Certificate I: Understanding AI and Machine Learning in Africa

Course AIML02: AI and Machine Learning in Africa

Module 1: The Potential of AI and Machine Learning in Africa

Lecture 2: Computational Sustainability and AI in the Developing World

Carnegie Mellon University
Africa

Learning Objectives

1. Explain how technology has created new opportunities to address poor management of resources and improve human well-being

2. Identify several examples of the use of AI in Africa in sectors such as

   – Health, for disease diagnosis & disease surveillance

   – Food security, for monitoring crop disease and predicting food insecurity

   – Transport, for monitoring road traffic congestion

   – Socioeconomics, for gathering information to guide policy decisions

Lecture Contents

1. The importance of understanding the local social and cultural behaviors when designing and deploying solutions

2. Three broad areas where AI can contribute to computational sustainability:

   – Intelligence gathering
   – Compensating for a lack of human experts
   – Choosing how to allocate scarce resources

3. Examples

4. Lecture summary

5. Recommended reading & references

Local Social & Cultural Behaviors in Designing Solutions

- In the previous lecture,
  we focused on the importance of
  - Trust
  - Respect for local & regional social & cultural behaviours

  in the adoption of any new technology

- We begin today by illustrating this with a practical example
  - Road traffic congestion

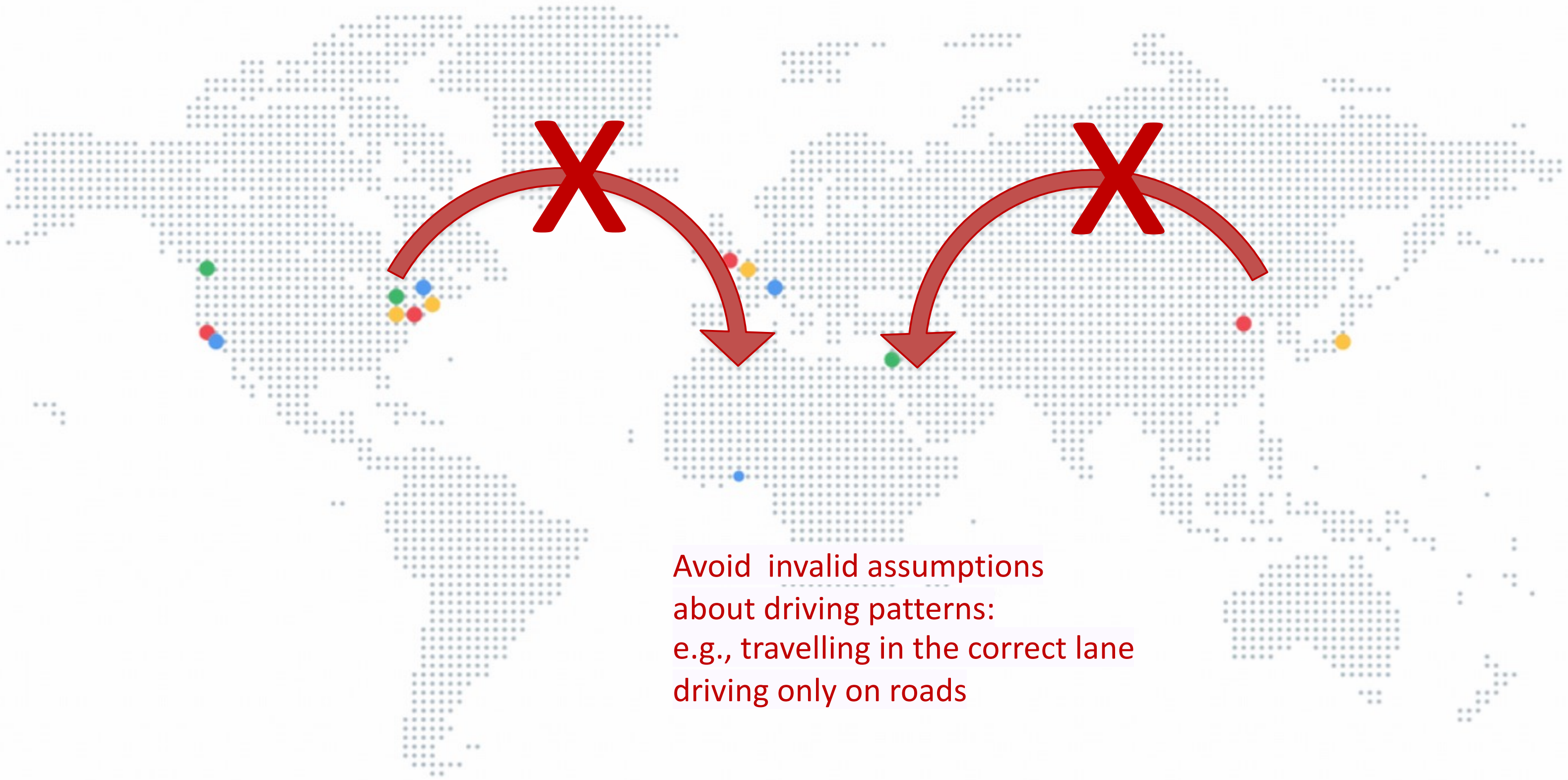
(Quin et al, 2014)

Local Social & Cultural Behaviors in Designing Solutions

- Causes
  - Inadequate infrastructure
    - Outdated road layouts
    - Unsealed roads
    - Pot-holes
  - Lack of resources to monitor and control
    - Scarce traffic police
    - Inoperative traffic lights
- Possible computational solutions
  - Gather data cheaply in real time
  - Provide advice on optimal routes
  - Dynamically redeploy traffic
  - Redesign road networks

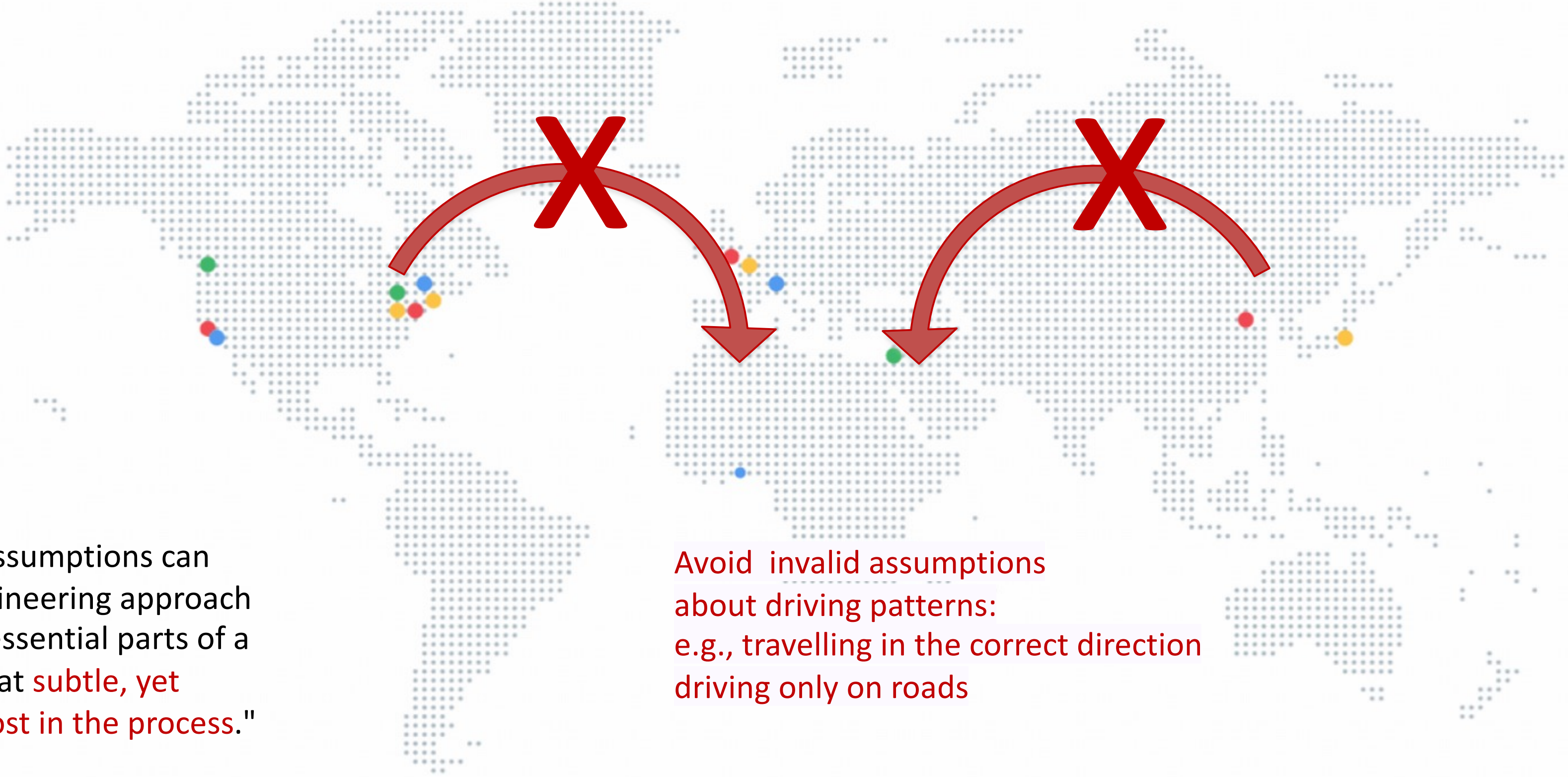
(Quin et al, 2014)

Local Social & Cultural Behaviors in Designing Solutions



https://www.blog.google/around-the-globe/google-africa/google-ai-ghana/

Local Social & Cultural Behaviors in Designing Solutions



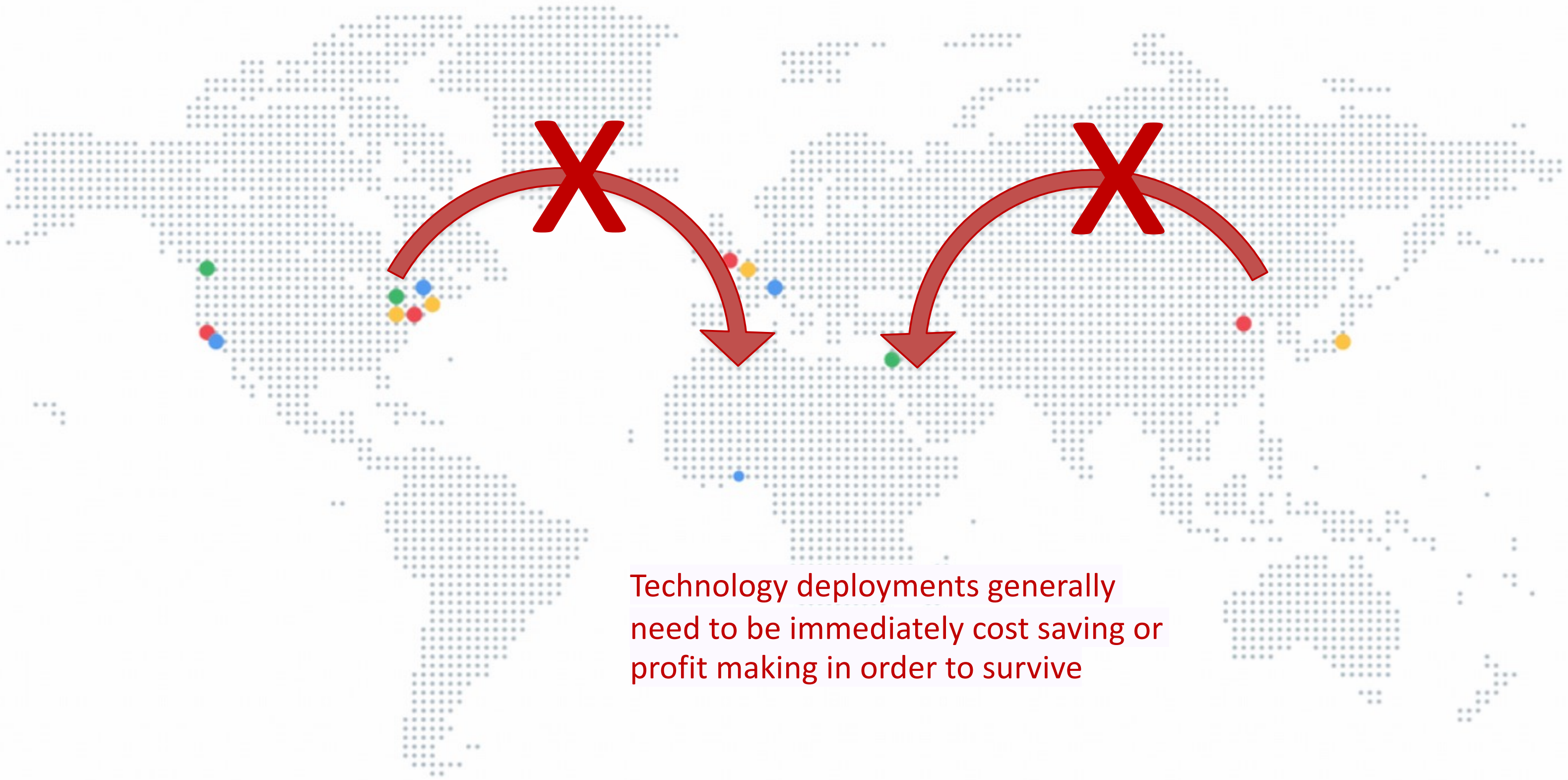
"Finding the right set of assumptions can also be difficult: in an engineering approach to abstract away the nonessential parts of a problem, we often find that subtle, yet crucial social factors are lost in the process."

(Quin et al., 2014)

Avoid invalid assumptions
about driving patterns:
e.g., travelling in the correct direction
driving only on roads

https://www.blog.google/around-the-globe/google-africa/google-ai-ghana/

Local Social & Cultural Behaviors in Designing Solutions



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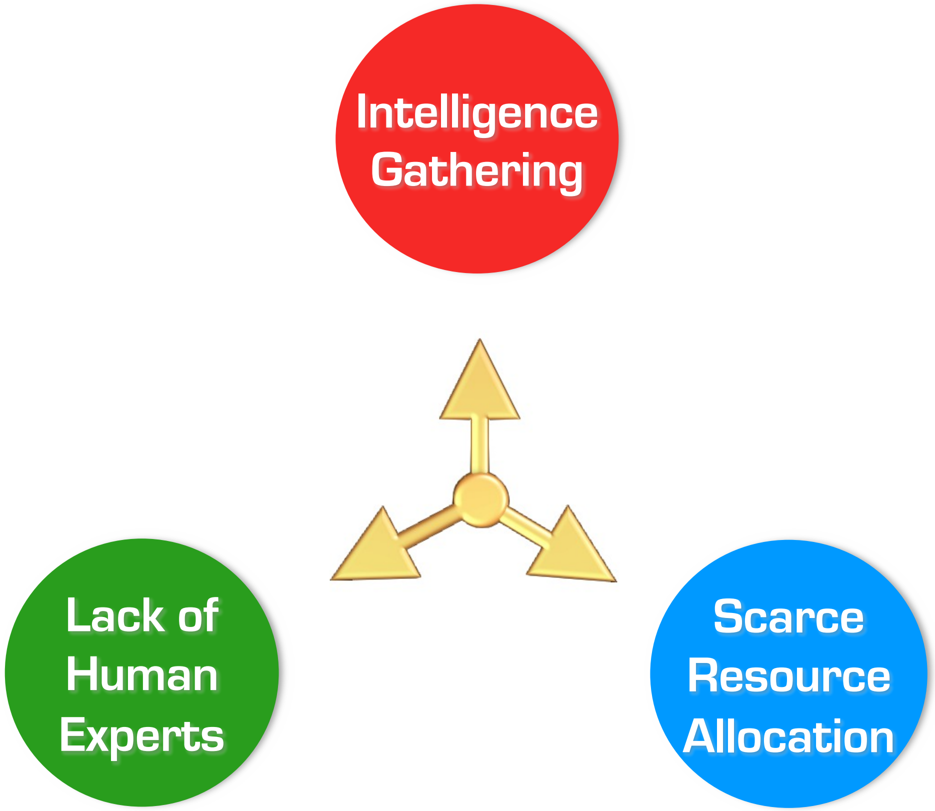
Areas where AI can Contribute to Computational Sustainability



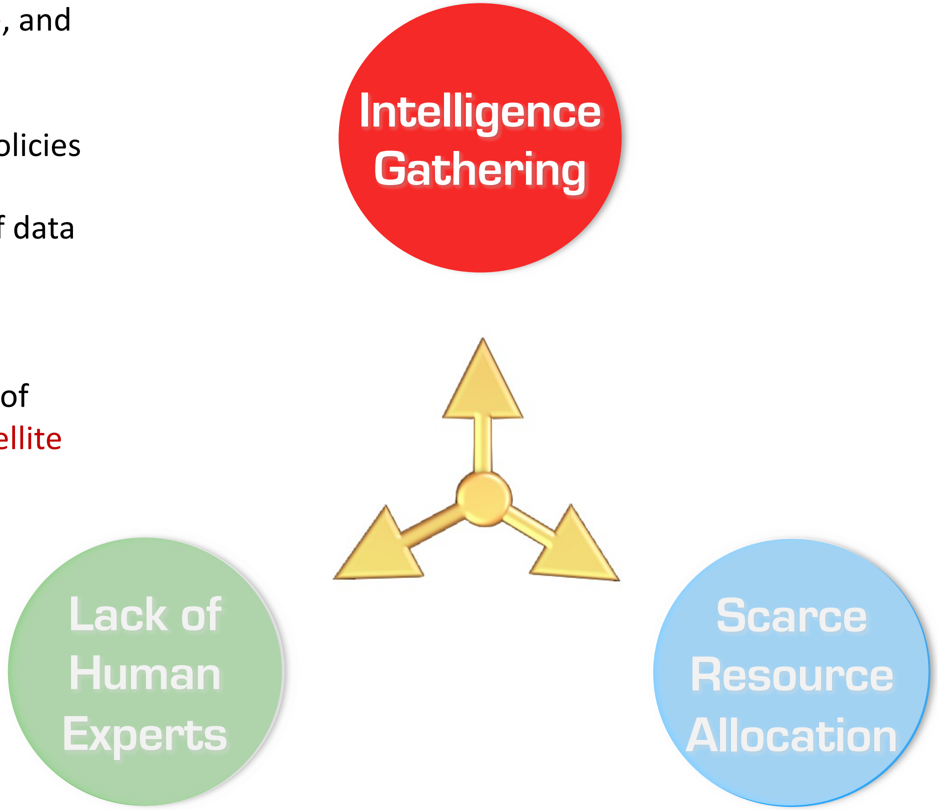
Areas where AI can Contribute to Computational Sustainability

Available data is often noisy and scarce, and expensive to gather.

This results in ill-formed decisions or policies

AI techniques allow the combination of data from many weak sources into a much stronger one

AI techniques also allow the collection of data from alternative sources, e.g., satellite imagery (see Lecture AIML02-02-05).



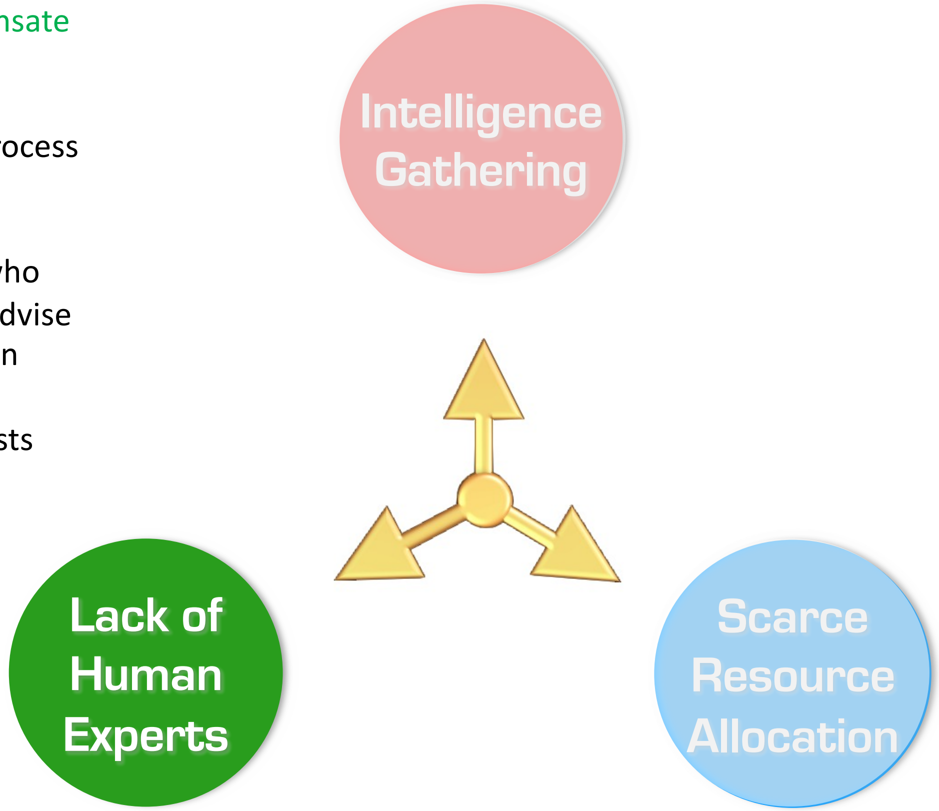
Areas where AI can Contribute to Computational Sustainability

Decision-making processes can compensate for a lack of skilled personnel

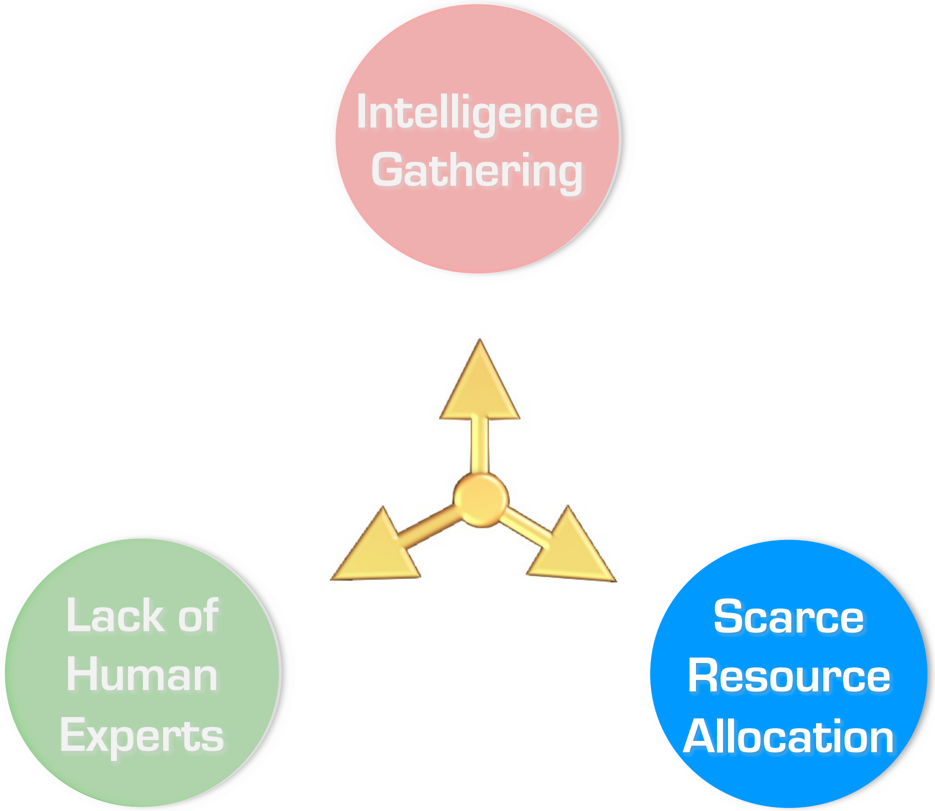
- Laboratory technicians who can process sample when diagnosing disease
- Experienced agricultural workers who can recognize plant infection and advise farmers on the best course of action

AI systems can automate laboratory tests and providing personalized advice to farmers

AI can also augment and enhance the abilities of an expert



Areas where AI can Contribute to Computational Sustainability



Developing countries have limited resources

It is a challenge to allocate them optimally

Specific cases can be framed computationally as optimization problems with different types of constraint

For example, at an agent level, an inspector traveling between pharmacies checking for counterfeit drugs ideally needs a travel schedule that is both cost-effective and difficult to predict

At a macroscopic level, data- and learning-driven policies lead to evidence-based decision-making and resource allocation

Health: Automating Diagnosis of Disease

The standard test for malaria involves the analysis of a blood smear under a microscope

1. Collect a small blood sample (by finger prick)
2. Prepare a glass slide using a staining solution
3. Examine the red blood cells for the characteristic shapes of malaria parasites

Little training required for steps 1 & 2

Significant experience required for step 3

(Quin et al, 2014)

Health: Automating Diagnosis of Disease

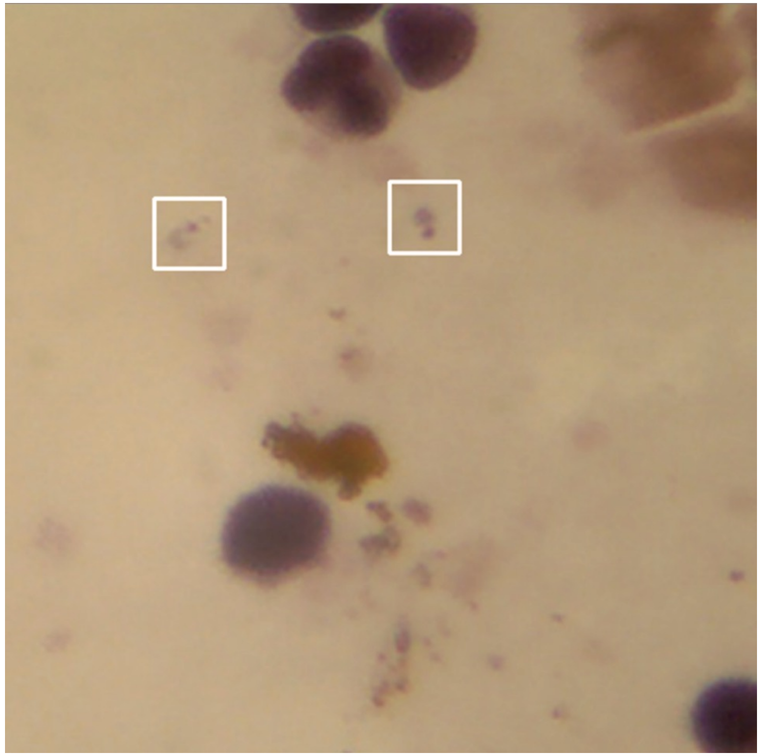
- Researchers in Uganda have investigated automating the diagnostic process using computer vision

  1. A data set of labeled images taken under field conditions from a Ugandan hospital was collected

  2. This was used to train a classifier using a set of morphological (that is, shape-based) image features.

- Artifacts and poor staining added to the complexity of the parasite detection problem

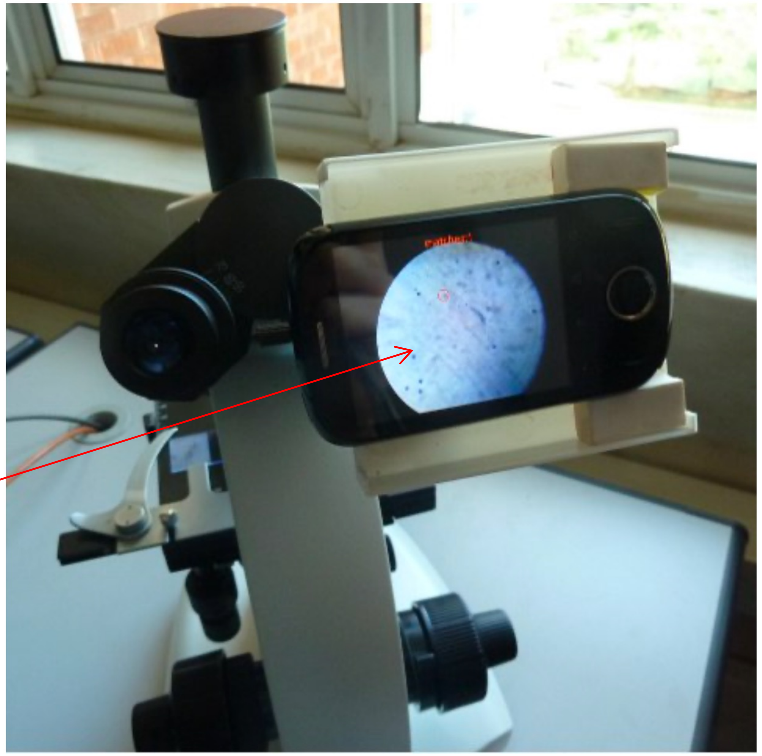
- Diagnostic performance is superior to antigen-based rapid diagnostic tests



(Quin et al, 2014)

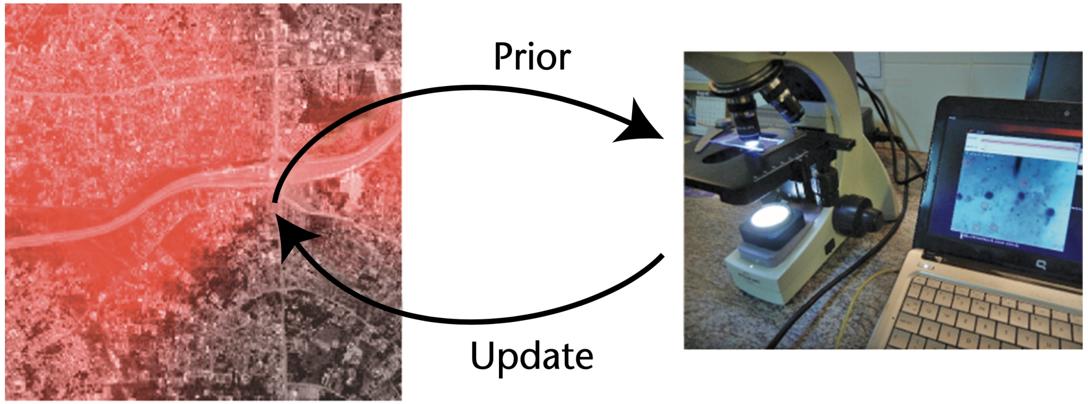
Health: Automating Diagnosis of Disease

Real time diagnosis is possible even on low-powered Android devices
(Mubangizi et al., 2012)



(Mubangizi et al., 2012)

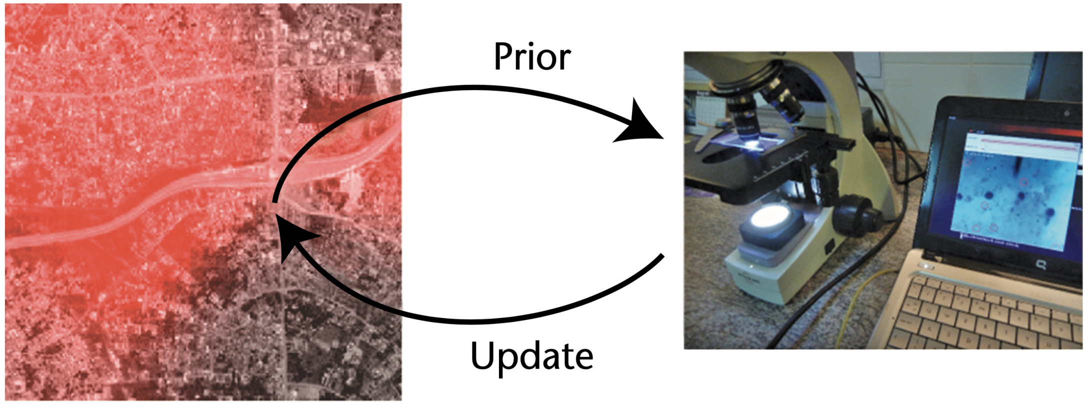
Health: Combining Disease Surveillance and Diagnosis



(Quin et al, 2014)

- The tasks of mapping disease density over space and time and of diagnosing individual cases are usually carried out separately
- However, a risk map can be used to provide prior knowledge in the diagnosis of an individual with a known location
- In turn, the results of individual diagnoses can be used to update the map in a way that is more effective than simply using summary count data

Health: Combining Disease Surveillance and Diagnosis



(Quin et al, 2014)

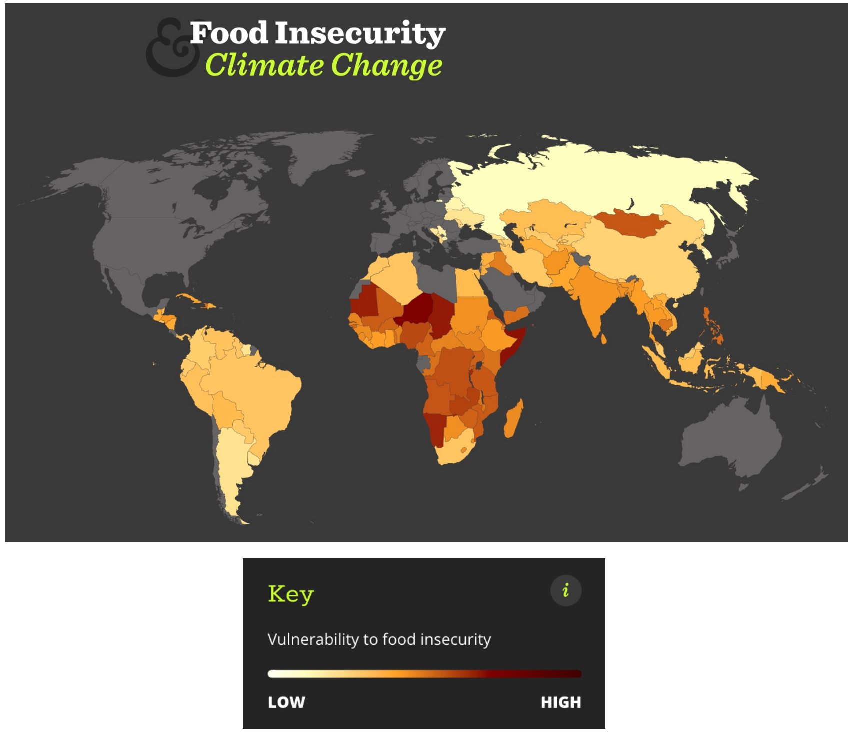
- This combination of mapping and diagnosis is possible due to networked location-aware diagnostic devices
- Researchers in Uganda and the UK showed that the accuracy in each case could be improved using this approach, compared to carrying out the tasks in isolation (Mubangizi et al., 2012)

Food Security

- The processes of food production and supply in developing countries can be easily affected by changes in climate or economic factors

- It is important to be able to anticipate threats to sustainability

- For example,
  - By measuring the spread of viral diseases in staple crops
  - By tracking the degradation of farmland
  - …



https://www.metoffice.gov.uk/food-insecurity-index/

Food Security: Crop Disease Monitoring

- The economies of many developing countries are dominated by small-scale agriculture
  - Smallholder and subsistence farmers are responsible for most production
  - Utilizing relatively low levels of agricultural technology
- Disease among staple crops presents a serious risk, with potentially devastating consequences
- Monitoring the spread of crop disease essential because it allows targeted interventions

https://www.icco-cooperation.org/en/wp-content/uploads/sites/2/2019/09/Final-stars-rwanda-smallholder-farmer-report-gecomprimeerd.pdf

Food Security: Crop Disease Monitoring

Sending teams of trained agriculturalists to visit farms and assess of crop health is expensive and inefficient

- Suitably-trained trained staff are scarce
- Transport is difficult and expensive
- Coordination of paper reports is time-consuming

https://www.icco-cooperation.org/en/wp-content/uploads/sites/2/2019/09/Final-stars-rwanda-smallholder-farmer-report-gecomprimeerd.pdf

Food Security: Crop Disease Monitoring

AI provides a more efficient and cost-effective alternative by performing data collection with mobile devices

The data collection can then be performed by survey workers with only basic training

(Quin et al, 2014)

Food Security: Crop Disease Monitoring

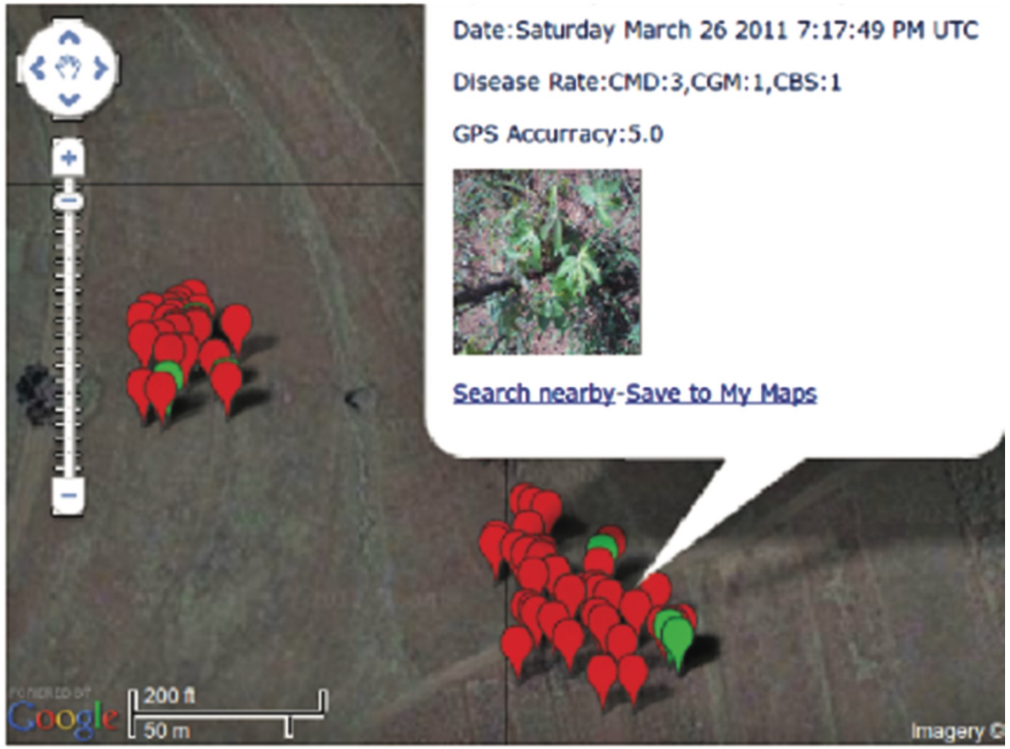
In this case for monitoring viral disease in cassava in Uganda (Quinn, Leyton-Browne, and Mwebaze, 2011)

The classification is based on a simple set of color and shape features (Aduwo, Mwebaze, and Quinn 2010)

(Quin et al, 2014)

Food Security: Crop Disease Monitoring

- Using this approach, a real-time map of crop disease can be constructed
- Active learning: survey teams can be dynamically directed to the most informative areas



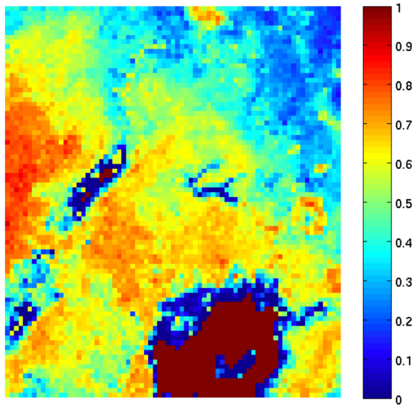
(Quin et al, 2014)

Food Security: Prediction of from Remote Sensing Data

- Features derived from satellite images
  - Normalized Difference Vegetation Index (NDVI)
  - Rainfall Estimate Data (RFE)

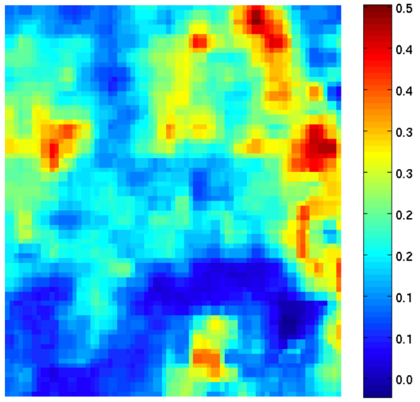
  are used for early warning of food shortages

- Does not directly predict which sectors of society or households are most at risk



Normalized Difference Vegetation Index (NDVI)

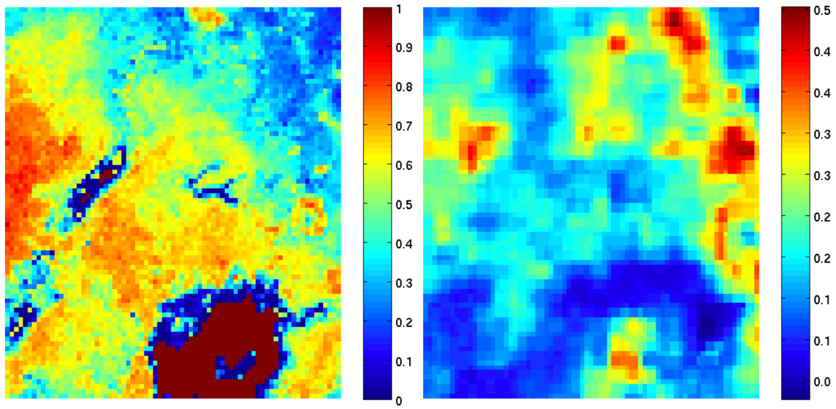
A value of 1 indicates a body of water, other values indicate the vigour of vegetation (Quin et al., 2010)



Rainfall Estimate Data (RFE)
(Quin et al., 2010)

Food Security: Prediction of from Remote Sensing Data

Better predictions at a household level are possible when both satellite data and demographic information are used



In one study, information on 3094 households across Uganda collected between 2004–2005 was combined with remote sensing images taken at 10-day intervals in the same period to model probabilistically the relationship between

- Satellite NDVI
- Rainfall estimate data RFD
- Calorific intake per person in a household
- Land size, household size, and livestock ownership

(Quinn, Okori, and Gidudu 2010)

Transportation: Vision-based Road Traffic Congestion Monitoring

- Small critical areas are common hot spots for congestion
- Resulting in major traffic jams due to poor traffic management
- Current technologies for collecting data is often prohibitively expensive in many developing countries
- Invalid assumptions about driving behavior can undermine conventional approaches to managing congestion

(Quin et al, 2014)

Transportation: Vision-based Road Traffic Congestion Monitoring

- Solar-powered units built around camera phones were found to be effective in collecting traffic flow data in Uganda (Nakibuule, Ssenyange, and Quinn 2013)

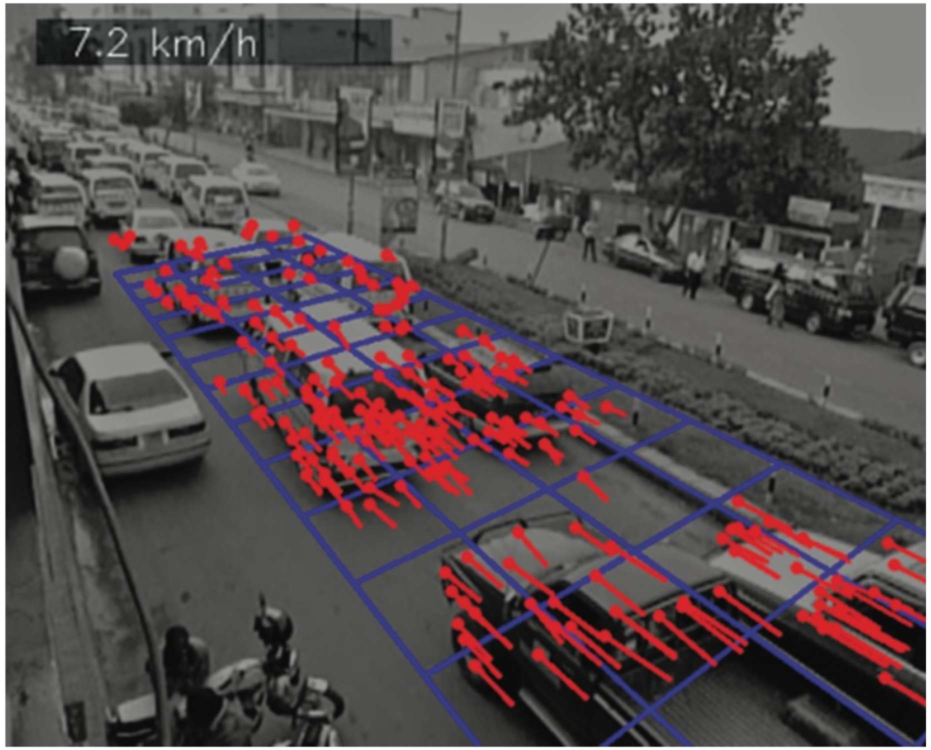
- Drastically cutting the cost of collecting congestion information compared to
  - CCTV systems
  - Other traffic sensors such as induction loops

(Quin et al, 2014)

Transportation: Vision-based Road Traffic Congestion Monitoring

The speed of traffic flow is calculated by

- Calibrating the camera
- Using key-point matches to identify motion
- Distinguishing vehicles from non-vehicles



(Quin et al, 2014)

Social Economics and Policy

- Socioeconomic maps contain important indicators about the status of households at urban, regional, and national scales

- Many policy decisions made by governments and institutions are based on information captured in these maps

- National statistical institutes (NSIs) conduct censuses every 5 to 10 years and typically require a large number of enumerators to carry out interviews and gather the required information

- Conducting these surveys is often challenging and comes at a high cost

- AI and machine learning provides ways of generating the same information at much lower cost

- See Module 2, Lecture 6, for a case study based on an article entitled "Using publicly available satellite imagery and deep learning to understand economic well-being in Africa".

Lecture Summary

1. It is essential to factor an understanding of local social and cultural behaviors into AI systems

2. AI systems can contribute to computational sustainability in Africa by

   - Gathering information efficiently
   - Compensating for a lack of human experts
   - Allocating scarce resources effectively

   in areas such as

   - Health, for disease diagnosis & disease surveillance
   - Food security, for monitoring crop disease and predicting food insecurity
   - Transport, for monitoring road traffic congestion
   - Socioeconomics, for informing government policies

Recommended Reading

Quinn, J., Frias-Martinez, V., and Subramanian, L. (2014). Computational sustainability and artificial intelligence in the developing world. AI Magazine, 35(3).

https://ojs.aaai.org/index.php/aimagazine/article/view/2529

References

Aduwo, J.; Mwebaze, E.; and Quinn, J. 2010. Automated Vision-Based Diagnosis of Cassava Mosaic Disease. In Proceedings of the Workshop on Data Mining in Agriculture (DMA). Berlin: Ibai Publishing.
http://cit.mak.ac.ug/staff/jquinn/papers/dma2010.pdf

Mubangizi, M.; Ikae, C.; Spiliopoulou, A.; and Quinn, J. A., 2012. Coupling Spatiotemporal Disease Modeling with Diagnosis. In Proceedings of the 26th AAAI Conference on Artificial Intelligence. Palo Alto, CA: AAAI Press.
https://ojs.aaai.org/index.php/AAAI/article/view/8180/8038

Nakibuule, R.; Ssenyange, J.; and Quinn, J. A. 2013. Low Cost Video-Based Traffic Congestion Monitoring Using Phones as Sensors. In Proceedings of the 3rd Annual Symposium on Computing for Development (ACM DEV). New York: Association for Computing Machinery
http://jquinn.air.ug/files/Nakibuule_2013_TrafficMonitoring.pdf

Quinn, J. A.; Leyton-Brown, K.; and Mwebaze, E. 2011. Modeling and Monitoring Crop Disease in Developing Countries. In Proceedings of the Twenty-Fifth AAAI Conference on Artificial Intelligence. Palo Alto, CA: AAAI Press
https://ojs.aaai.org/index.php/AAAI/article/view/7811

References

Quinn, J. A.; Okori, W.; and Gidudu, A. 2010. Increased- Specificity Famine Prediction Using Satellite Observation Data. In Proceedings of the 1st Annual Symposium on Computing for Development (ACM DEV). New York: Association for Computing Machinery.

http://jquinn.air.ug/files/Quinn_2010_ACMDEV.pdf