Near Real-time Decision Making Under Uncertainty for Disease Mapping, Monitoring, and Prediction

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Overview

- Data
 - Remote Sensing
- Analytics
 - Machine Learning Based Simulations
- Near-Real Time Decisions
 - Edge Computing

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Data Preparation

- Remote sensing provides a global coverage.
 - Usually in 1-2 weeks scale.
 - Landsat and Sentinel 2 data is free.
- Remote sensing data is widely used for disease diagnosis.
- Images from different months/seasons can be used to compare the infected and healthy plants.
 - For the year that the plant has no infection, we can set up a baseline.
 - For those result lower than the baseline, it is a sign of a potential infection.





Remote Sensing Spectral Data

- Spectral reflectance shows how land surface reflects radiant energy.
 - Part of the energy was absorbed, and we can compare the observed reflectance value and the original value.
- The plots are generated by SeNtinel Applications Platform (SNAP)
- Two spectral curves display the spectral reflectance of the same area, Transylvania County, in different timestamps.
 - Top: the image was taken in early March, without cloud covering the area.
 - Bottom: the image was taken in late March, with cloud covering the whole area.



Spectral Reflectance





- Image (a) shows the Sentinel-2 RGB image taken from Transylvania County.
 - A spectral reflectance chart (b) displaying the results of Transylvania County in different timestamps of 2017.
- B3, B7, and B10 are the wavelength that we are focusing on, as
 - A study has shown that these three
 bands provide significant difference
 between the healthy plant and the
 plant get infected.

NDVI Profiles







Normalized Difference Vegetation Index (NDVI) value can be used to determine the greenness of a plant.

- Chart shows a NDVI plot for the Transylvania County in 2017.
 - One can observe a curve that the highest value is centered around July and August, and the value drops as the plant get matured.

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Address the limitations of clouds

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Band_1





Challenges: In reality there is no ground truth for "anomalous" class Krishna Karthik Gadiraju, Zexi Chen, Bharathkumar Ramachandra, Ranga Raju Vatsavai: Real-Time Change⁸ Detection At the Edge, ICMLA 2022: 776-781

Band_1

Reinforcement Learning for Decision Making Task

- Q-Learning is a reinforcement learning approach for helping decision making tasks under uncertainty.
- The cycle of Q-Learning process
 - Starts with receiving environmental input as the state
 - Updates its own q value table with the slot of previously selected action with current state
 - Chooses the action with the highest q value among all possible actions
- The q value

$$q_{st}\left(s,a
ight)=E\left[R_{t+1}+\gamma\max_{a'}q_{st}\left(s',a'
ight)
ight]$$

- The new q value will be the sum of the current reward under current state with a given action and the maximum q value in the current state action space multiplied by gamma, the discount factor.
 - Discount factor is the weight of how we evaluate the future state compared to immediate reward.



Learning from interaction with given environment to achieve some long-term goal (reward) that is related to the state of the environment.

Q-Learning Performance in Simulation

- Compared to the standard Q-Learning, our improved algorithm receives a much higher reward from simulated environment.
- We improved the accuracy of the experimental result by 56%.

Performance Evaluation			
Approaches	Reward	Accuracy	fertilizer usage
Baseline Q-Learning	10.11	0.44	46.31
Proposed Q-Learning	7045.13	0.69	51.79

Applying Reinforcement Learning on Tomato Disease Management

- Reinforcement learning can be used for fungicide management in tomato field.
- Under different states of tomato, the RL is capable to make the optimal decision for minimizing the damage to the tomato.
 - The state is a collection of factors, including:
 - The tomato's health condition
 - Spectral reflectance
 - Environment
 - Soil fertilization
 - Precipitation
 - Temperature
 - Irrigation method

Disease Spreading

- With the observation of how COVID spreads within human community¹, we can also develop a simulation of how P. Infection spread through tomato field.
 - In COVID experiment, the spreading coefficient is determined by the environment that simulated individual is exposed to, including public contact, in-door contact, etc. Corresponding weights are applied to different cases.
 - Two contact networks are formed for people carrying the COVID.
 - One is a simulated network between possible places that people will go.
 - The other is a random network that fully discover all the possible places that a carrier can go for spreading disease.

Kerr, C. C., Stuart, R. M., Mistry, D., Abeysuriya, R. G., Rosenfeld, K., Hart, G. R., ... & Klein, D. J. (2021). Covasim: an agent-based model of COVID-19 dynamics and interventions. *PLOS Computational Biology*, *17*(7), e1009149.

Simulation for Late Blight Spreading

- P. infection, the cause of late blight, can be spread through air, irrigation, and soil.
 - A research¹ has shown that overhead irrigation can significantly increase the chance of a plant get infected by late blight.
- The blight can penetrate the leaf easily, and infected the whole plant within 2 days.
- Two common approaches to deal with rapid infection
 - Mate with other species to have stronger resistance to late blight.
 - Apply fungicide at the beginning of a season.
- Therefore, real-time on-field remote sensing data is necessary to closely monitor the health condition of the crop.

Becktell, M. C., Daughtrey, M. L., & Fry, W. E. (2005). Epidemiology and management of petunia and tomato late blight in the greenhouse. *Plant disease*, *89*(9), 1000-1008.

Demo