Smart Cities Tech

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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…

![Map of Silicon Valley with top 10 smart cities chart]

**TOP 10 SMART CITIES**

<table>
<thead>
<tr>
<th>CITY</th>
<th>INDEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Tokyo</td>
<td>100%</td>
</tr>
<tr>
<td>2. London</td>
<td>84%</td>
</tr>
<tr>
<td>3. New York</td>
<td>81%</td>
</tr>
<tr>
<td>4. Zurich</td>
<td>80%</td>
</tr>
<tr>
<td>5. Paris</td>
<td>79%</td>
</tr>
<tr>
<td>6. Geneva</td>
<td>76%</td>
</tr>
<tr>
<td>7. Basel</td>
<td>71%</td>
</tr>
<tr>
<td>8. Osaka</td>
<td>69%</td>
</tr>
<tr>
<td>9. Seoul</td>
<td>68.3%</td>
</tr>
<tr>
<td>10. Oslo</td>
<td>68%</td>
</tr>
</tbody>
</table>
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?
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, 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)
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)
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 = 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

Map of National Smart Cities Pilot of the MOHURD
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
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
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
  – …
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**

$$E(v) = -\frac{1}{2} \sum_{i,j} w_{ij} v_i v_j - \sum_i I_i v_i + \sum_i \frac{1}{R_i} \int_{0}^{v_i} f_i^{-1}(z) dz$$

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

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

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

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

\[
P(v, h^1, h^2, h^3) = \frac{P(v|h^1) P(h^1|h^2) P(h^2, h^3)}{P(v|h^3)}
\]

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

\[
P(h^1|h^2) = \prod_j P(h^1_j|h^2)
\]

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

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
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

Classification Error (%)

ImageNet: Large Scale Visual Recognition Challenge (ILSVRC)

Accuracy (Top 5 error)
Recurrent Neural Nets

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

Google Research Blog
November 17, 2014
Posted by Google Research Scientists Oriol Vinyals

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

*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

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

Classifies data
Uncovers information
Builds a model
Discovers optimizations
Decision making
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
Case Studies

- IBM Smarter Planet (2009)
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
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
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?
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
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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)
  - Wicked problems are not isolated, they are sets of problems, each one influencing others
Positive Engagement

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
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)
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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