

# Smart Cities Tech

Piero Scaruffi

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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**

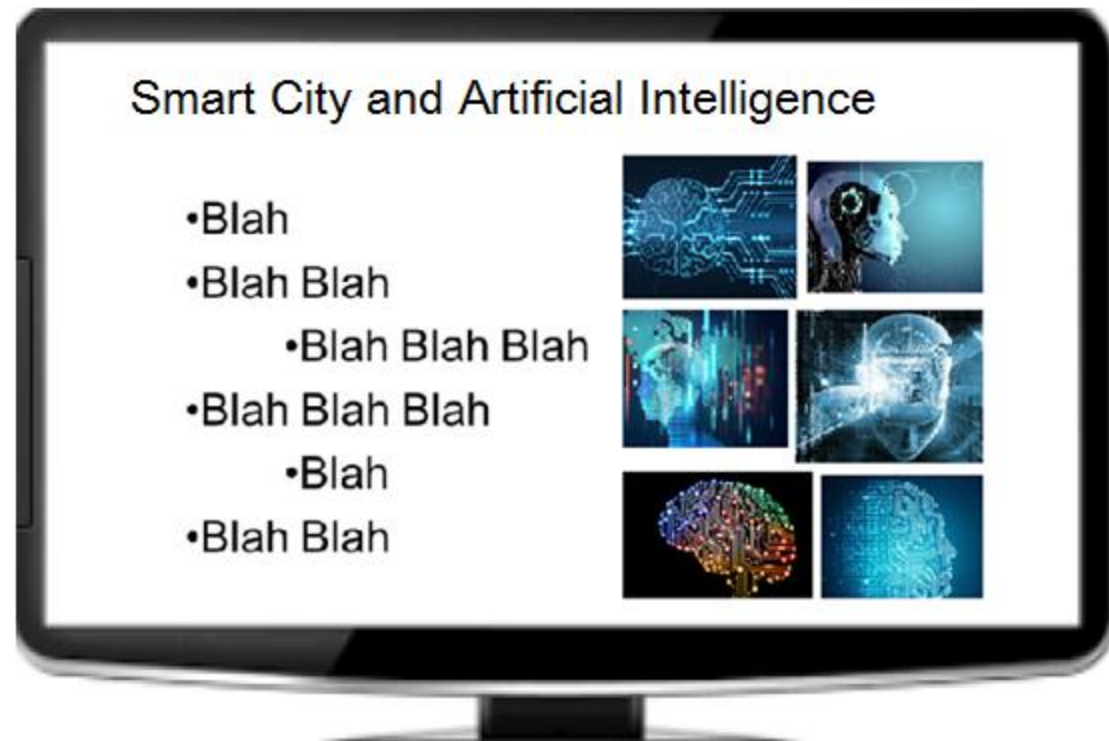
**Silicon  
Valley is  
not smart**

**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

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

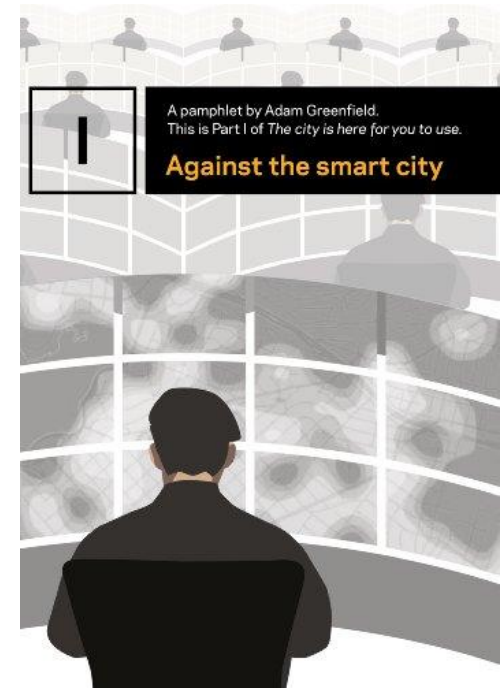
(I'm not sure I like smart cities!)

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 Glaeser: “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



## HUDSON YARDS ENGINEERED CITY

Hudson Yards will be far more than a collection of tall towers and open spaces. It will be a model for the 21st century urban experience; an unprecedented integration of buildings, streets, parks, utilities and public spaces that will combine to form a connected, responsive, clean, reliable and efficient neighborhood.

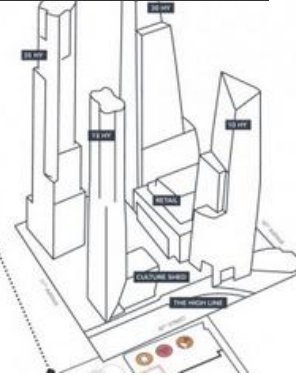
### CONNECTED NEIGHBORHOOD

Communications will be supported by a fiber loop, designed to optimize data speed and service continuity for rooftop communications, as well as mobile, cellular and two-way radio communications. This will allow continuous access via wired and wireless broadband performance from any device at any on-site location. We're as good as future-proofed.



### RESPONSIVE NEIGHBORHOOD

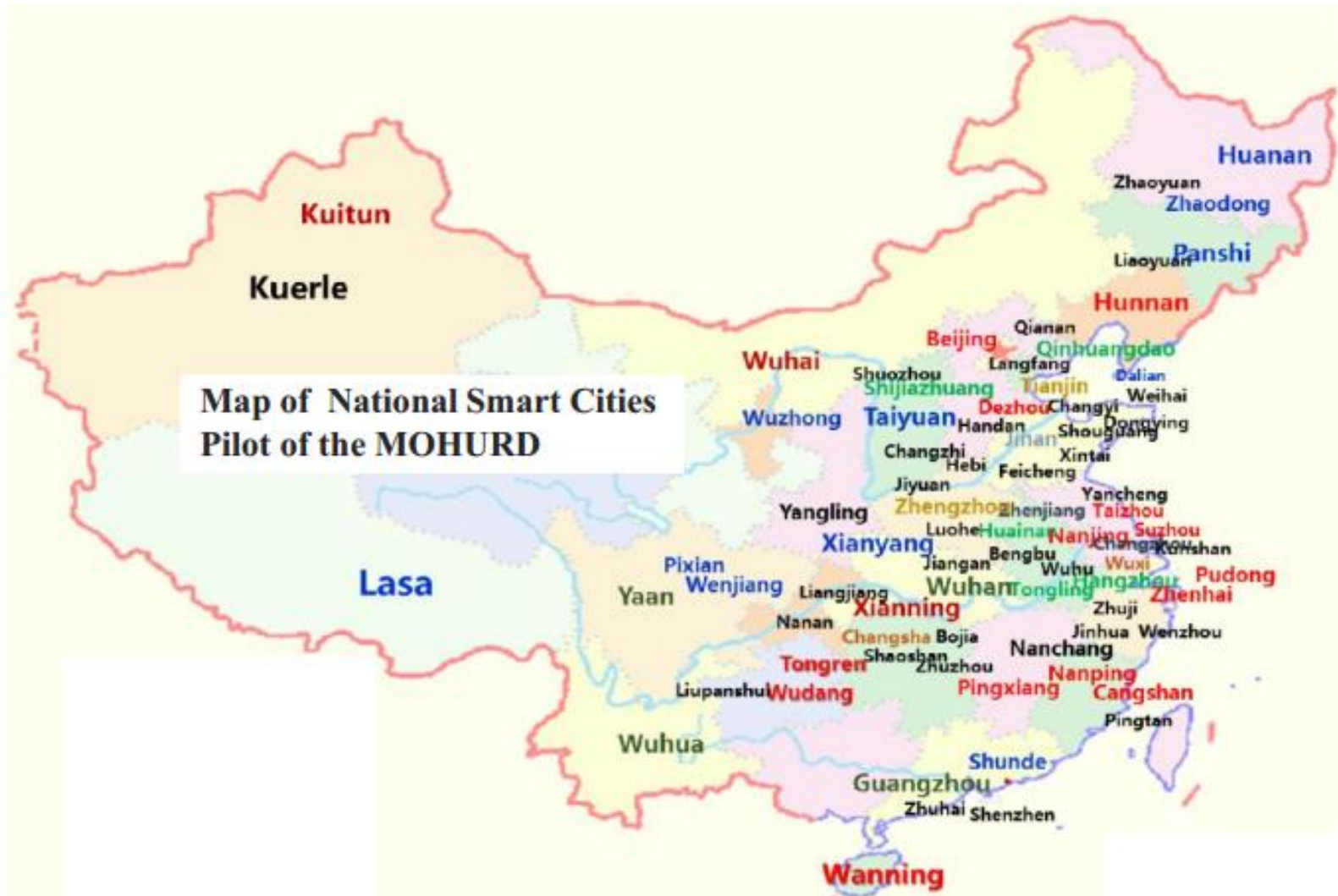
Hudson Yards will harness big data to innovate, optimize, enhance and personalize the



SIDE WALK LABS

**Sidewalk Labs is reimagining cities to improve quality of life.**

# Smart Cities in China





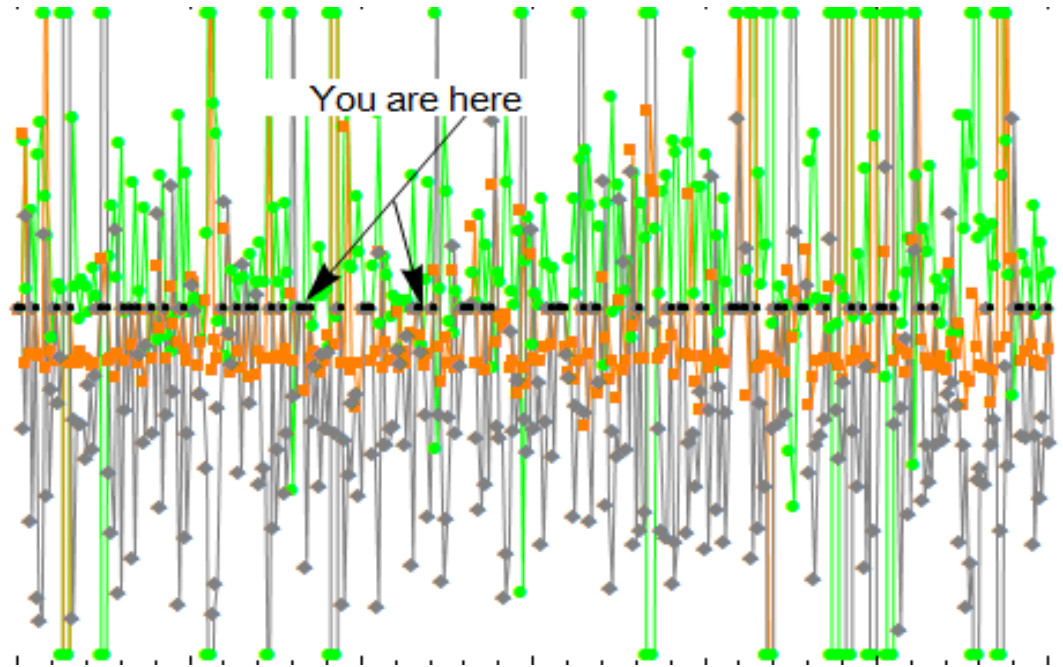
# Smart City

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

San Diego to Deploy  
World's Largest Smart City  
IoT Platform with Current,  
powered by GE



February 2017





# Smart City

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

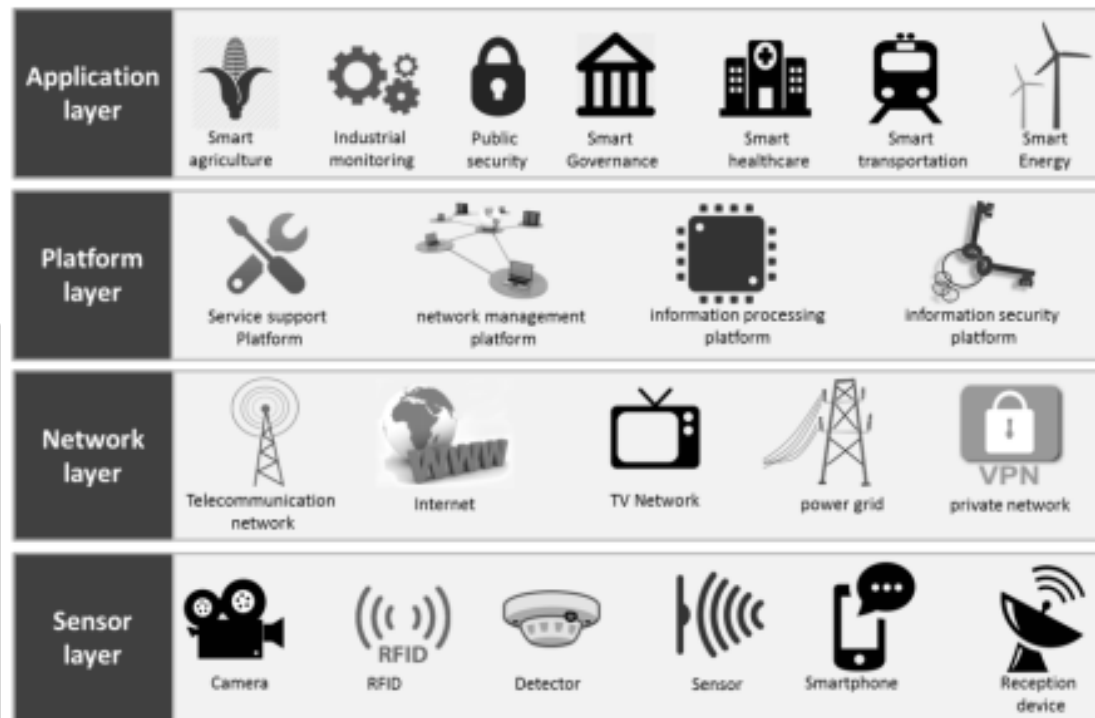


Figure 2. Four layers of smart city Yongling Li, Yanliu Lin and Stan Geertman

## Four layer architecture

### Application and services layer

- Code-centric and situation-aware system, agent intelligence

### Information handling layer

- Cloud computing, data mining, intelligent agent system

### Information delivering layer

- Internet, mobile communication, cellular, WLAN, P2P, social network

### Object sensing and information gathering layer

- Wireless sensor networks, body area networks, RFID

# Smart Apps



Smart  
Energy

Smart  
Healthcare

Smart  
Security

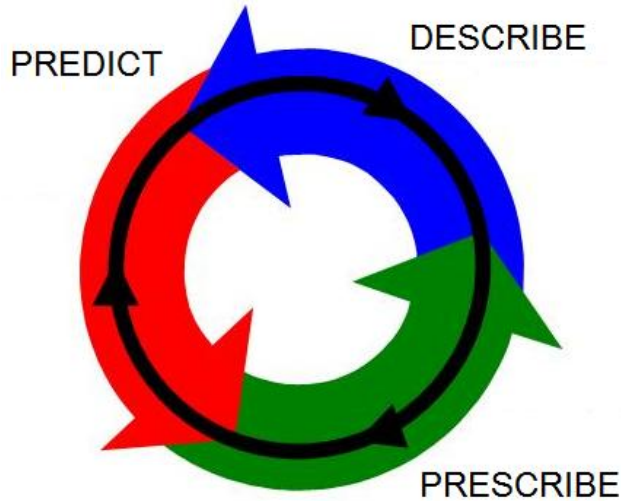
Smart  
Waste

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)



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

By Alison Griswold • May 7, 2018



# 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
  - ...

By 2020, it's estimated that

**90%**

of cars will be connected to the Internet.



Image Credit: U.S. Department of Transportation

# What next?

“Smart” does not mean “intelligent”



OVE Decors Smart  
1-piece 1.28 GPF  
Elongated Toilet and  
Bidet with Seat in  
White

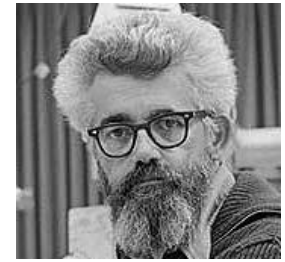
**\$1,086.36**

Home Depot



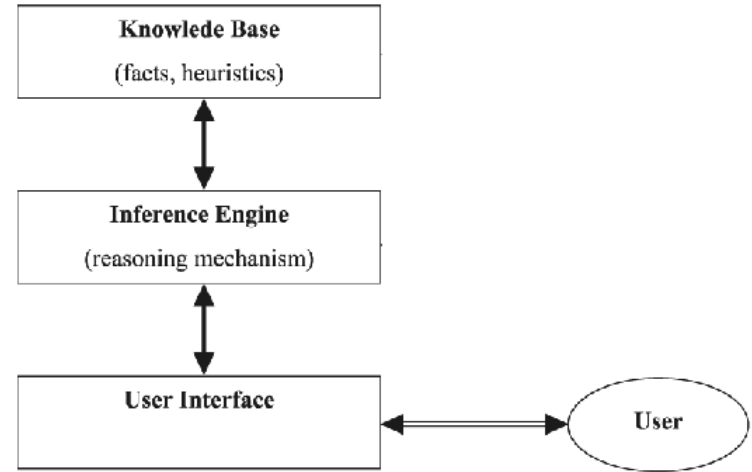


# The two schools of A.I.

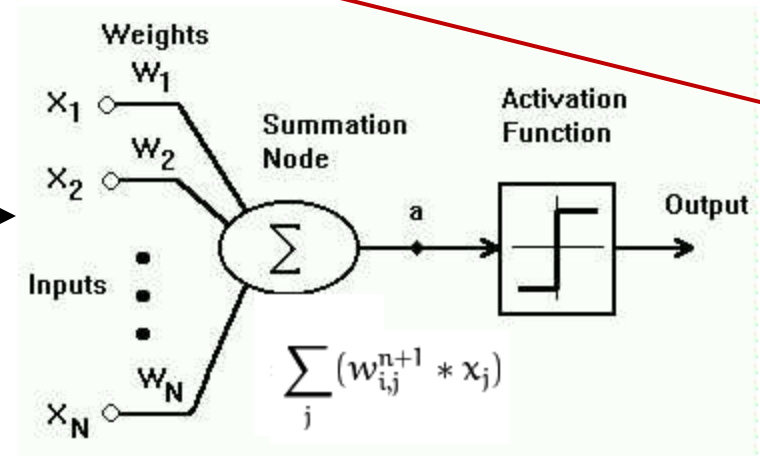
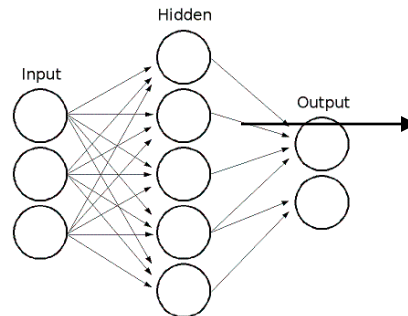
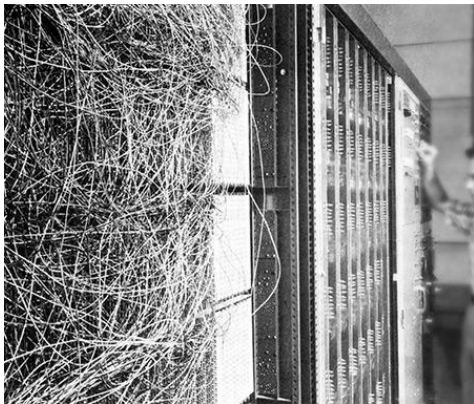


## Artificial Intelligence (1956)

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



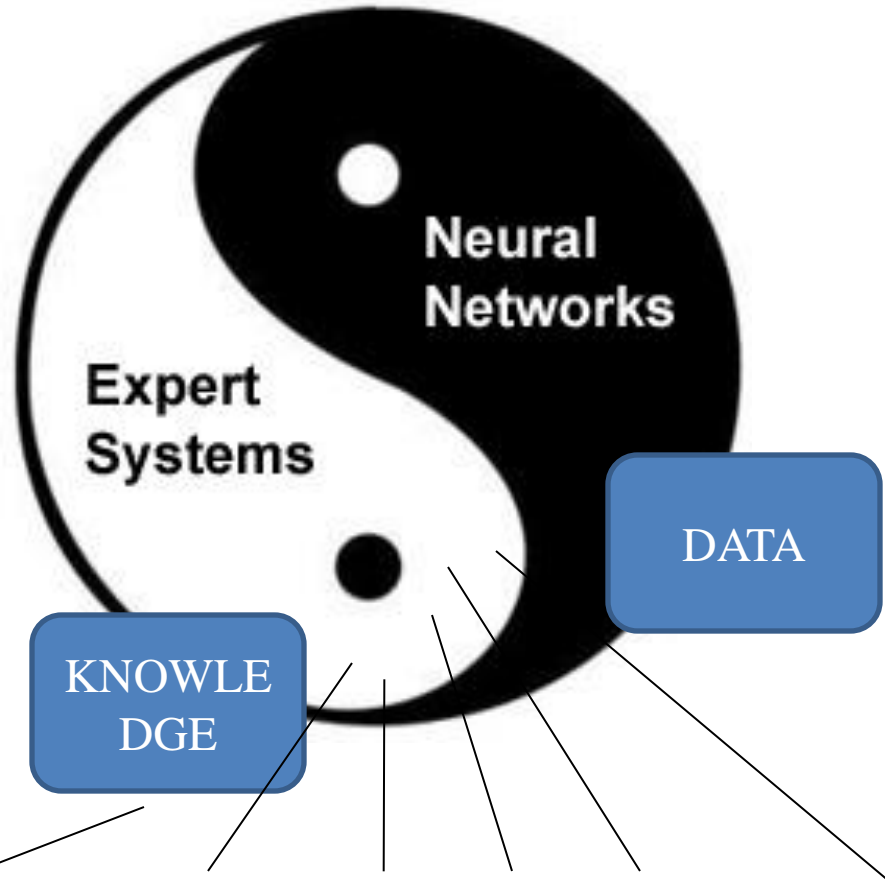
- Neural-net approach simulates the structure of the brain



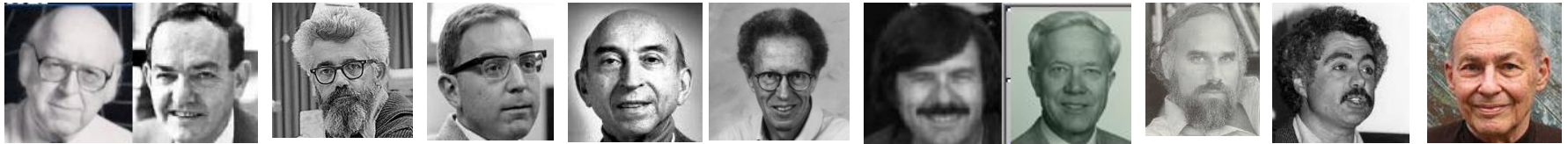




# The two schools of AI



- 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"*

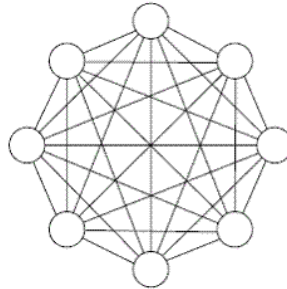


1970: Marvin Minsky: *"In from three to eight years we will have a machine with the general intelligence of an average human being"*



# 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**



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

> 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**



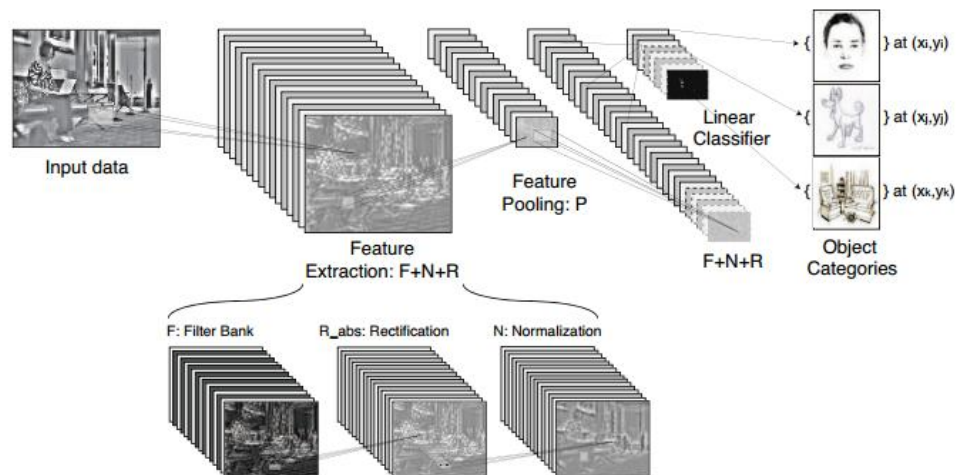
Given functions  $x(t)$  and  $w(t)$ , their convolution is a function  $s(t)$

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

Written as

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

## Convolutional Network

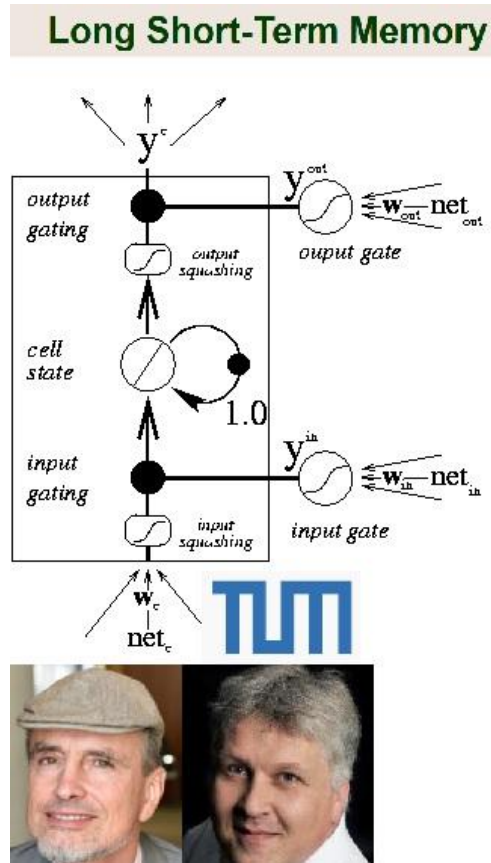


Architecture of a typical convolutional network for object recognition

From a paper by Yann LeCun

# Neural Networks

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

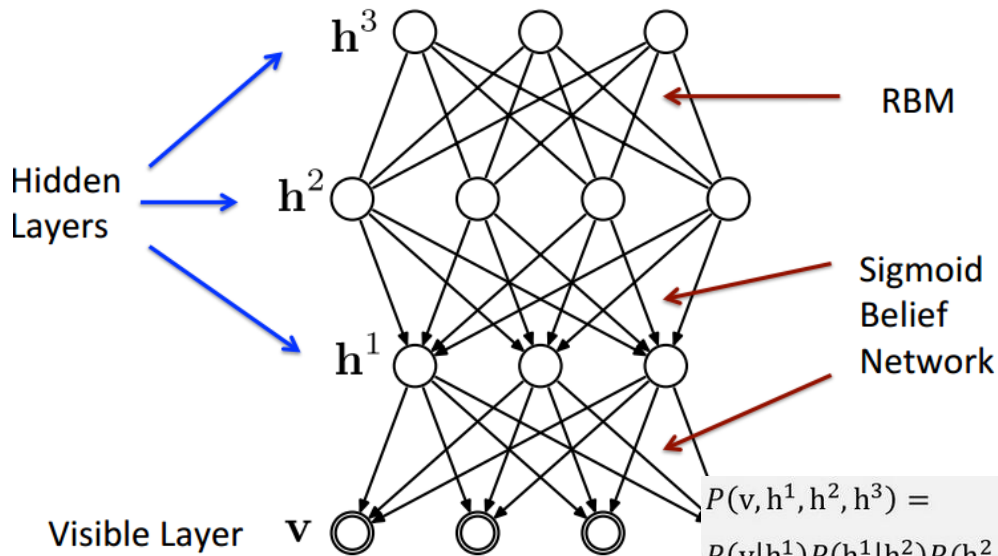


# Deep Learning



2006: Geoffrey Hinton's **Deep Belief Networks**

## Deep Belief Network



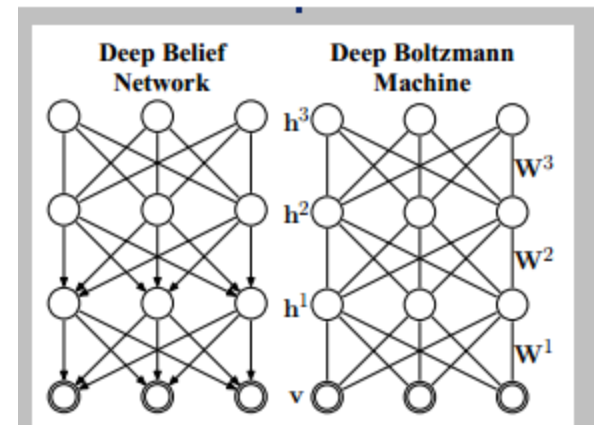
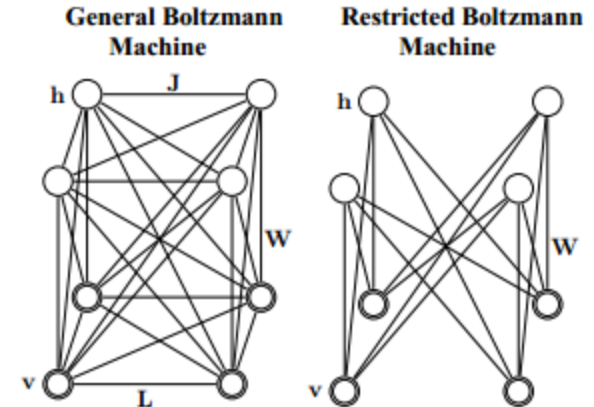
(Hinton et.al)

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

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

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

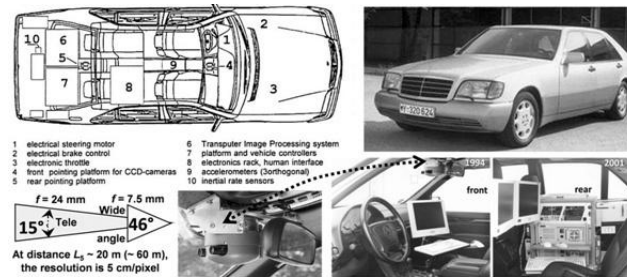
$$P(h^2, h^3) = \frac{1}{Z(W^3)} \exp(h^{2T} W^3 h^3)$$





# 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

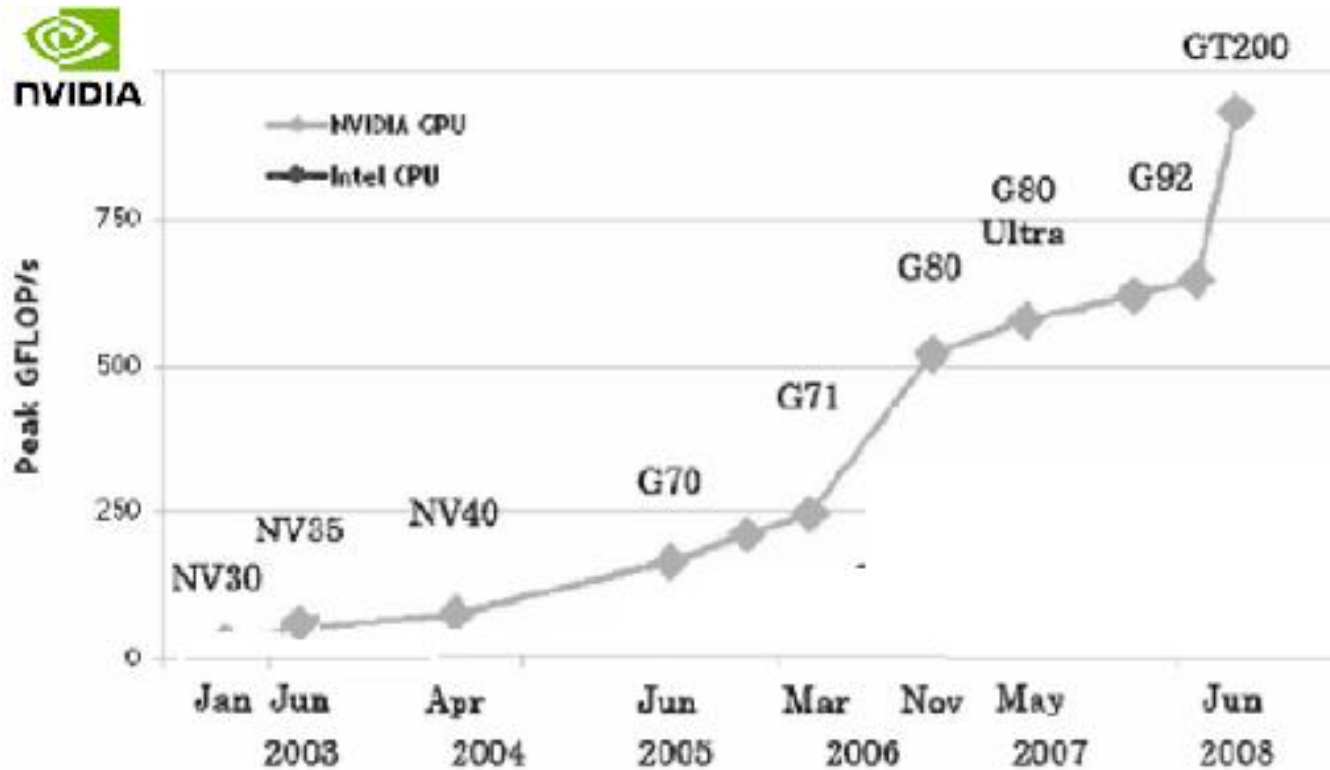


2011: Apple Siri (2011)



# 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

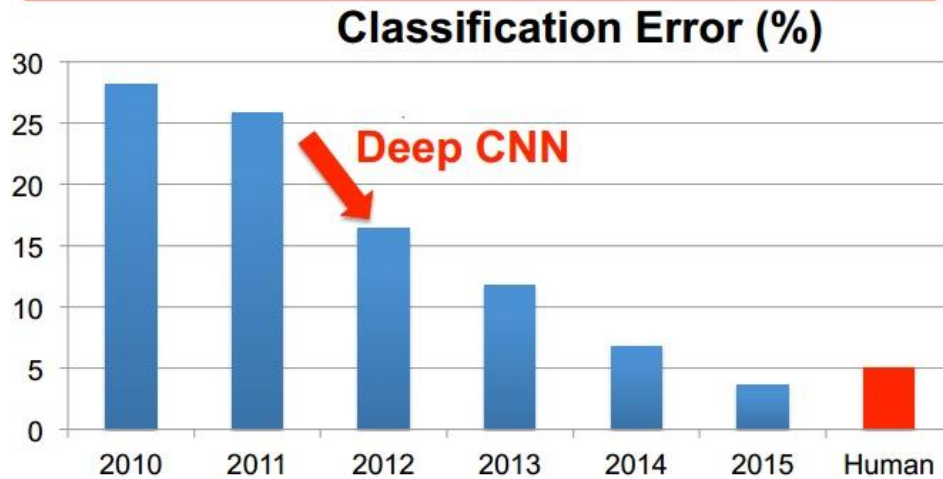
# Reinforcement Learning

Google/DeepMind's AlphaGo beats weichi champions

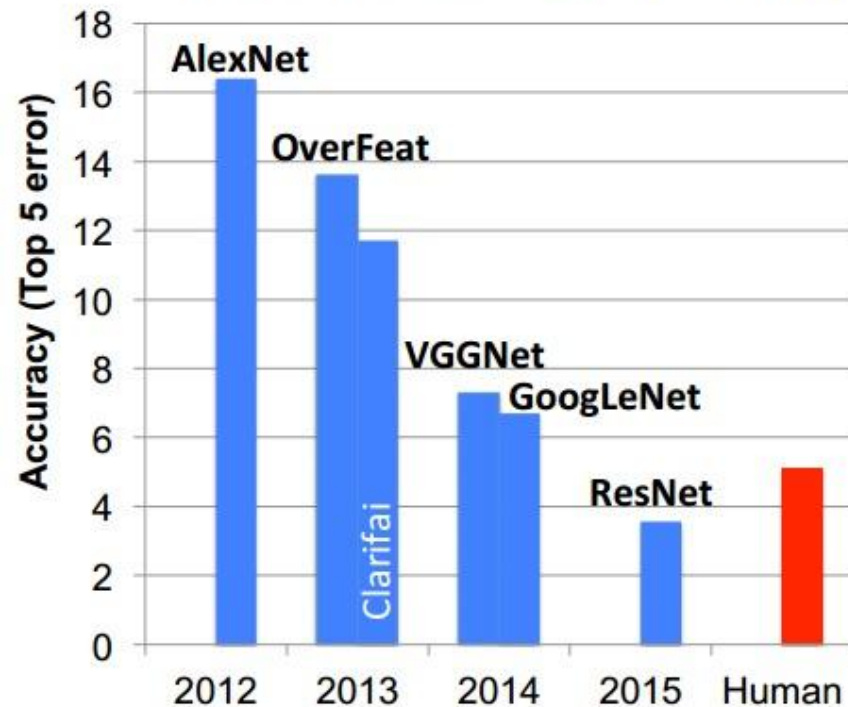


# Convolutional Nets

## ImageNet: Image Classification Task



## ImageNet: Large Scale Visual Recognition Challenge (ILSVRC)





# Recurrent Neural Nets

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

## Google Translate now provides live translation of Japanese text

Posted 10 hours ago by Darrell Etherington (@etherington)



2017

# Recurrent Neural Nets



Google Research Blog

November 17, 2014

Posted by Google Research Scientists Oriol Vinyals

Describes without errors	Describes with minor errors	Somewhat related to the image	Unrelated to the image
 <p>A person riding a motorcycle on a dirt road.</p>	 <p>Two dogs play in the grass.</p>	 <p>A skateboarder does a trick on a ramp.</p>	 <p>A dog is jumping to catch a frisbee.</p>
 <p>A group of young people playing a game of frisbee.</p>	 <p>Two hockey players are fighting over the puck.</p>	 <p>A little girl in a pink hat is blowing bubbles.</p>	 <p>A refrigerator filled with lots of food and drinks.</p>
 <p>A herd of elephants walking across a dry grass field.</p>	 <p>A close up of a cat laying on a couch.</p>	 <p>A red motorcycle parked on the side of the road.</p>	 <p>A yellow school bus parked in a parking lot.</p>

<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, Xinchun Yan, Lajanugen Logeswaran  
Honglak Lee, Bernt Schiele

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



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



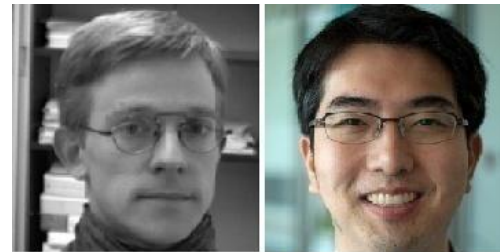
this magnificent fellow is almost all black with a red crest, and white cheek patch.



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.



**Bernt Schiele** **Honglak Lee**








# Generative Adversarial Networks

- Video generation



Vondrik Torralba

## Generating Videos with Scene Dynamics

<b>Carl Vondrik</b> MIT	<b>Hamed Pirsiavash</b> University of Maryland Baltimore County	<b>Antonio Torralba</b> MIT
<b>Beach Generated Videos</b>		
Frame 1	Frame 16	Frame 32
		
		
		
		
<b>Train Station Generated Videos</b>		
Frame 1	Frame 16	Frame 32
		
		
		
		
<b>Golf Course Generated Videos</b>		
Frame 1	Frame 16	Frame 32
		
		
		
		
<b>Hospital / Baby Generated Videos</b>		
Frame 1	Frame 16	Frame 32
		
		
		
		



# 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

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

Uncovers information

Builds a model

→ Network layer: A new generation of network optimization algorithms

Discovers optimizations

Decision making

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



# Pattern Recognition

Application layer:

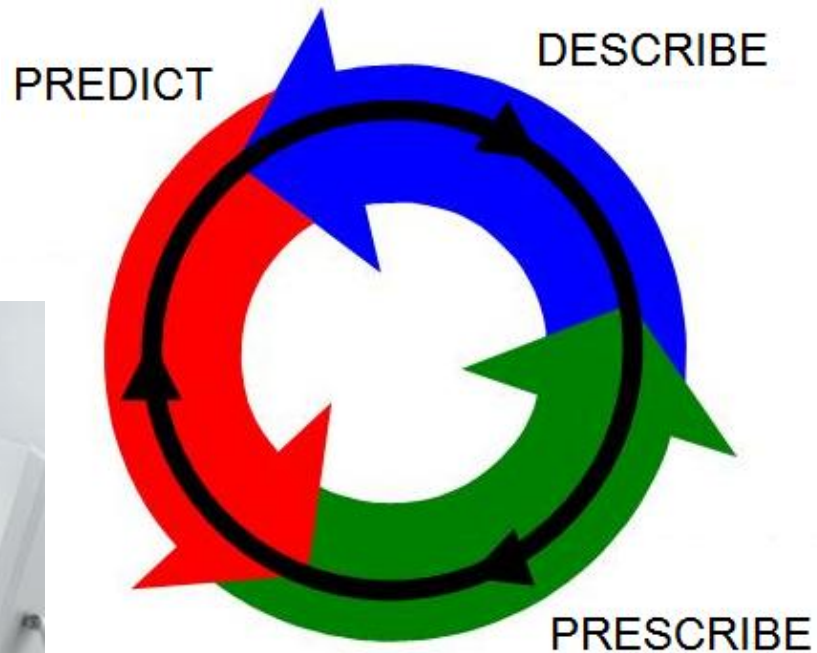
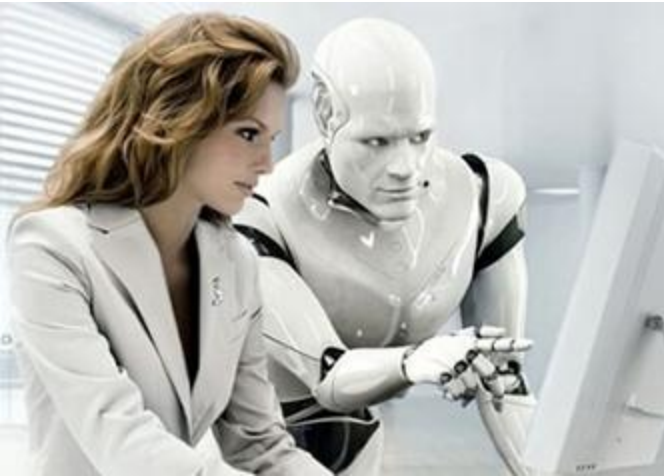
A new generation of situation-based applications (e.g. emergencies)

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



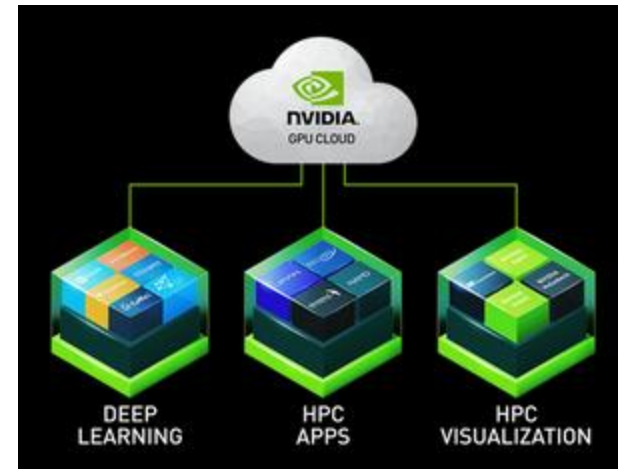
# Pattern Recognition

Can it help city planners?



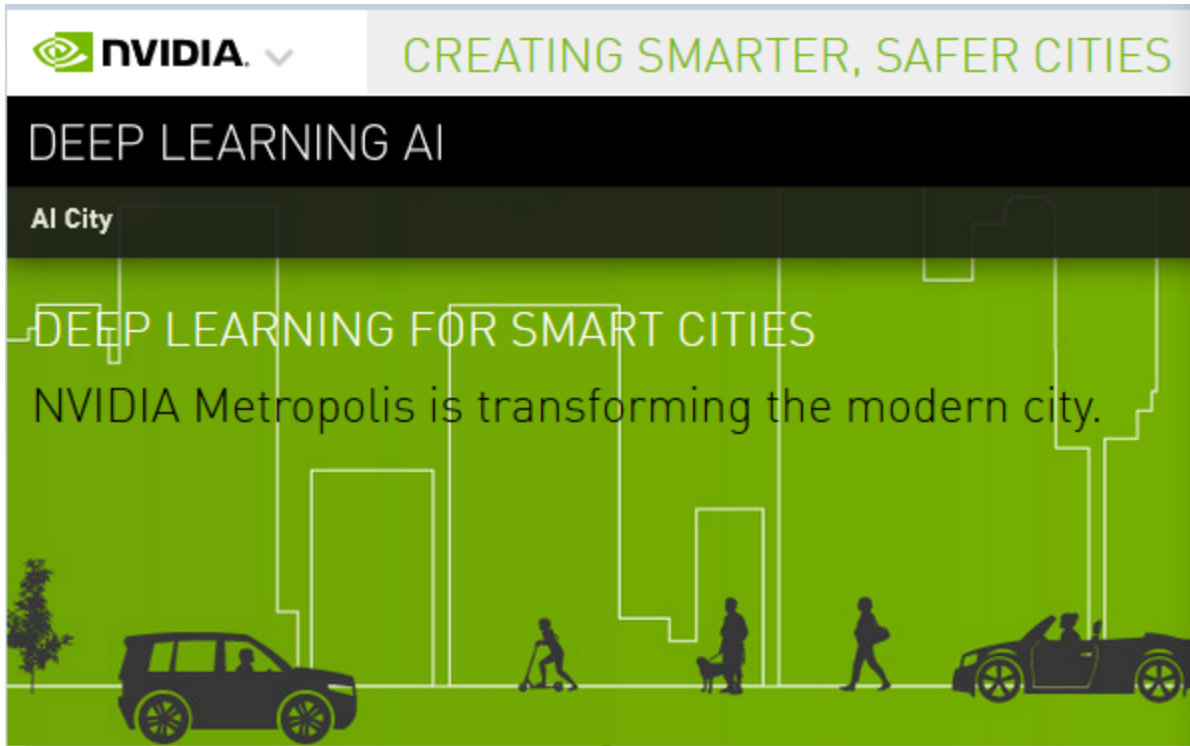
# Case Studies

- 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



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



San Diego to Deploy  World's Largest Smart City IoT Platform with Current, powered by GE

February 2017



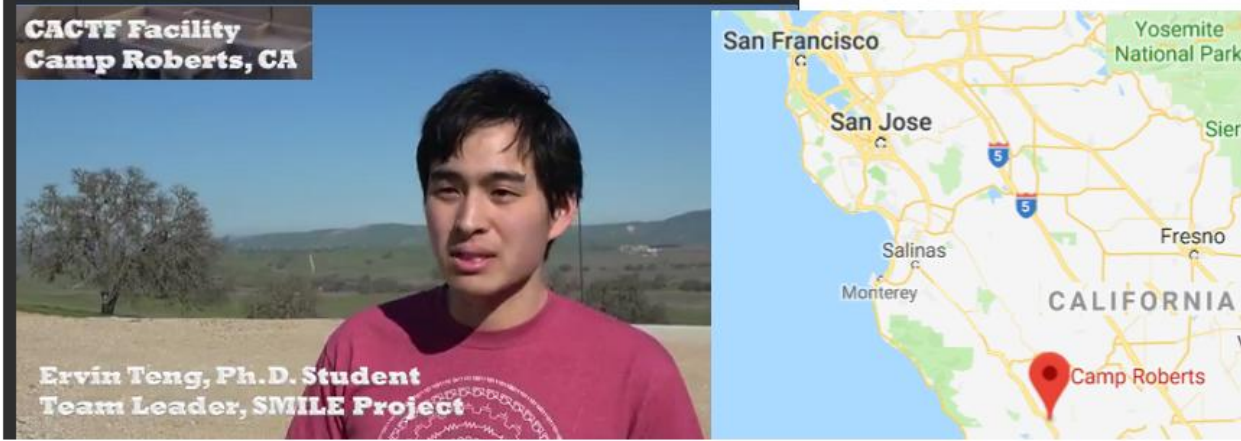
# Case Studies

- 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



**Carnegie Mellon University**  
**Silicon Valley**

**SMILE: Synchronized Multi-Sensor Integrated Learning Environment**



# 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**

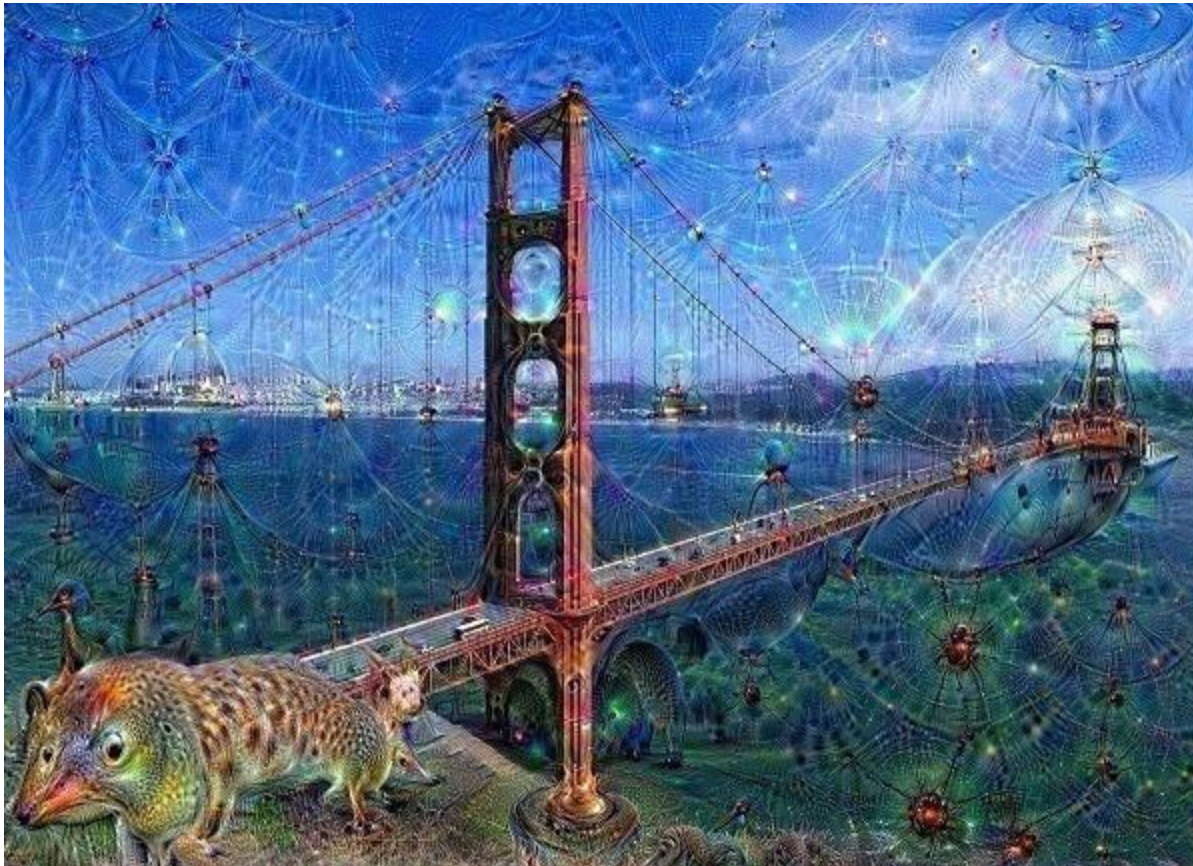
**Silicon  
Valley is  
not smart**

**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

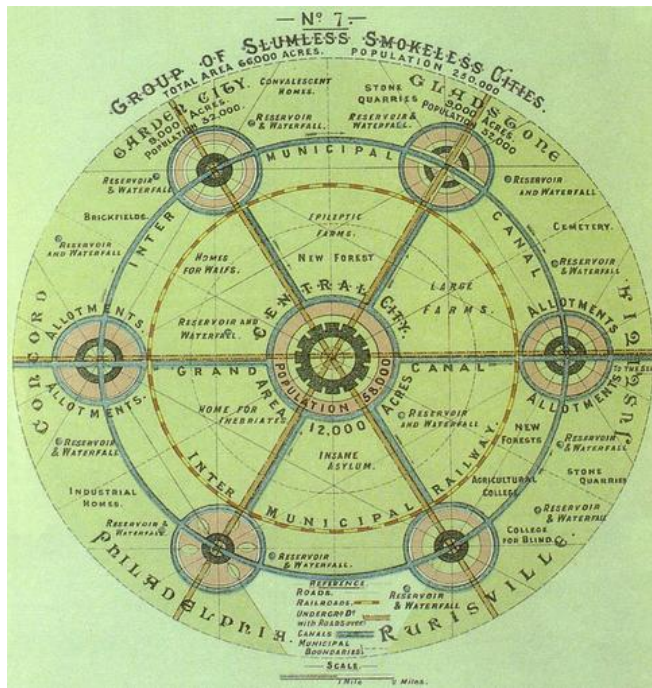
Enable citizen innovation

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



# 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?



### 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%

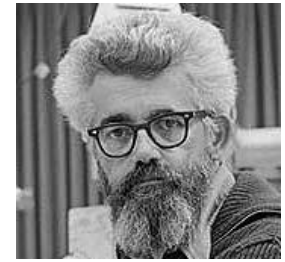
# Making smart cities creative

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



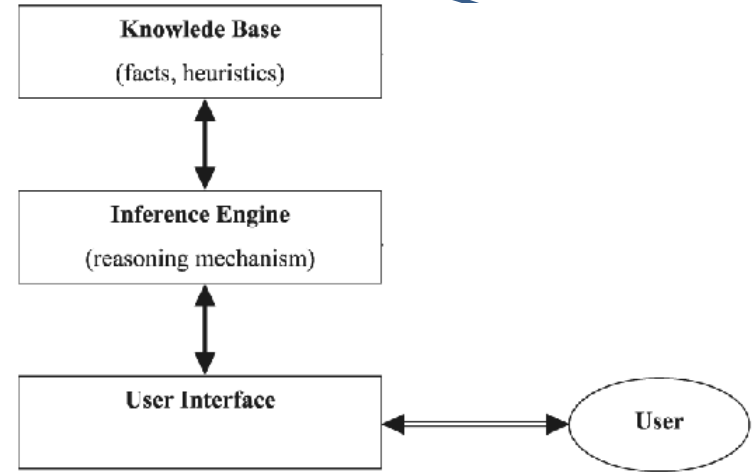


# The two schools of A.I.

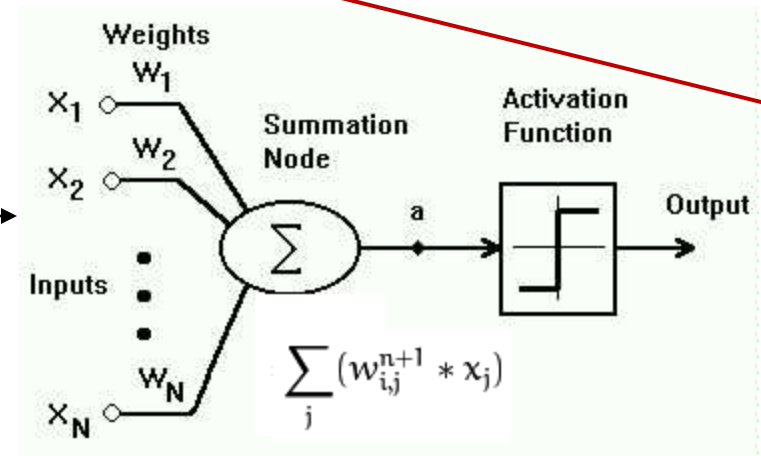
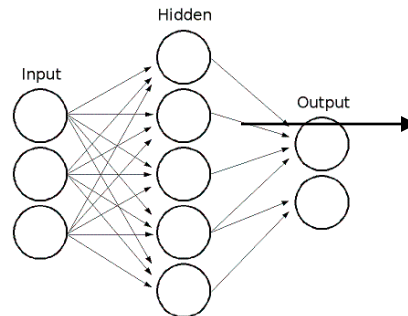
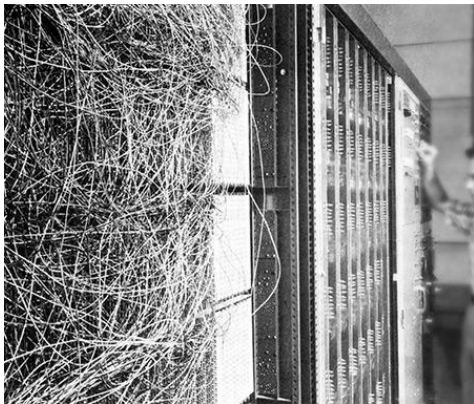


## Artificial Intelligence (1956)

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



- Neural-net approach simulates the structure of the brain



# Peace Innovation Lab



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





Robert E. Horn



Visiting Scholar  
Stanford University

- Brief bio
- CV
- Recent speeches & articles
- hornbob@earthlink.net

## Visual Analytics for Public Policy

A research program to model, communicate, and resolve complex issues

What is visual analytics?

NASA Project on Strategic Science Policy



GLOBAL STRUGGLE OF NARRATIVES Project



Discriminate Force Project



National Missile Defense Debates



Genetically Modified Food Project



HUMAN COGNOME Initiative National Science Foundation



## Social Messes

Helping groups get started and stay on the same page in dealing with seemingly intractable "wicked" problems  
For more info



What are Social Messes?

Social Mess Projects

## Summaries of My Current Work

Thinking Bigger Thoughts

Connecting the Smudges

## My other interests and writings

Visual language, human-computer interface, knowledge mapping

Philosophy, cognitive science, artificial intelligence

Information Mapping®, structured writing, reusable learning objects, hypertext

Simulation gaming /scenarios

Educational research & methods

Argumentation mapping

Art and information design

Electronic democracy, governance

## INFO-MURALS / PUBLIC ART

STRATEGY for dealing with RADIOACTIVE WASTE



ARGUMENTATION MAPS about RADIOACTIVE WASTE



Avian Flu Pandemic Scenario Info-Mural



Are Info-Murals New Genre? A New Article

STRATEGIC POLICY OPTIONS for GLOBAL CLIMATE CHANGE

Current project - watch this space



CARNEGIE TRUST Info-Mural Convention on the Rights of the Child watch this space

## My Primary Tools (These Days)

Book

Visual Analytics™ Workshops

Posters

Info-murals

Visual Language



To order

Visual Thinking and Visual Communication



For more info

Mess Mapping™ Process



For more info

Argumentation Mapping for Public Policy Debates



For more info

Can Computers think?



To order

For Public Policy



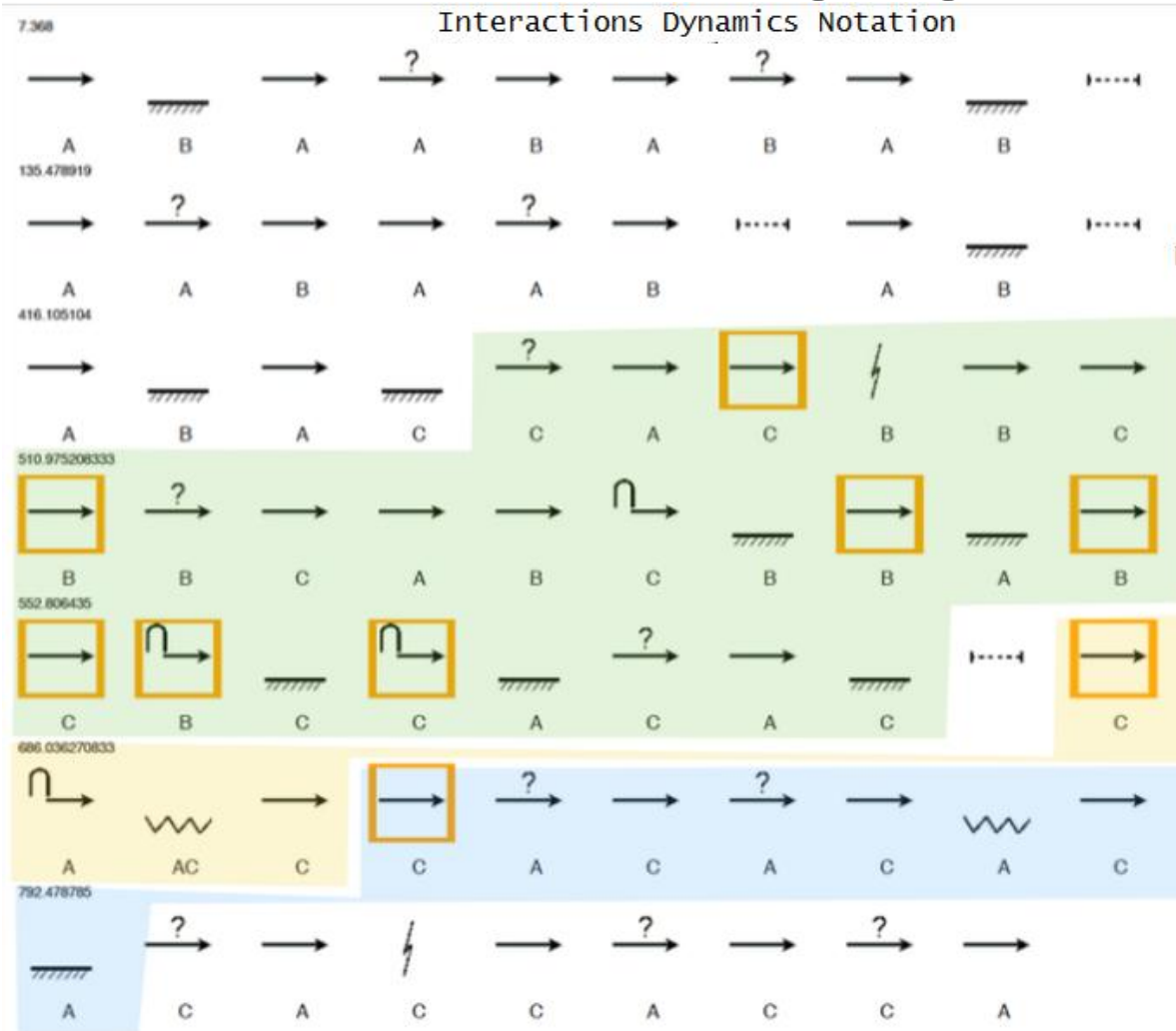
For more info

History of Cybernetics and Systems Science Info-Mural

My publishers MacroVU ©, Inc. XPLANE

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# Positive Engagement



Neeraj Sonalkar

Interaction sequence 1

Interaction sequence 2

Interaction sequence 3



# 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



Strategic Social Interaction Modules  
(SSIM)

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

## Human Social Interaction Modeling Using Temporal Deep Networks

Mohamed R. Amer  
SRI International

David A. Salter  
SRI International

Behjat Siddiquie  
SRI International

Brian J. Lande  
UC Santa Cruz

Ajay Divakaran  
SRI International

Amir Tamrakar  
SRI International

Darius Mehri  
UC Berkeley

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:

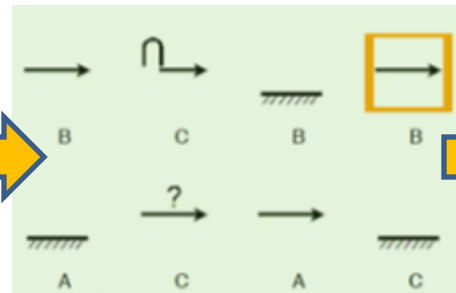
- Define "essential social interaction predicates" (ESIPs)
- Investigate the interactive and cooperative aspects of the social interactions (i.e. detects ESIPs)
- decompose this meaningful events (these ESIPs) into constituent actionable behaviors

## 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



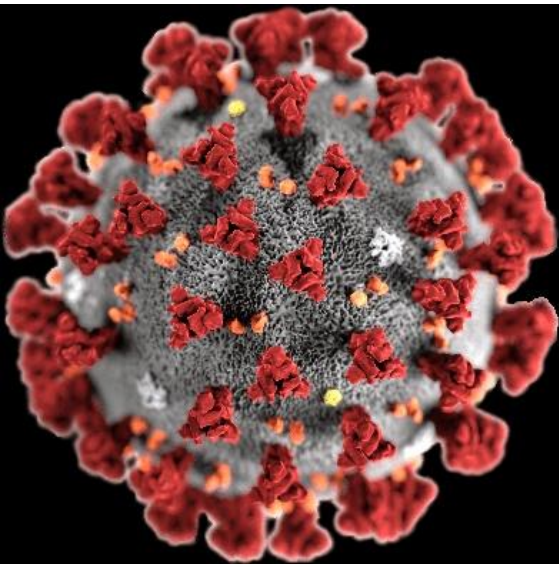


# Smart City or Creative City?





# 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)

[www.scaruffi.com](http://www.scaruffi.com)

