

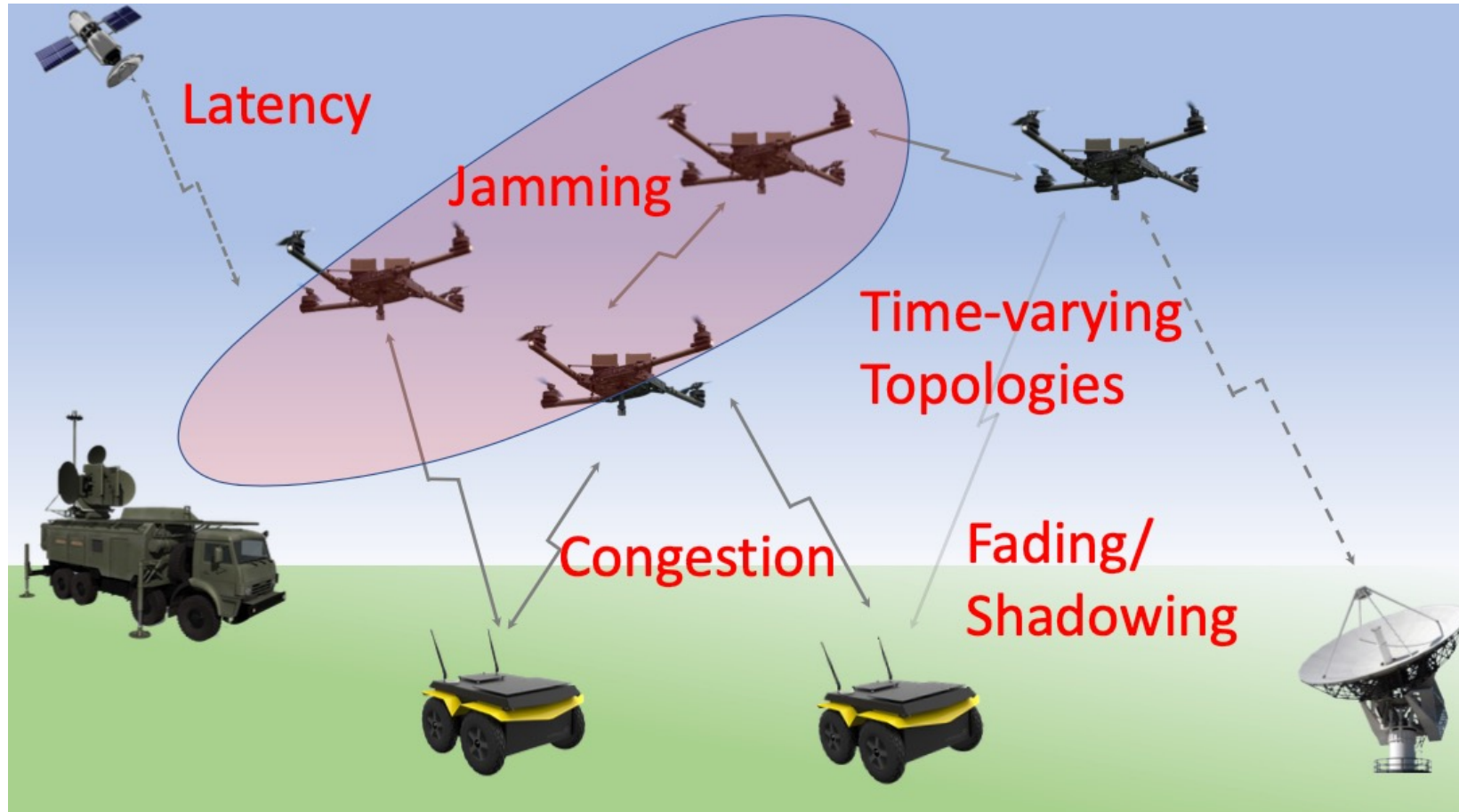
# Distributed Sensor Fusion Reporting over a Shared Wireless Channel



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# Big Picture



**Multi-objective, distributed, partially observable**  
**⇒ Partially observable stochastic game**



# Distributed Sensing Problem



**Distributed Sensing and Coordination: Who senses and transmits?  $\Rightarrow$  Partially observable, multi-agent MDP**

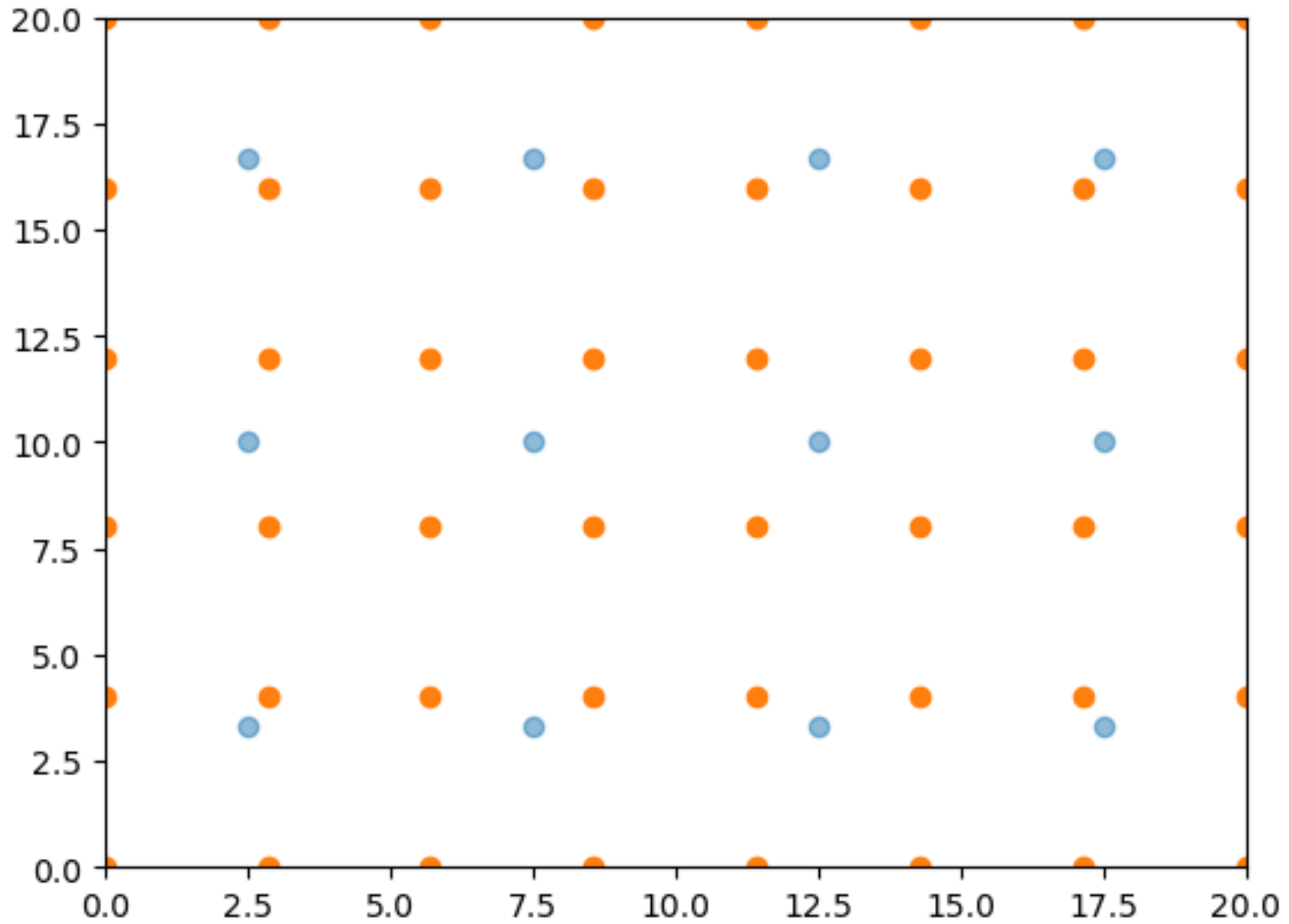


# Sensing Model

- Use distributed sensors to localize a moving vehicle
- Sensors listen to channel for signal energy (e.g., audio or RF)
- Received signal energy decreases with  $d^2$
- Noise modeled as iid Gaussian
  - Equal variance across sensors and time
  - Independent across sensors and time
- Sensors are distributed in a uniform grid over a rectangular area to be monitored



# Sensors and Vehicle Positions





Average signal strengths when vehicle is at (2.86,4)

```
[[1.74826561 0.02767971 0.00622774]
 [0.04545337 0.01737435 0.00549449]
 [0.0107033 0.00775286 0.00394588]
 [0.00465424 0.0039934 0.00266768]]
```

More than 2 orders of magnitude  
difference in received power

**=> Drastically different SNRs across sensors**



# Fusion Model

- Sensors transmit measured data to a centralized fusion agent over a shared wireless channel
- All sensors have a direct link to the fusion agent
- Slotted ALOHA MAC:
  - Transmissions occurs in slots of fixed duration
  - A collision occurs if more than one agent transmits in a slot
    - **Sensing data is received at the fusion agent only if exactly 1 sensor transmits in a slot**



# MAC Transmission Control

- Agents individually decide whether to transmit
- Information agents may use in making this decision:
  - Received signal strength indicator (RSSI)
  - Result of last channel access (success/failure)
  - Current beliefs (need to be broadcast by fusion agent)
  - # slots since last successful transmission by this agent
- **Optimal rule is likely stochastic:**
  - For example, always transmitting from sensor with highest SNR prevents ability to triangulate vehicle
- Our goal: **decide optimal transmission probability at each sensor to minimize error in location estimate**





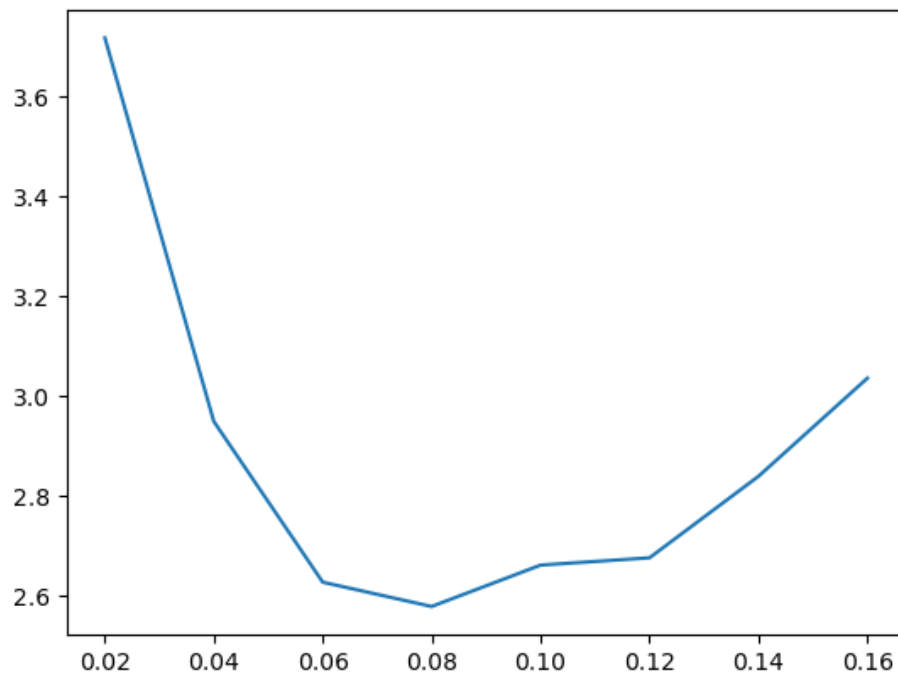
# POMDP Model

- Vehicle being tracked moves according to Markov Model
- *A posteriori* state probabilities (beliefs) updated using Bayesian approach in each interval, fusing model knowledge with signal strength measurements (if available)
- Maximum *a posteriori* location estimate used in calculating vehicle position

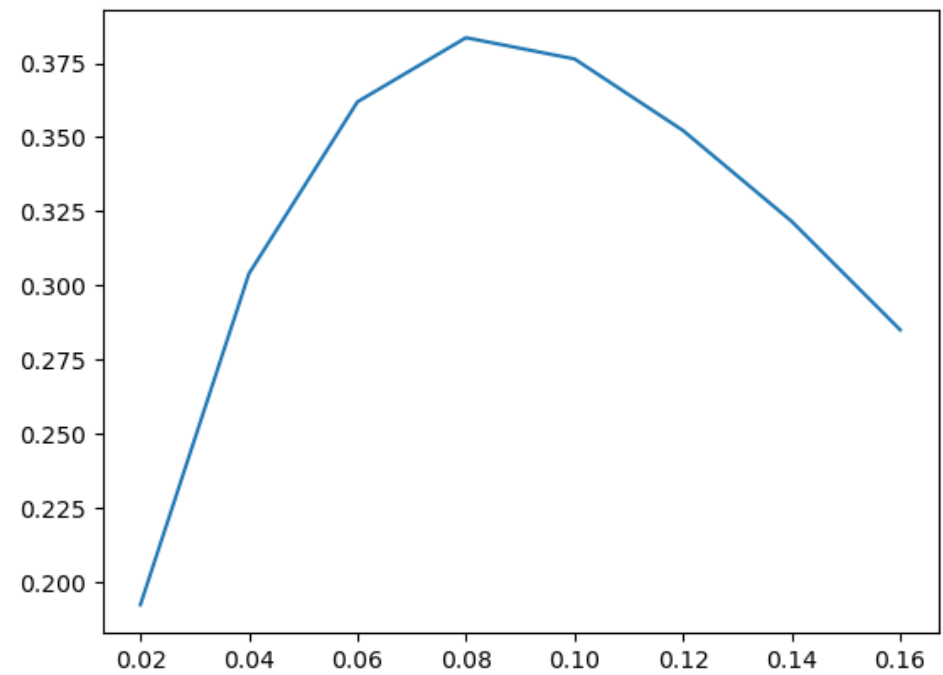


- Baseline 1: All nodes transmit

Avg Location Error



Prob (Tx Success)

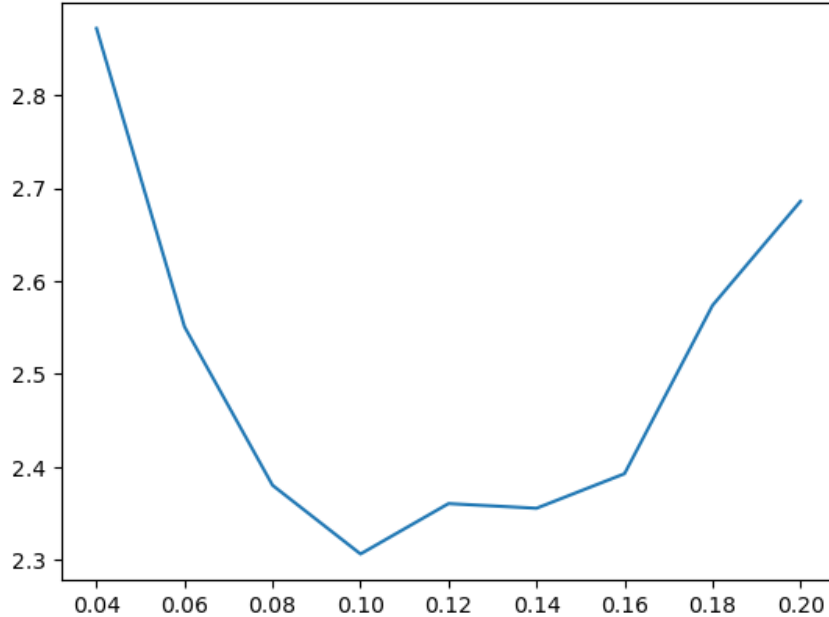


Transmission Probabilities

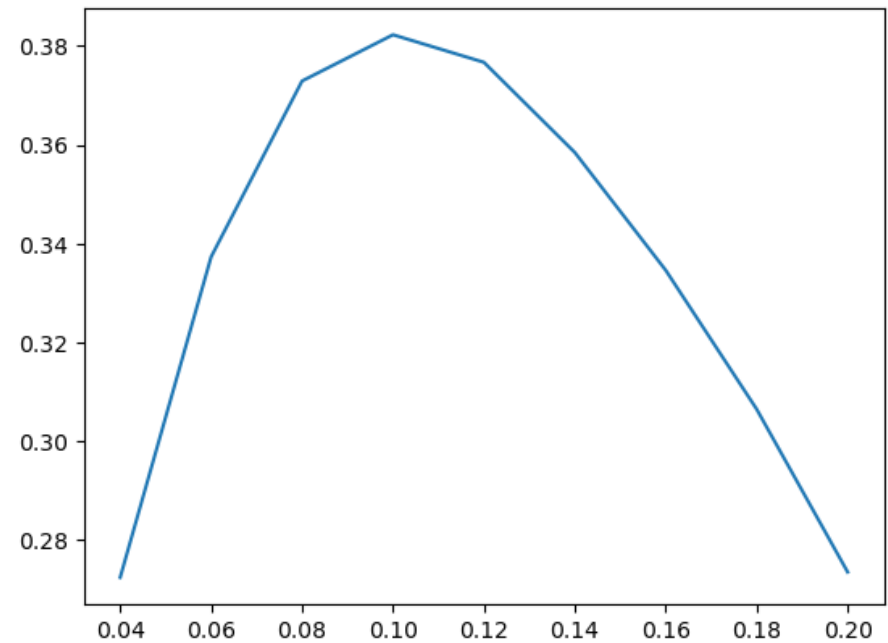


- Baseline 2: Nodes with valid data transmit

Avg Location Error



Prob (Tx Success)



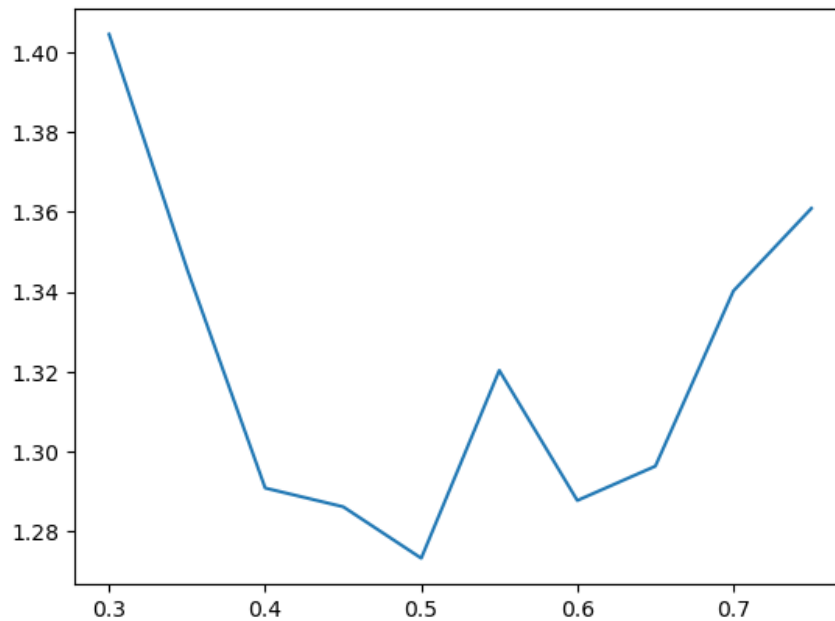
Transmission Probabilities



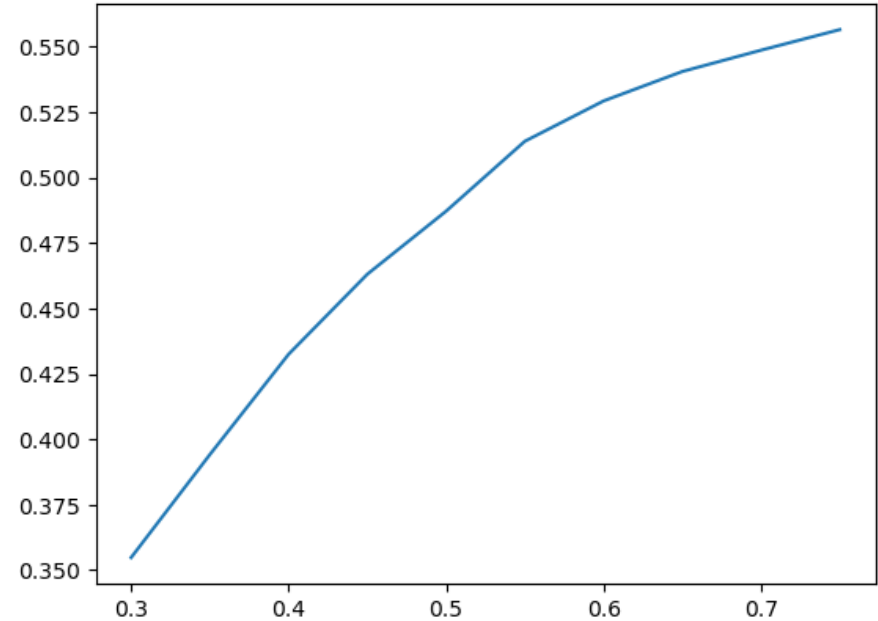
# Signal Power-Thresholding

- Sensors eligible to report if their measurement exceeds a pre-determined threshold

Avg Location Error



Prob (Tx Success)



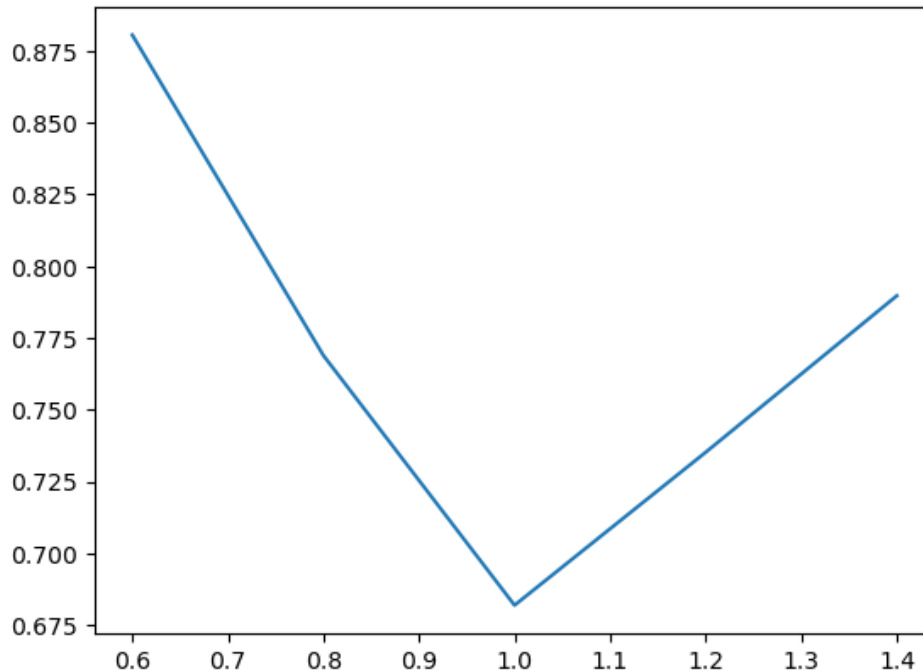
Transmission Probabilities



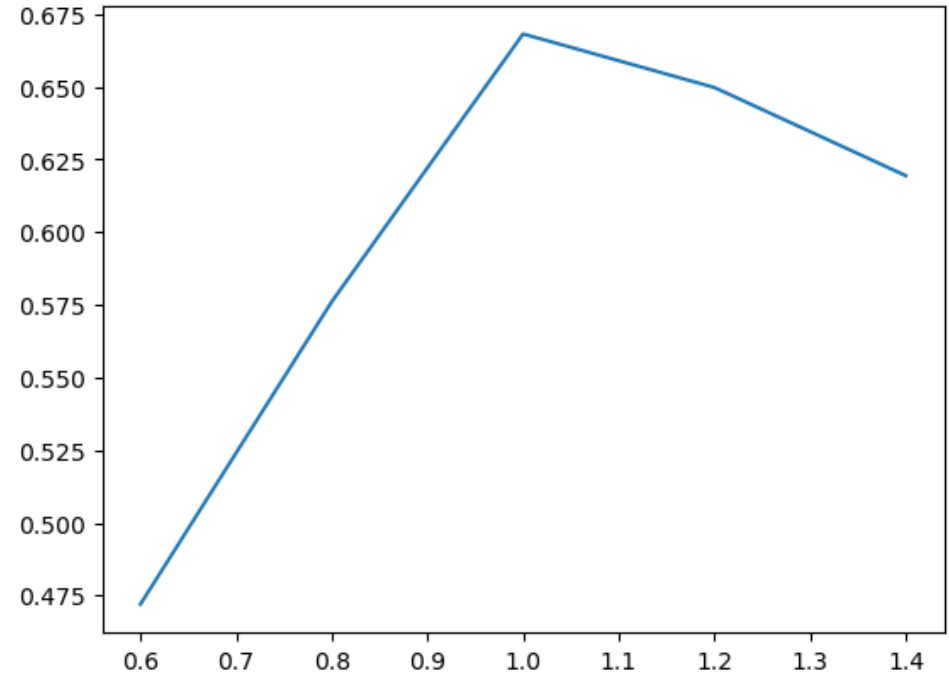
# Belief-Based Limiting

- Sensors eligible to report if they are within a fixed distance of last MAP estimate

Avg Location Error



Prob (Tx Success)



Transmission Probability Scaling



# Conclusions

- For operation on shared wireless channel, MAC transmission control is essential
- Need to optimize transmission parameters at each sensor based on estimated value of that sensor's measurement to the localization process
- Model knowledge turns out to be essential to achieving good performance: ML estimate without model knowledge has terrible performance
- POMDP + RL provides good framework for optimizing systems across domains (here, sensing & communications)