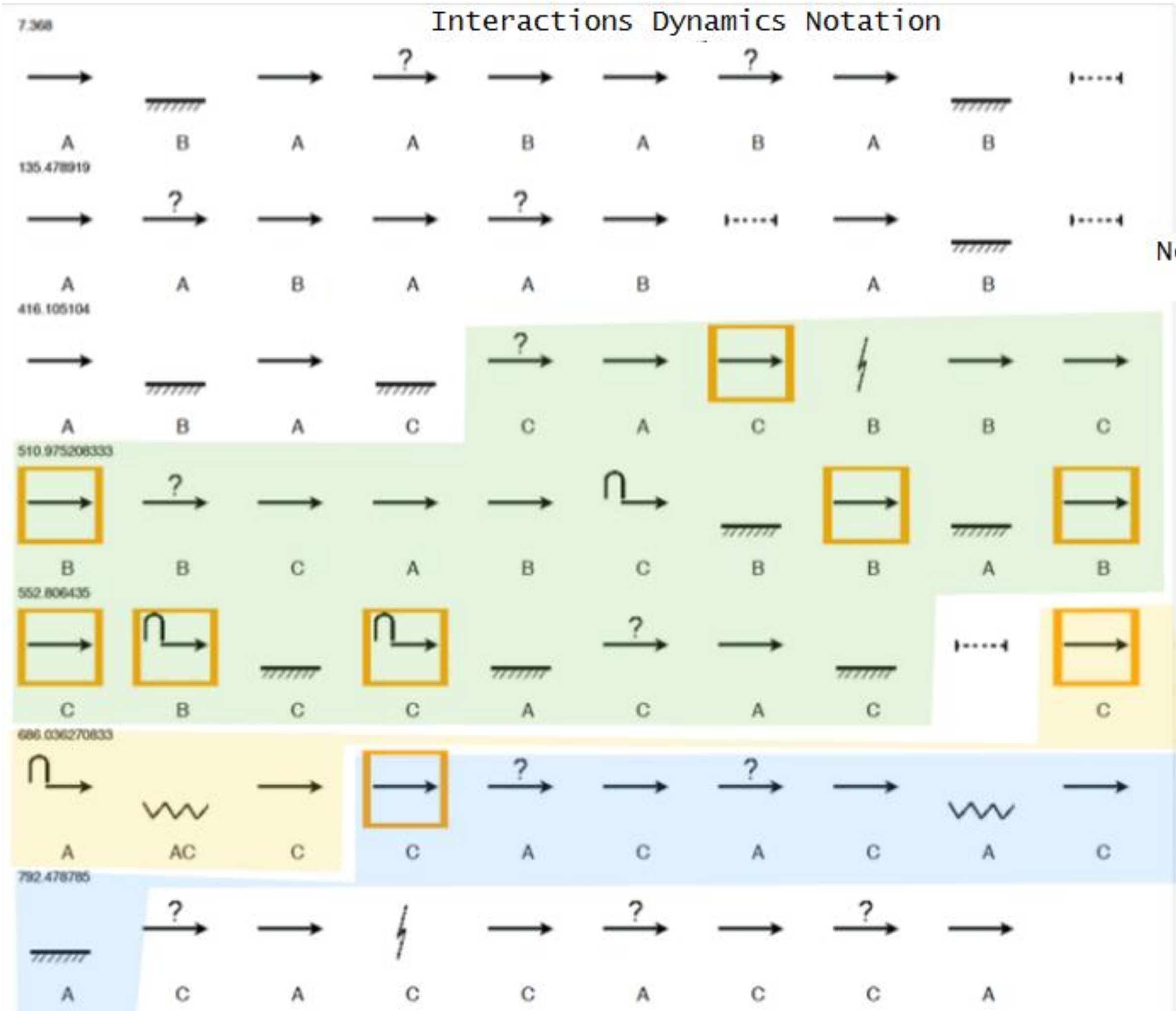
Positive Engagement

- Augmented Intelligence for insoluble problems ("wicked problems" or "messes")
  - Horst Rittel and Melvin Webber: "wicked problems" (1972)
  - Russell Ackoff: "messes" (1974)
  - Wicked problems are not isolated, they are sets of problems, each one influencing others



Bob Horn's digital murals

Positive Engagement



Interaction sequence 1

Interaction sequence 2

Interaction sequence 3

Neeraj Sonalkar

Neeraj Sonalkar's IDN

Case Study: SSIM at SRI

DARPA's Strategic Social Interaction Modules (2011-15): to train soldiers on how to engage with civilians in war zones

- “Kinetic training" is about fighting skills
- “Blended training" is about social skills

SRI Intl, UC Berkeley, UC Santa Cruz, UC Davis

DARPA DEFENSE ADVANCED RESEARCH PROJECTS AGENCY

Strategic Social Interaction Modules (SSIM)

Human Social Interaction Modeling Using Temporal Deep Networks

Mohamed R. Amer, SRI International
Behjat Siddiquie, SRI International
Amir Tamrakar, SRI International
David A. Salter, SRI International
Brian J. Lande, UC Santa Cruz
Darius Mehri, UC Berkeley
Ajay Divakaran, SRI International

May 2015

Case Study: SSIM at SRI

Psychological/anthropological research on what constitutes positive social interaction (good social skills)

A VR-based simulation of social interaction using a rule-based A.I. (UCSC)

A multimodal system to capture human interaction - verbal, gestural, facial communication (SRI)

A notation to tag social interactions (UC Berkeley)

A dataset of annotated gestures - a way to measure what constitutes a positive interaction (UC Davis)

Deep-learning A.I. to automatically detect positive social interaction (SRI)

Ajay Divakaran
SRI Intl & Princeton

Brian Lande
UCSC

Darius Mehri
UC Berkeley

Michael Neff
UC Davis

Mohamed Amer
SRI Intl

Case Study: SSIM at SRI

Goals:

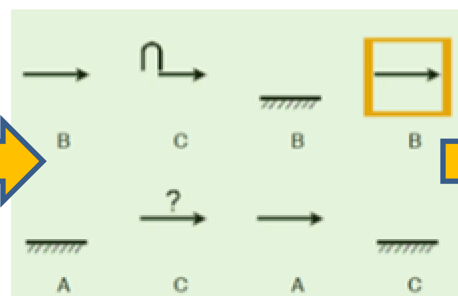
- Define "essential social interaction predicates" (ESIPs)
- Investigate the interactive and cooperative aspects of the social interactions (i.e. detects ESIPs)
- decompose this meaningful events (these ESIPs) into constituent actionable behaviors

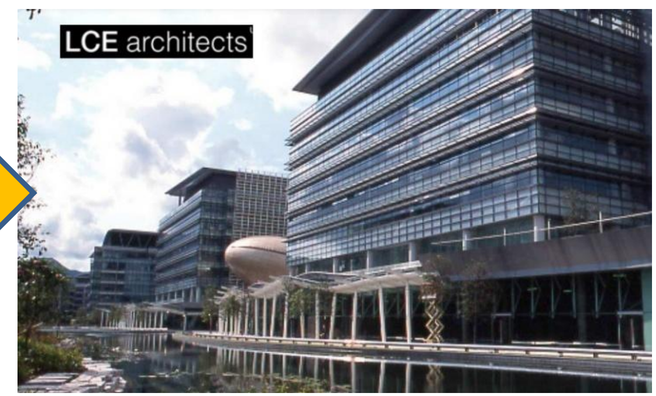
Results:

- A dataset of social dynamics, Tower Game
- An A.I. system to detect ESIPs

Peace Innovation Lab

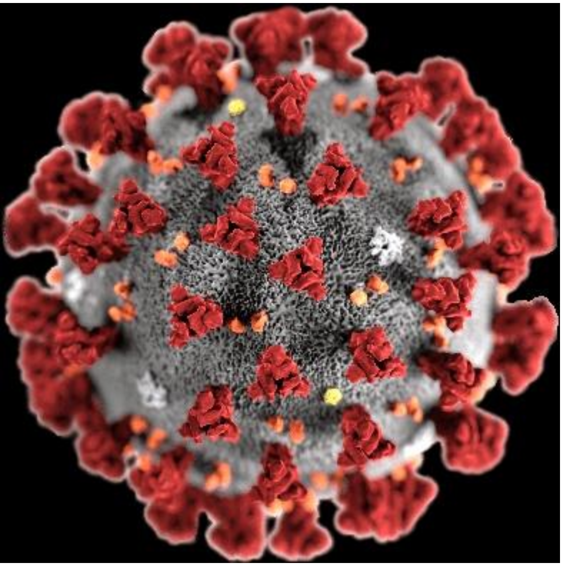
- From Computational Social Science to Technology Park:
  - A methodology to discover needs in society
  - A factory of hundreds of startups
  - A social innovation park





Smart City or Creative City?

Smart, Safe, Resilient City



January 2020

Smart, Safe, Resilient City

- Aspects of "smart cities" that were neglected:
  - It has to be safe
  - It has to be resilient to a crisis
- A virus can spread quickly because of fast transportation and big urbanization
- Covid-19 spread a lot faster than Ebola in Africa
- Smart cities still depend on agriculture from the rural areas, i.e. millions of city dwellers depend on mass transportation to deliver the food to city shops
- Perishable produce becomes rare if transportation stops

Smart, Safe, Resilient City

- The original smart city is a IT-intensive city
- The safe smart city is a Biotech-intensive city with a lot of automation
  - More hospitals, and more automation in hospitals
  - Smartphone apps and wearables that can quickly detect infections
  - Robots that can expand hospitals quickly
  - Robots that can replace nurses and doctors in hospitals
  - Robots and drones to deliver food and medicines to self-quarantined people
  - Biotech and robots to grow food on demand

The End (for now)

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