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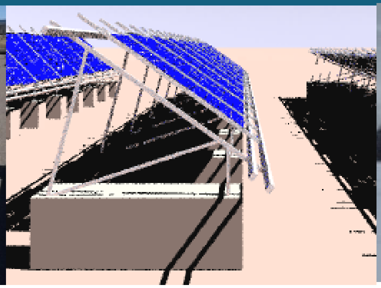
Approaches to Sky Image Based Single Axis Tracker Algorithms



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Single axis tracking in varied weather conditions

- Most SAT algorithms (such as pvlib's) **only follow the Sun**
- This is optimal when there are **no clouds**
- Cloud covering the Sun = less direct, more diffuse
  - When it's very cloudy, **move trackers towards the horizonal to maximize**

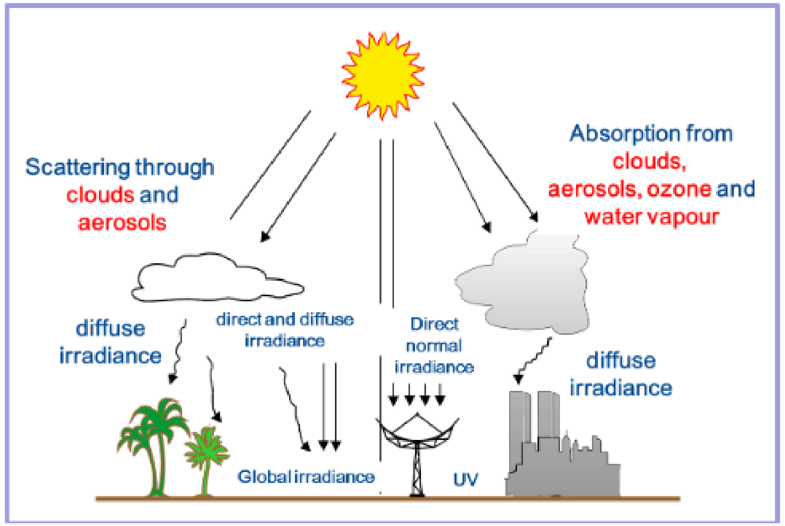
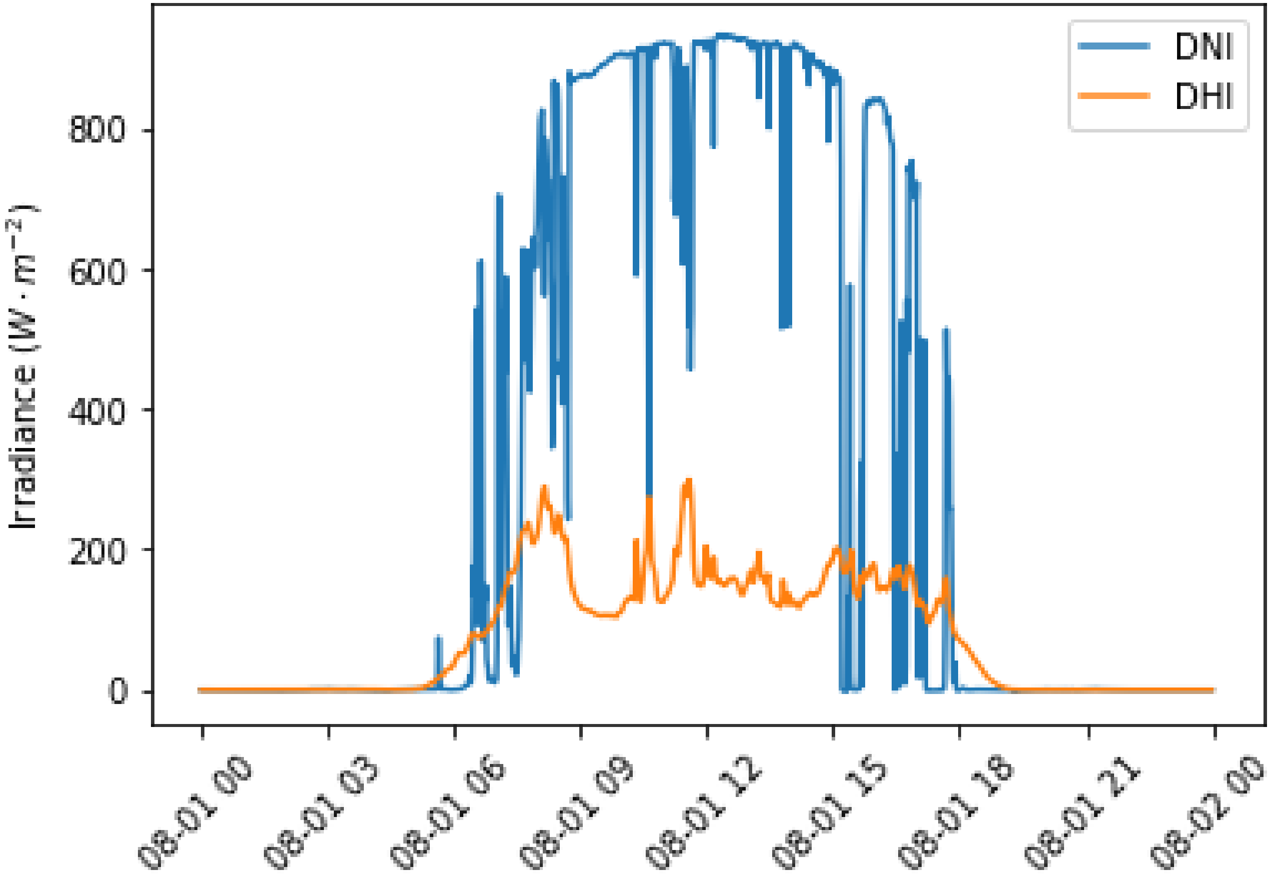


Figure: Copernicus Atmosphere Monitoring Service

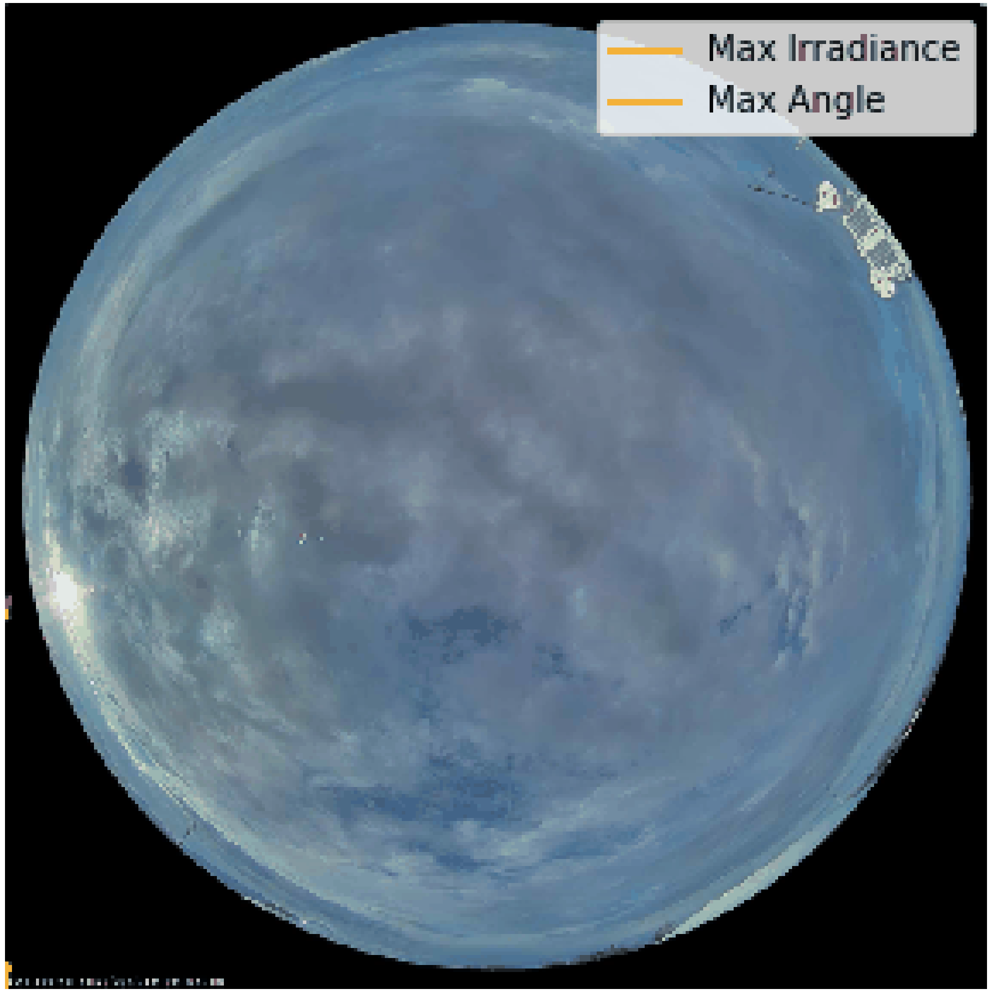


Relationship between angles, irradiance, and weather

- Orange line: Normalized angle of max irradiance
- Red line: Normalized irradiance at max angle

- "Spiky" signal- **angle of max irradiance would not be a good tracking strategy**
- Short-term effects **often not modeled** due to coarser aggregations, but are impactful

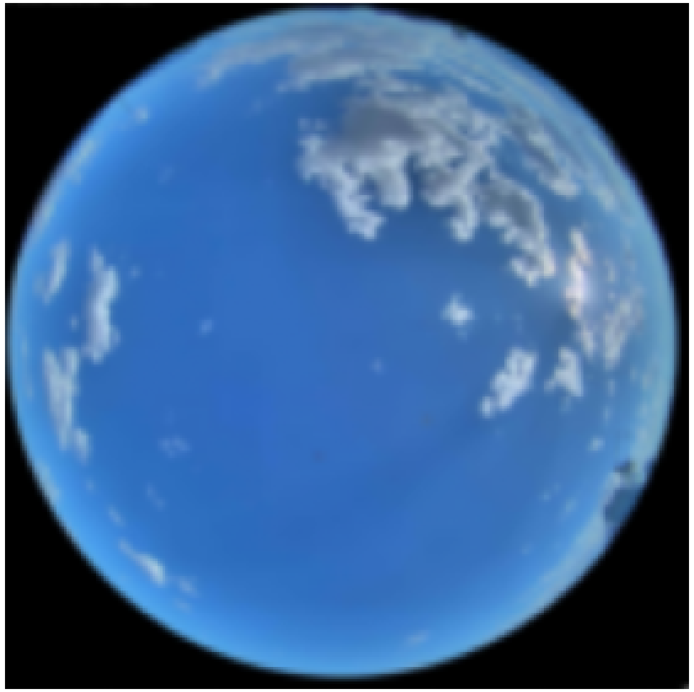
180°
~800 W/m^2

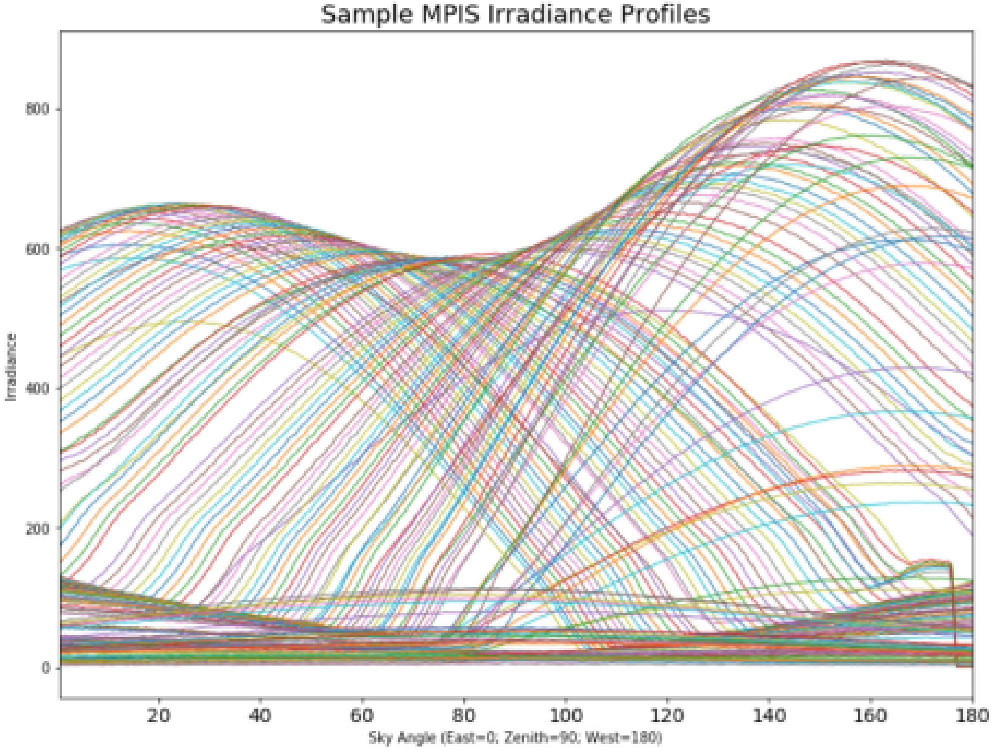


0°
0 W/m^2

Data collection and sensors

- Sky images collected in real time
- Validation data is collected with a Multi Planar Irradiance Sensor (MPIS)
  - Irrad. sensor rotating on same axis as tracker
- Physical MiniSATs as testbench





Multiple possible approaches

- We plan to implement and test three different types of algorithms
  - Cloud coverage heuristic
  - Past-*n* regression
  - Deep Reinforcement Learning
- Each approach uses a neural network of some type to do:
  - Cloud segmentation
  - Prediction of angle of *maximal irradiance*
  - Prediction of optimal *movement strategy*

These are different, due to tracker movement costs, wear and tears, etc

- Each has different drawbacks, such as
  - Manual input & bias for movement strategy
  - Reliant on accurate angle predictions
  - Difficult to train & generalize

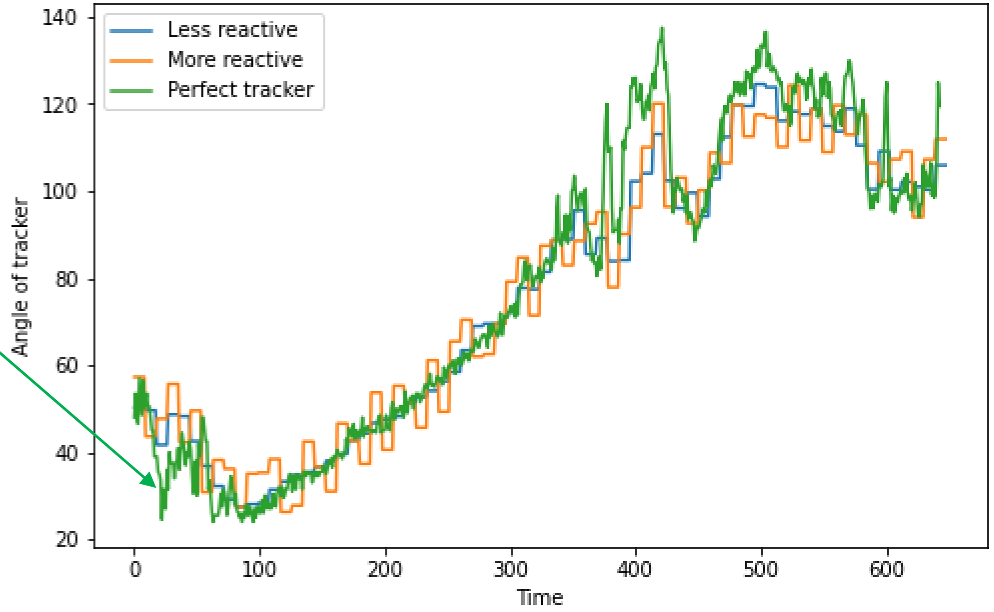
These two are also less explainable due to lack of explicit decision tree

Cloud Coverage Heuristic

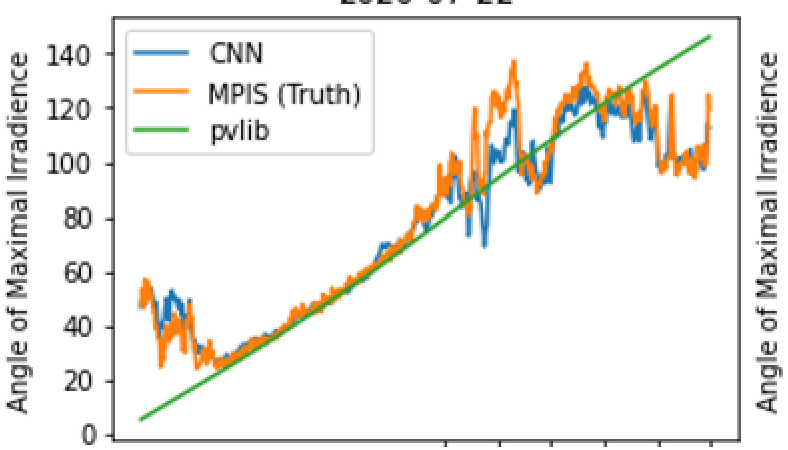
- Concept:
  - If extended cloud cover: **Move towards the horizontal by some amount**
  - Else, **follow the Sun**
  - Further conditions based on **system knowledge**
- Many methods of calculating cloud coverage in literature
  - Your sky camera probably has one already
  - I presented a **neural network** based model at PVSC
- Has additional parameters:
  - **% coverage** to be considered cloudy
  - **Number of previous timesteps** to consider
- Simulations find this algorithm to be a **~0.06-0.08% gain in ABQ, NM**
  - Grid search over parameter space yields highly reactive tracker
- <u>Advantages:</u> Simple, configurable
- <u>Disadvantages:</u> Site specific heuristics/parameters

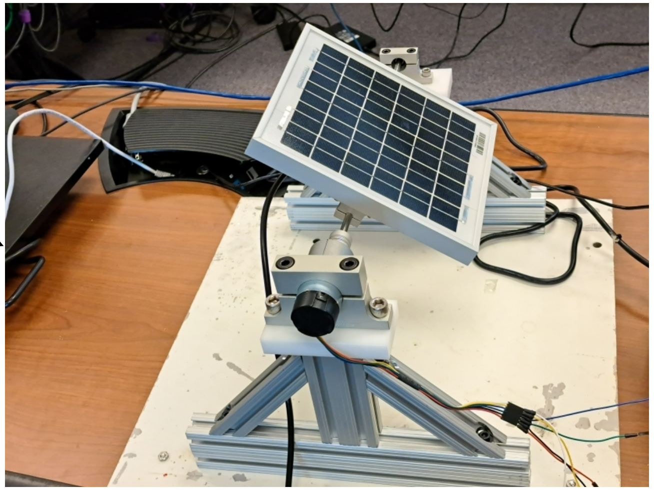
Past-*n* regression for tracker motion

- Use past *n* minutes of angles of maximal irradiance
- Move by **some threshold *r*** in direction of slope
- Update tracker **every *k*** minutes
- <u>Advantages</u>: explainable, adjustable
- <u>Disadvantages</u>: requires specialized device (eg MPIS) to find angle of max irradiance
  - Prototype sensor for wide deployment
  - Convolutional neural network (CNN)



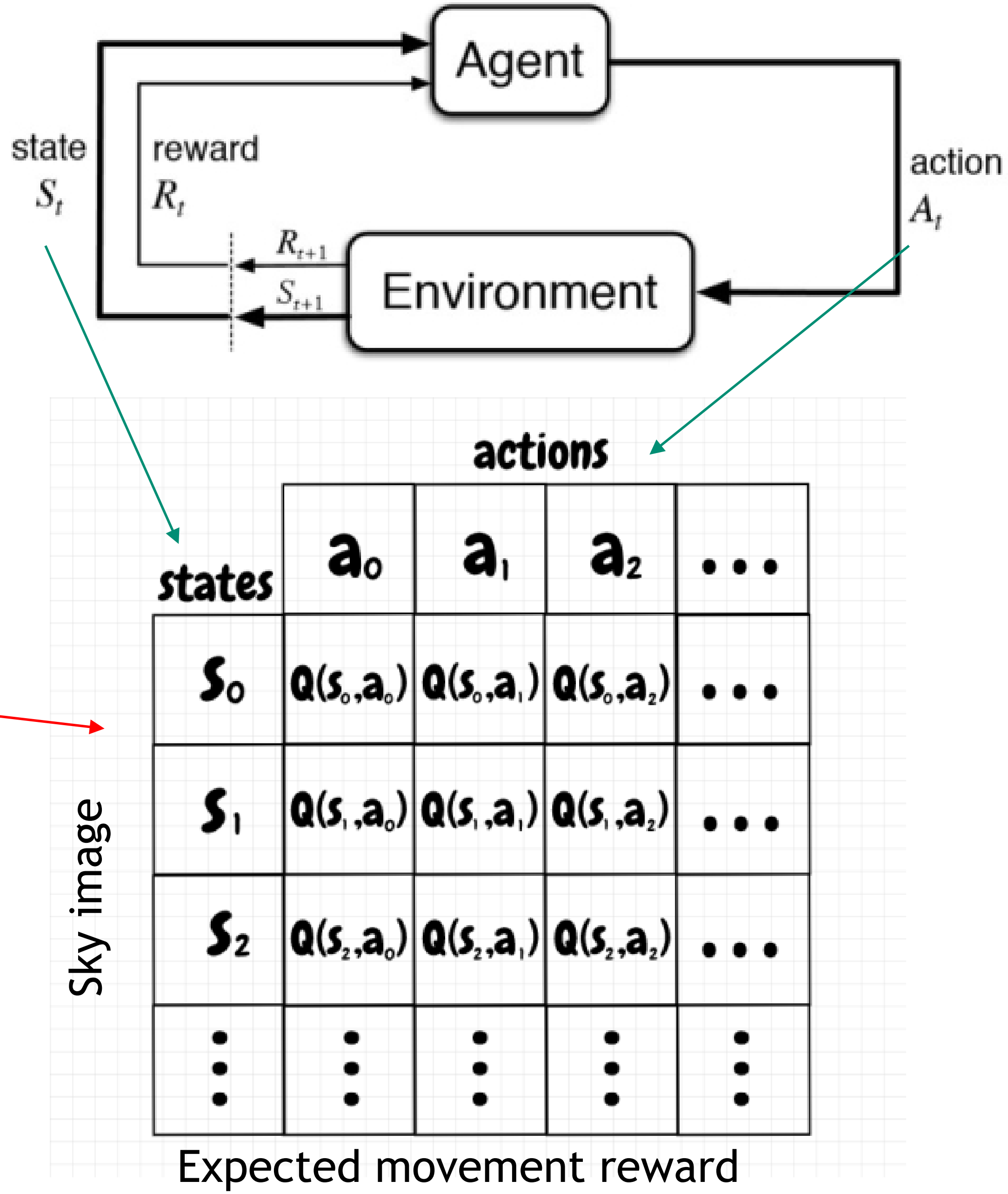
Algorithm can be adjusted by changing *n, r, k* to desired specificity





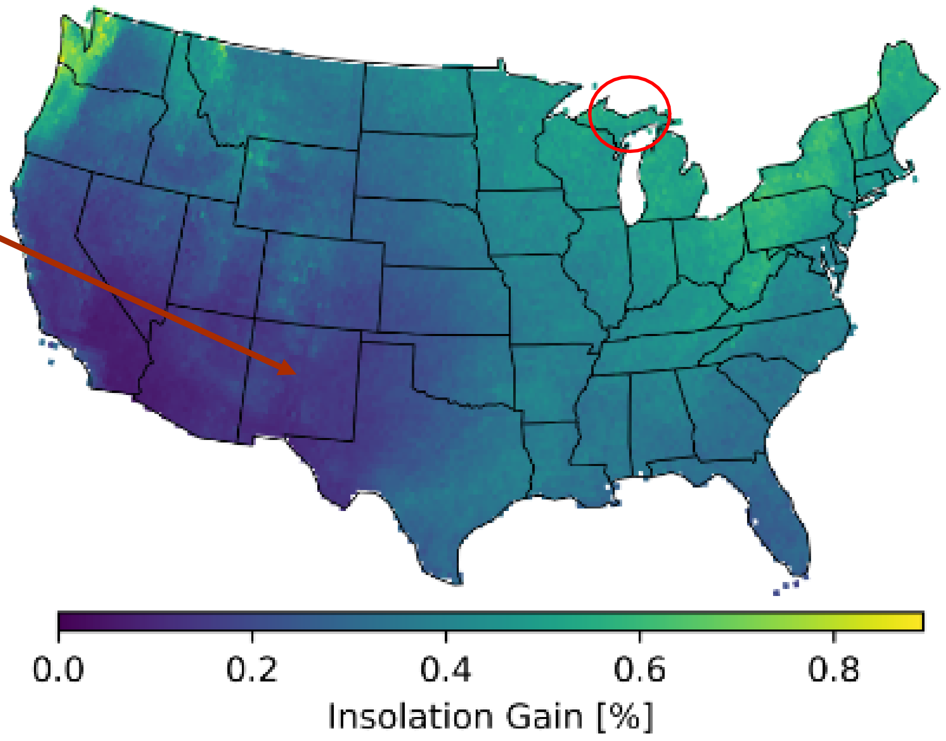
Deep Q Learning for tracker motion

- Use Deep Q Learning, a type of reinforcement learning (RL) to predict **optimal movement strategy**
- Agent receives **rewards** (eg irradiance received) and **learns** based on expected future reward.
    - "What move will result in the maximal power received at the end of the day?"
- Approximate decision lookup table (function) with ANN
- <u>Advantages</u>: data-driven, adaptable
- <u>Disadvantages</u>: "black box", computationally intensive to train



Current Results & Next Steps

- Problem: **ABQ, NM is too good for PV!**
  - Extended periods of cloudiness are **rare** for much of the year
  - High overall irradiance dominated by direct component
- So, models behave “unrealistically” in most cases
  - Cloud coverage is **too reactive** (teleportation)
  - Past-*n* regression **oscillates**
  - RL **doesn’t move at all** (risk vs reward!)
- **Other conditions** must be considered
  - Snow shedding
  - Wind
  - Terrain
- Next step: **Install MPIS & Sky Camera at Michigan Tech RTU**



Anderson & Aneja PVSC 2022

Questions?

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