Wireless Futures Research
Connected Aerial Vehicles and Machine Learning for Communications

Professor Robert W. Heath Jr.

Wireless Networking and Communications Group
Situation Aware Vehicular Engineering Systems
Department of Electrical and Computer Engineering
The University of Texas at Austin

TEXAS
The University of Texas at Austin

http://www.profheath.org

Thanks for support from the National Science Foundation, DARPA, Federal Department of Transportation, Texas Department of Transportation, Huawei, and Toyota ITC.

Connected Aerial Vehicles

Slides developed by Dr. Nuria Gonzalez Prelcic

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Big numbers for the commercial drone industry

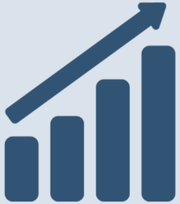
82.1 billion

2025

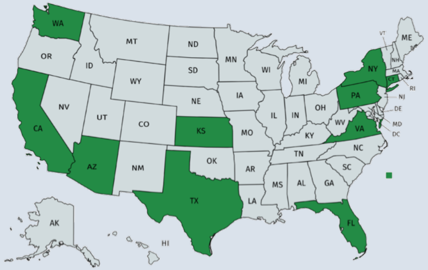
Jobs by 2025
100,000

Tax revenue 2015-2025
$482 million

Commercial drone fleet



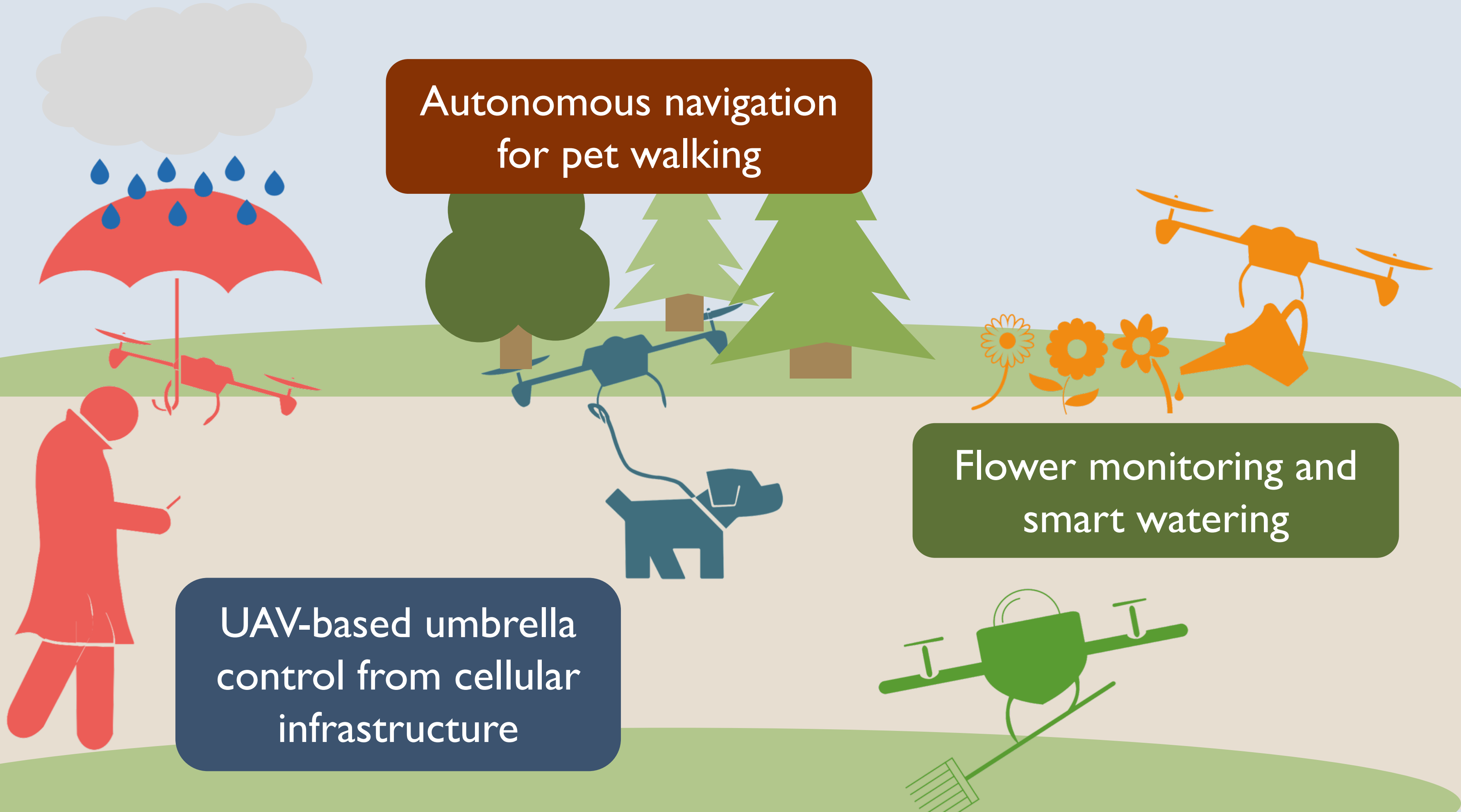
States predicted to see the most gains in terms of job creation and additional revenue



The estimated economic impact of the drone industry is enormous

*Numbers predicted by the FAA and the Association for Unmanned Vehicle Systems International (AUVSI) https://www.dartdrones.com/blog/drone-industry-impact/

Disruptive application areas



UAVs as imaging sensors

Real state marketing*

Panoramic VR streaming of live video

Professional photography (news coverage, events, …)

Consumer photography

Footage is directly used; role for wireless is control and/or live streaming

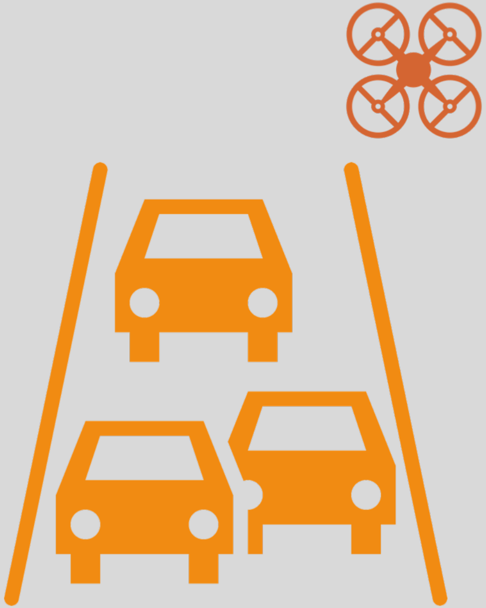
https://bestdroneforthejob.com/drone-buying-guides/fly-it-or-buy-it-the-complete-guide-to-using-camera-drones-for-real-estate-marketing/

UAVs for sensing and monitoring

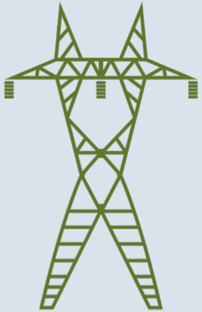
Agriculture (growth and health monitoring, plantation estimation)

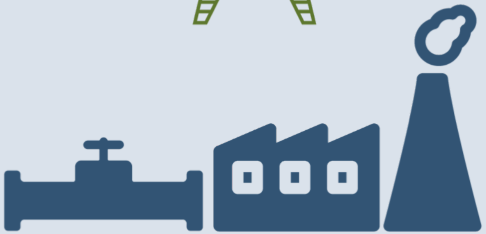
Forestry (species identification, de-forestation monitoring)

Traffic monitoring



Powerline/pipeline monitoring



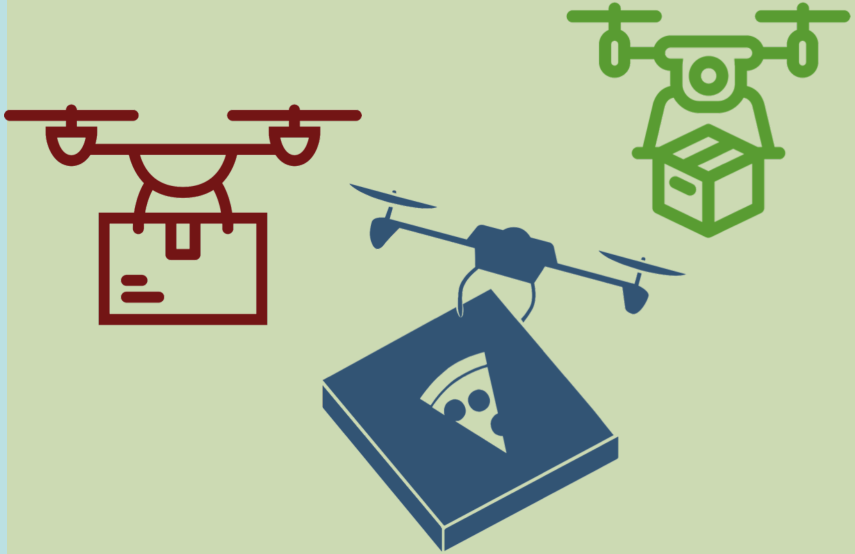


UAVs collect pictures or videos which are later processed

Transportation/delivery

Personal transport

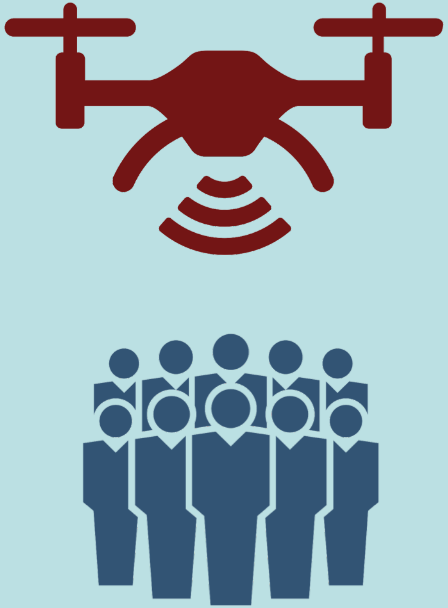
Package/letter/food delivery



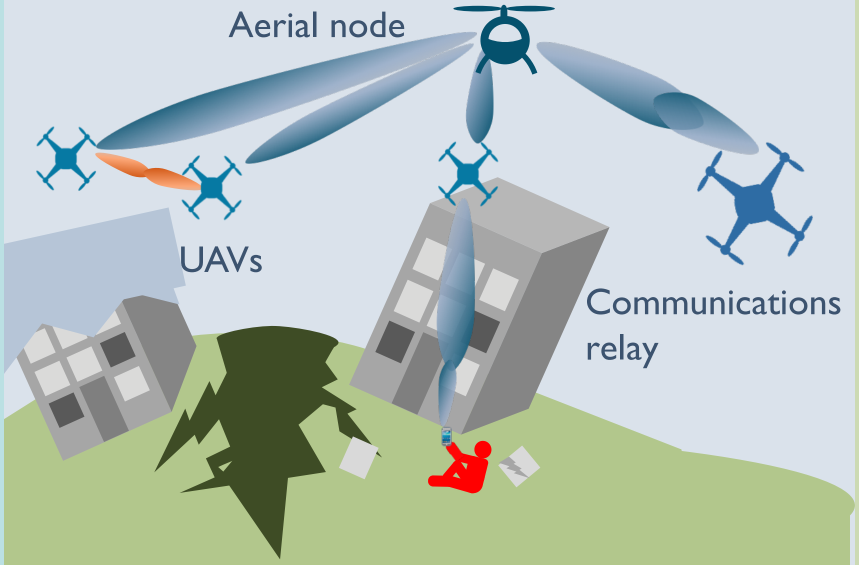
UAVs as transportation vehicles

UAVs for wireless

Mobile hotspot for crowds



Wireless access in disaster areas

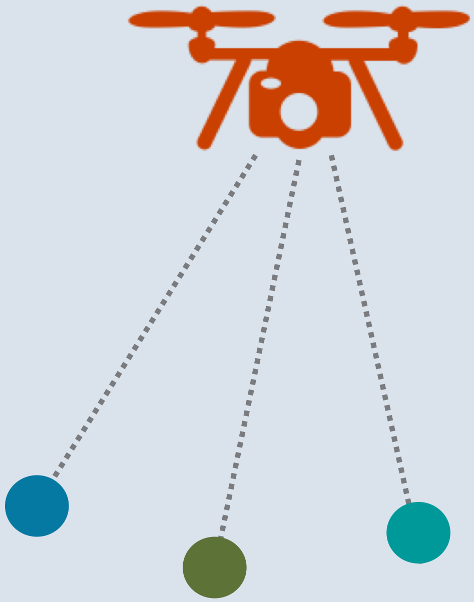


Drive testing (cellular coverage)

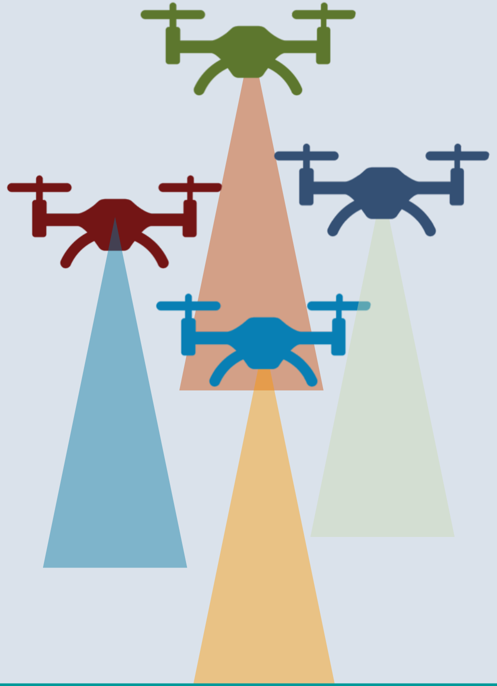
UAVs also enable disruptive applications for communications

Technologies for disruptive UAV applications

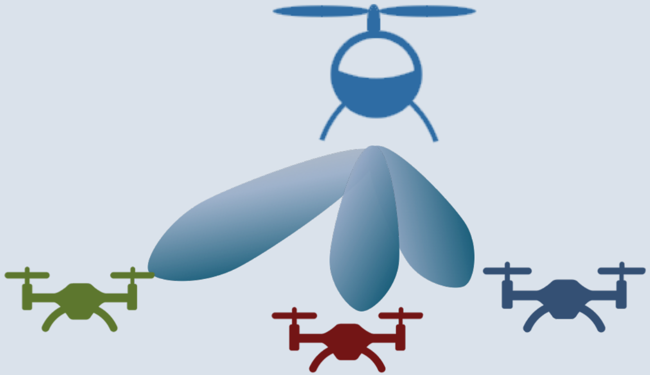
Positioning/mapping/ navigation



Collaborative sensing



MIMO communication



SAVES faculties are well positioned on key UAV technologies

Machine learning for communications

Thanks to Yuyang Wang, Monica Ribero, Vutha Va, and Aldebaro Klautau for providing content for this section.

Supported in part by the U.S. DOT Tier 1 University Transportation Center D-STOP and by TX-DOT under Project 0-6877 CAR-STOP, a gift from TOYOTA ITC, and by a gift from Huawei.

Machine learning for classification

Supervised learning

Given labeled data, devise rule for predicting the label for new data

raw data → **Front end** → features $\boldsymbol{x} \in \Re^p$ → **Classifier** → labels $y \in \{1, \dots, C\}$

Shallow learning uses expert knowledge and experiments to reduce dimensionality, deep approach may skip this step

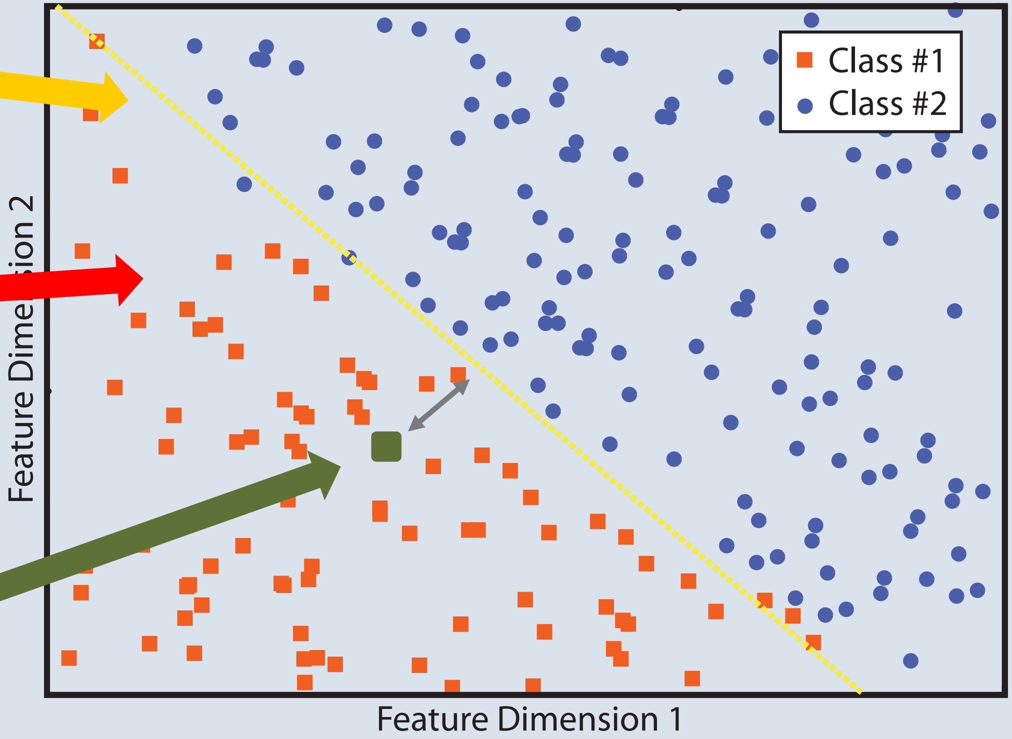
Trained based on past performance data, e.g. feature / label pairs

Machine learning for classification

Machine learning algorithm devises rule to separate classes

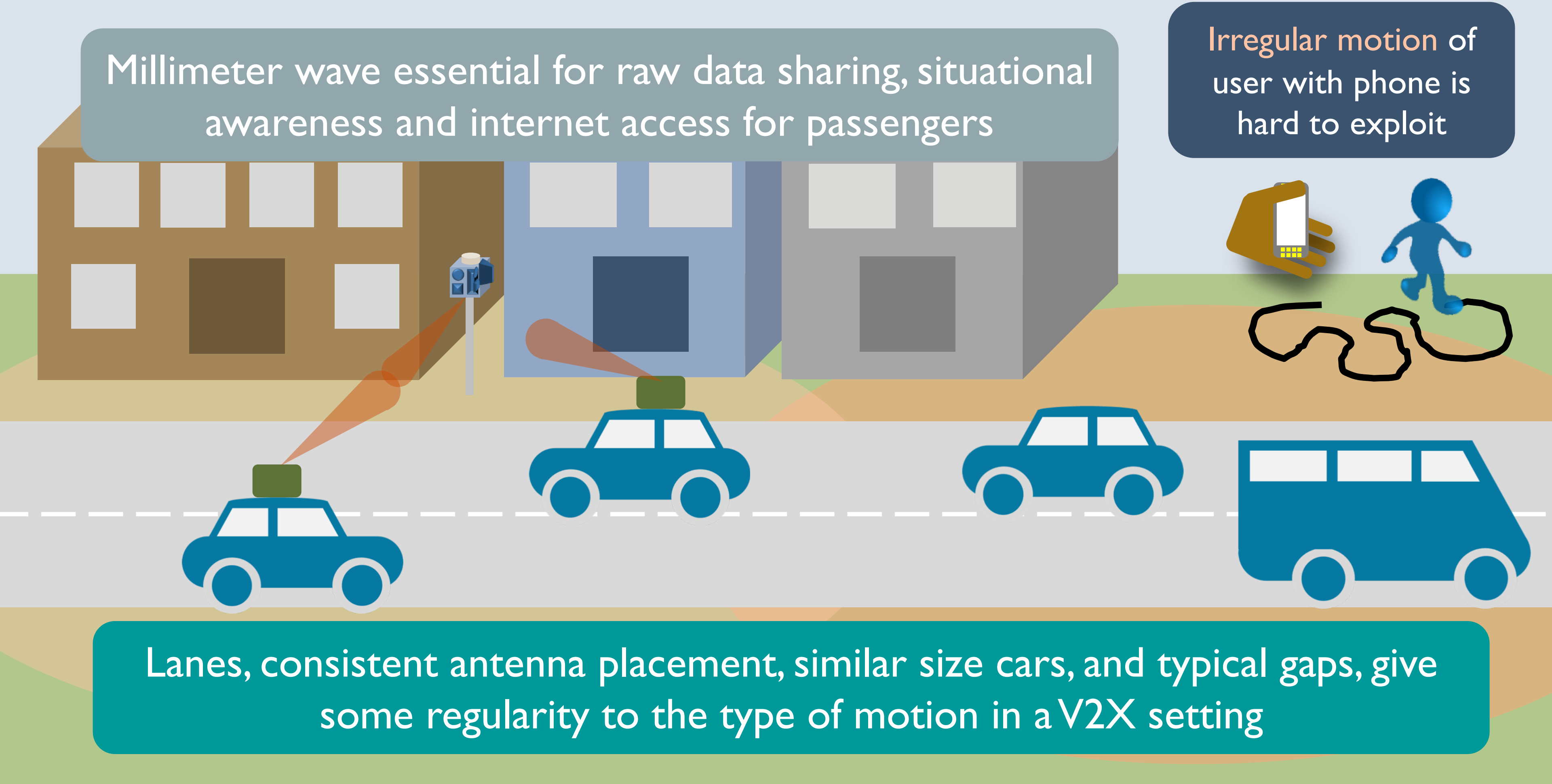
Labeled data from two classes

New point is compared with the boundary curve to identify its class



(two dimensional features in this example)

Vehicular applications of millimeter wave

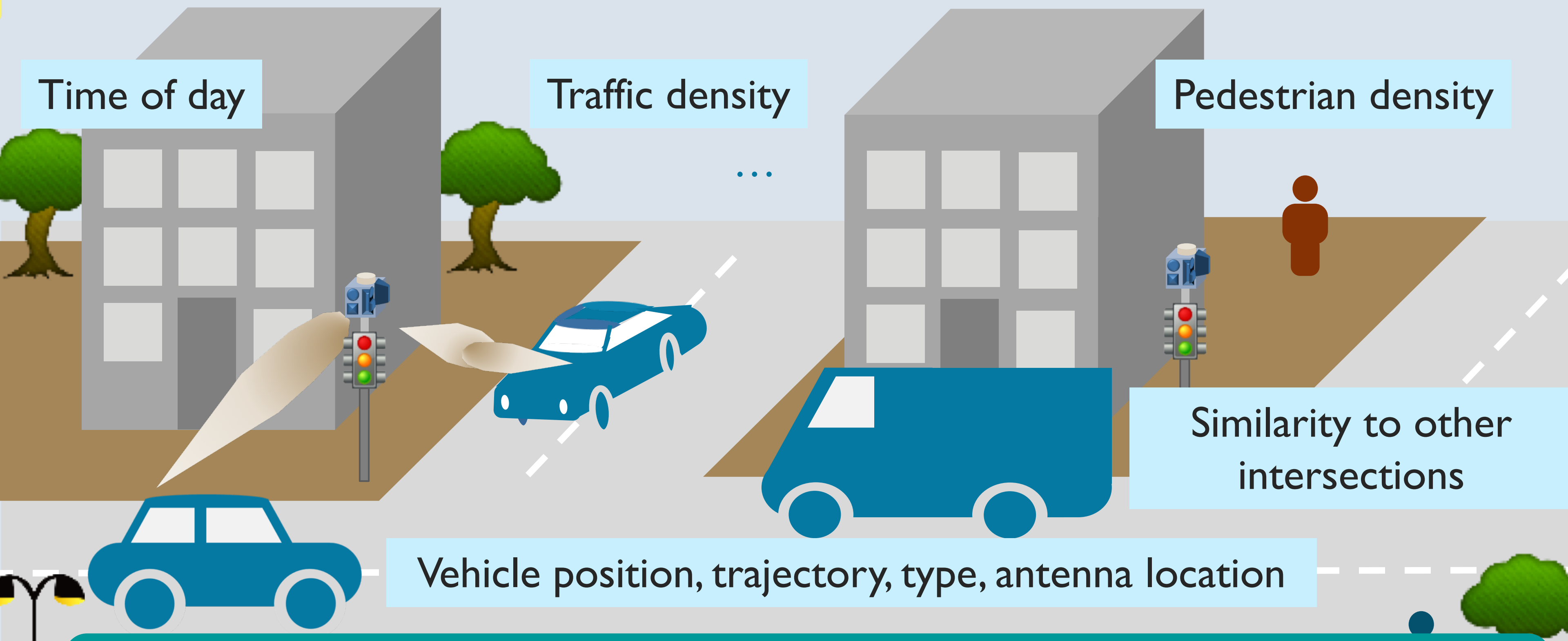


Millimeter wave essential for raw data sharing, situational awareness and internet access for passengers

Irregular motion of user with phone is hard to exploit

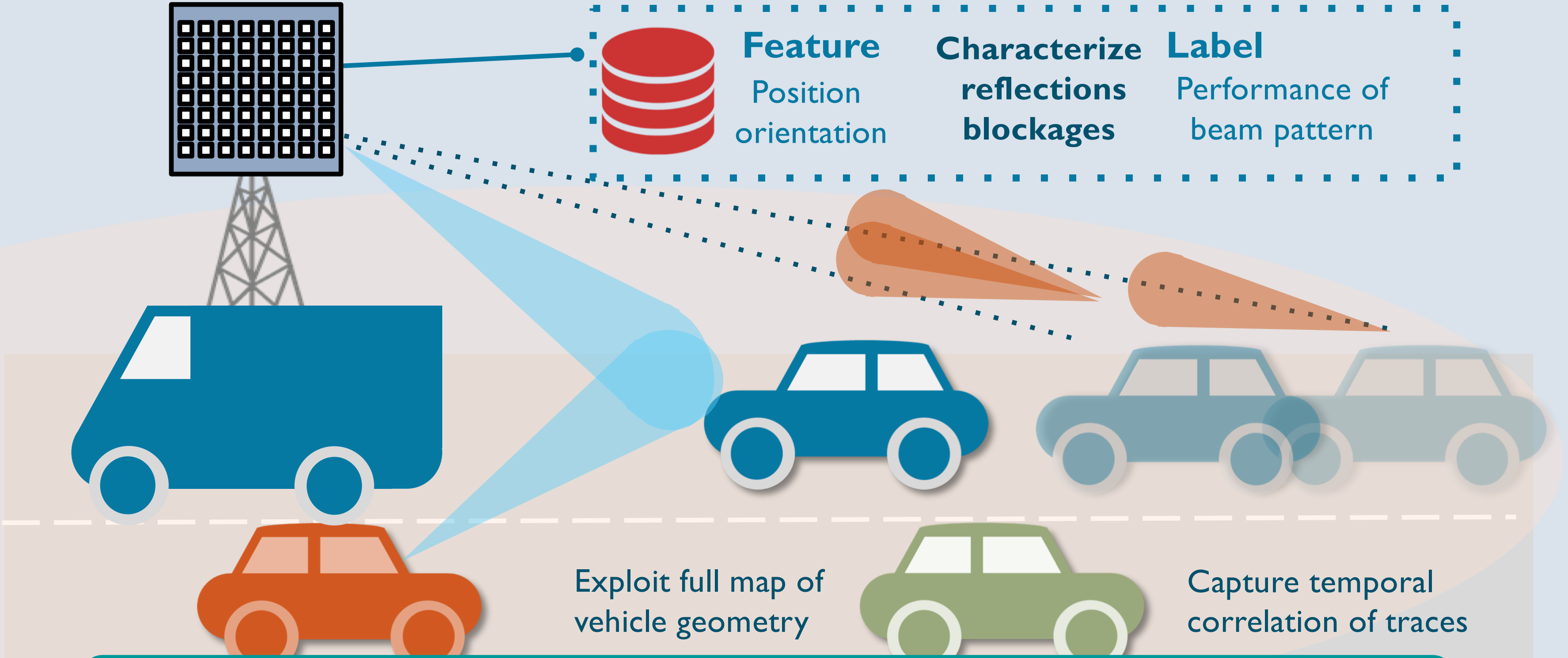
Lanes, consistent antenna placement, similar size cars, and typical gaps, give some regularity to the type of motion in a V2X setting

Side information exploitation opportunities



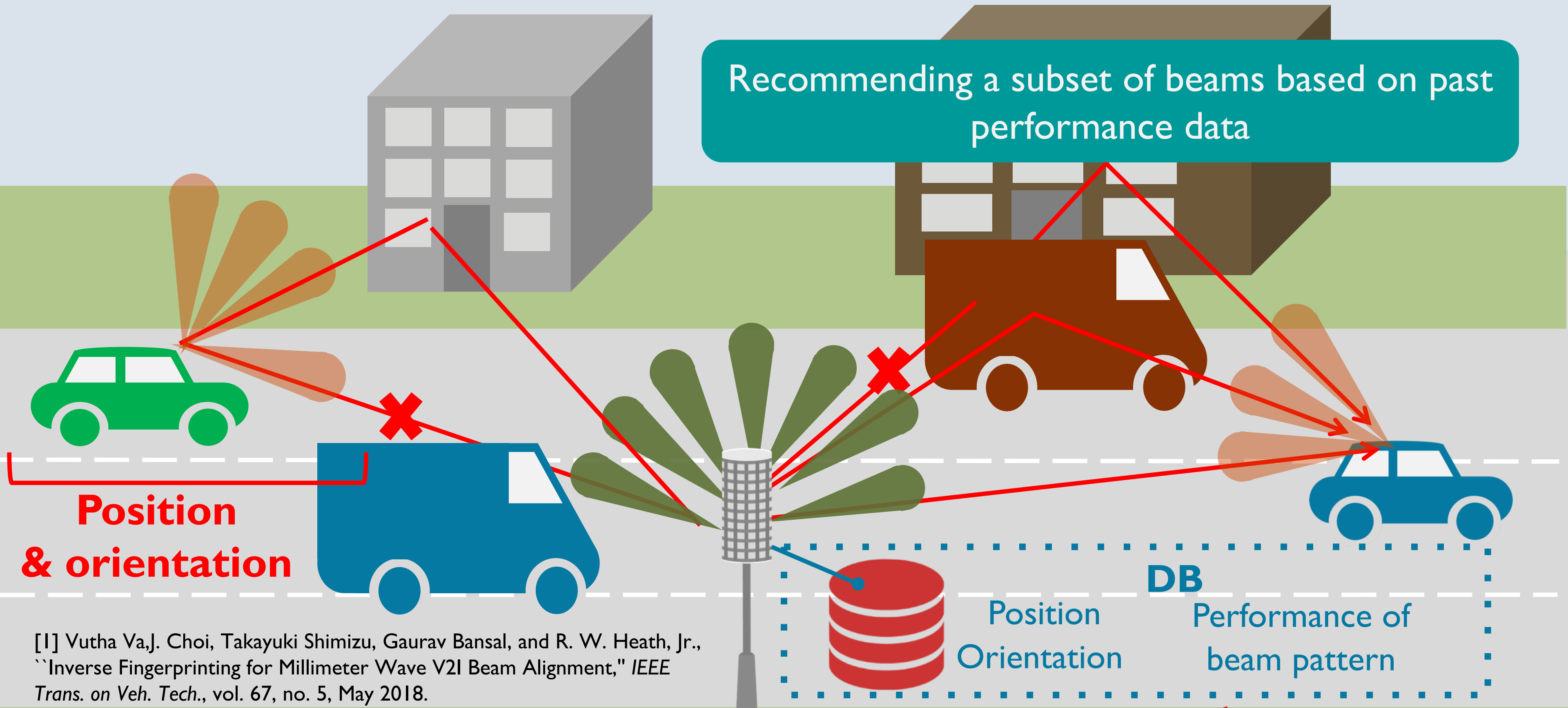
Car position information, time of day, traffic density, pedestrian density, and other data can be leveraged by machine learning algorithms

Machine learning is a tool to exploit structure



ML is a good framework to exploit correlations between large sets of data with different kinds of entries

Machine learning approach based on location

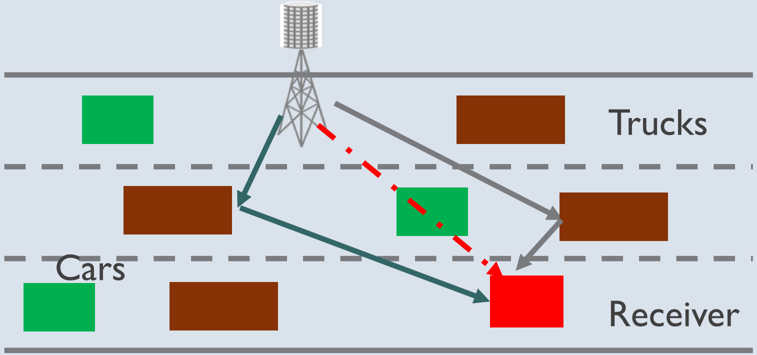


[1] Vutha Va,J. Choi, Takayuki Shimizu, Gaurav Bansal, and R. W. Heath, Jr., ``Inverse Fingerprinting for Millimeter Wave V2I Beam Alignment," *IEEE Trans. on Veh. Tech.*, vol. 67, no. 5, May 2018.

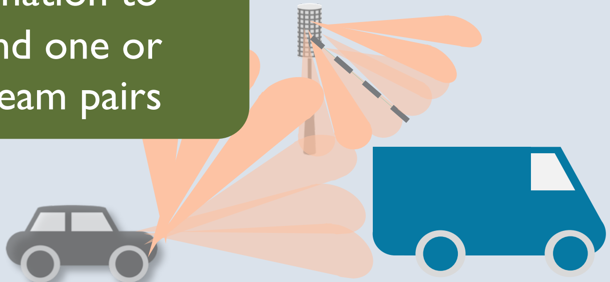
[2] Vutha Va, Takayuki Shimizu, Gaurav Bansal, and R. W. Heath, Jr., "Online Learning for Position-Aided Millimeter Wave Beam Training," (invited) submitted to IEEE Access, September 2018. Available on arXiv.

MmWave V2X with full situational awareness

Use knowledge of the receiver and the surrounding vehicle sizes / locations



Use information to recommend one or multiple beam pairs



[1] Yuyang Wang, A. Klautau, M. Ribero, M. Narasimha, and R. W. Heath, Jr., " MmWave Vehicular Beam Training with Situational Awareness by Machine Learning," in the Proc. of GLOBECOM Workshops, Dec. 2018

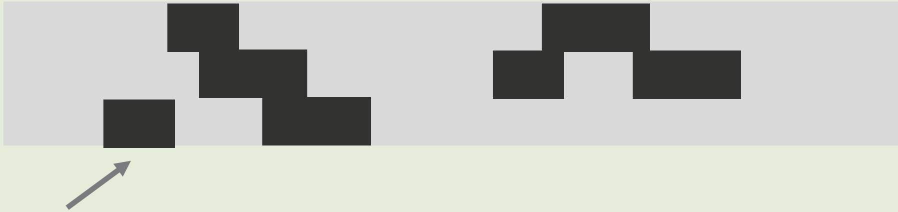
Ordered vehicles based on **type** and **location**

First lane vehicles
Trucks with larger size
Vehicles *closer* to the RX

→ Have larger impacts on reflections & beam selection

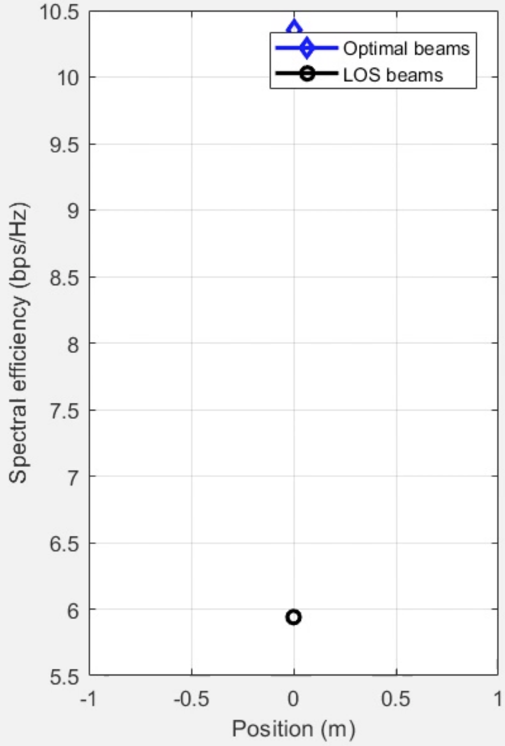
$$\mathbf{v} = [\underbrace{\mathbf{r}}_{\text{Location of RSU}}, \underbrace{\mathbf{t}_1, \mathbf{t}_2}_{\text{1st \& 2nd lane trucks}}, \underbrace{\mathbf{c}_1, \mathbf{c}_2}_{\text{1st \& 2nd lane cars}}]$$

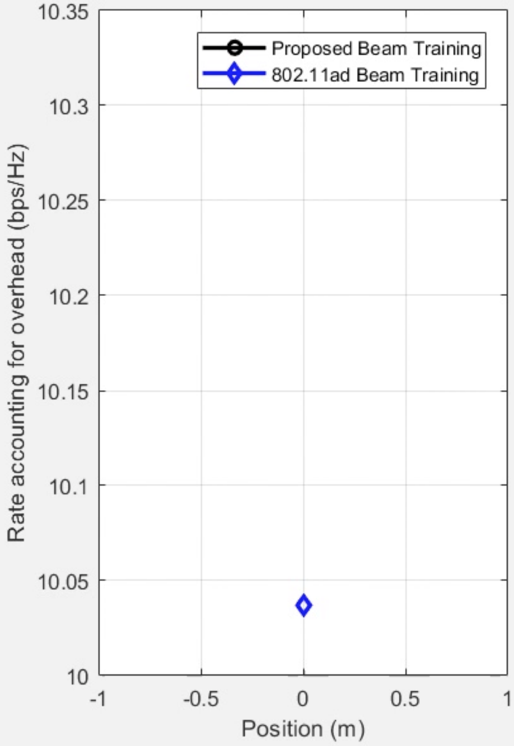
Situational awareness as occupancy image



Pixels correspond to road space occupied by cars

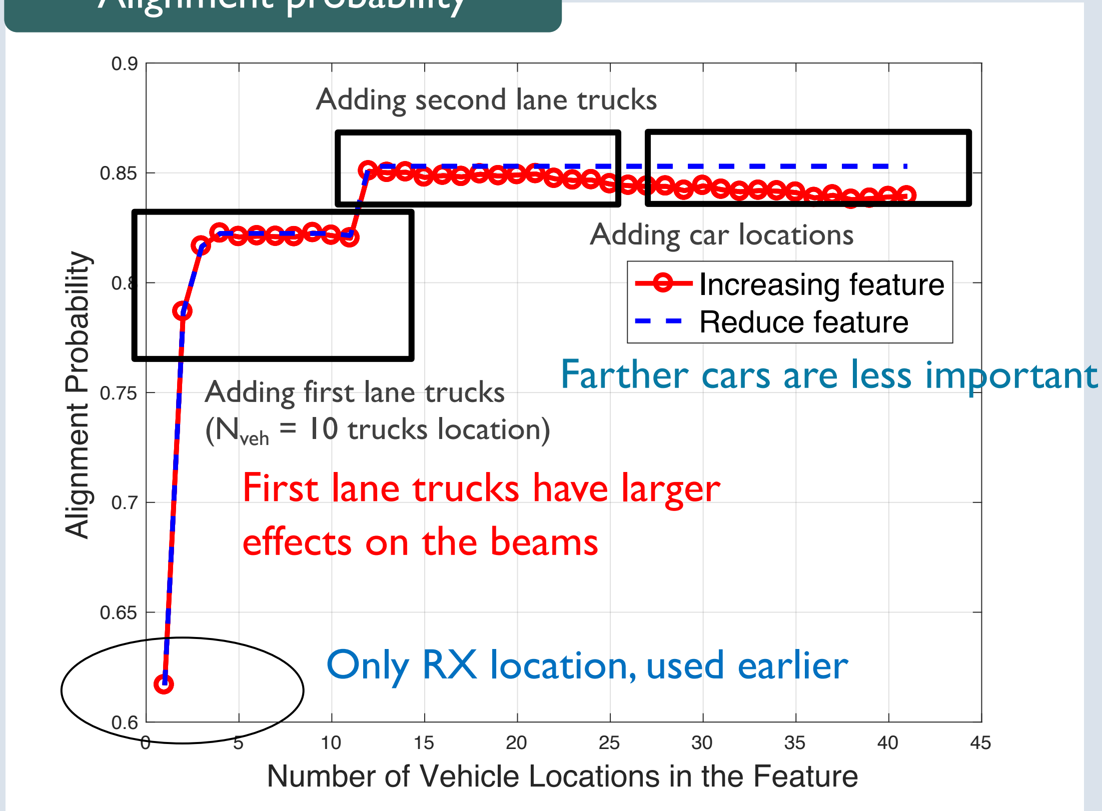
Spectral efficiency and overhead





Performance example

Alignment probability



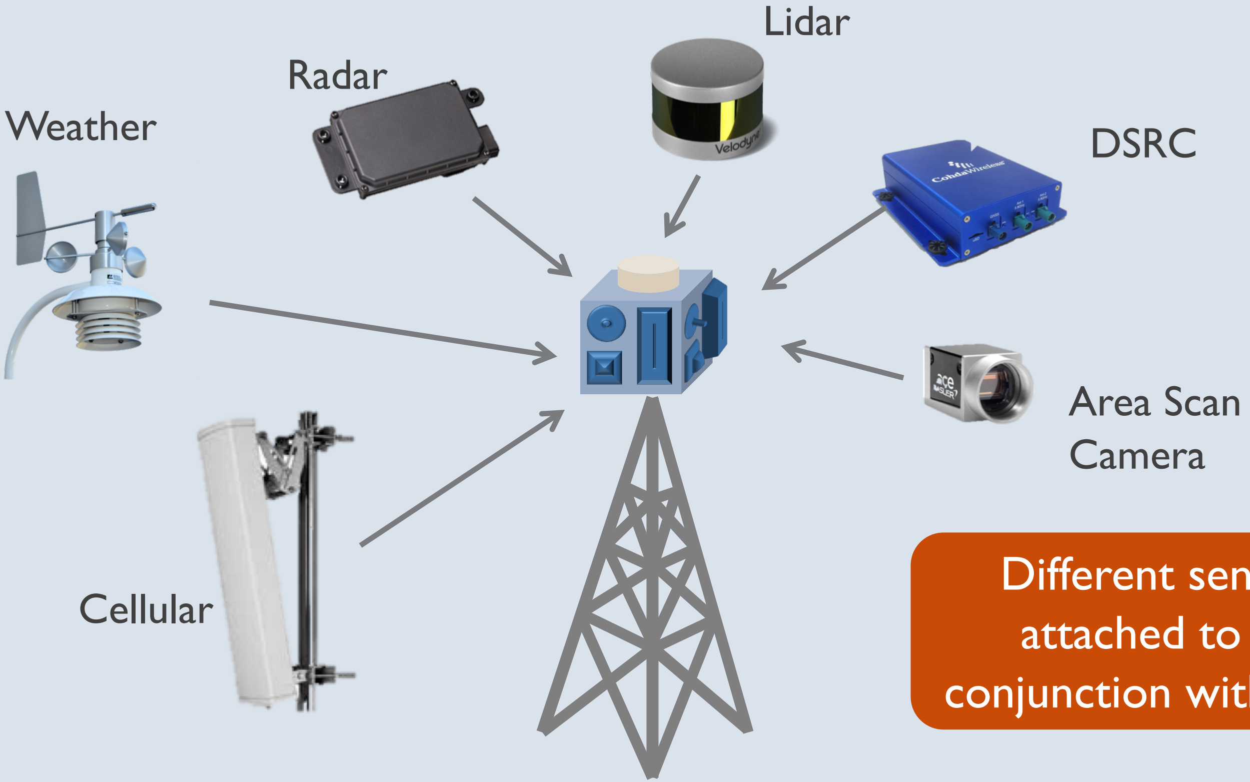
Rate example

Achievable Data rate (bps/Hz)	LOS samples	NLOS samples
LOS beamforming	1.588	0.094
Optimal beam pair	4.183	1.784

LOS beamforming when there are NLOS multi-paths may fail

A concise set of vehicle location can largely improve beam prediction

Incorporating other forms of side information

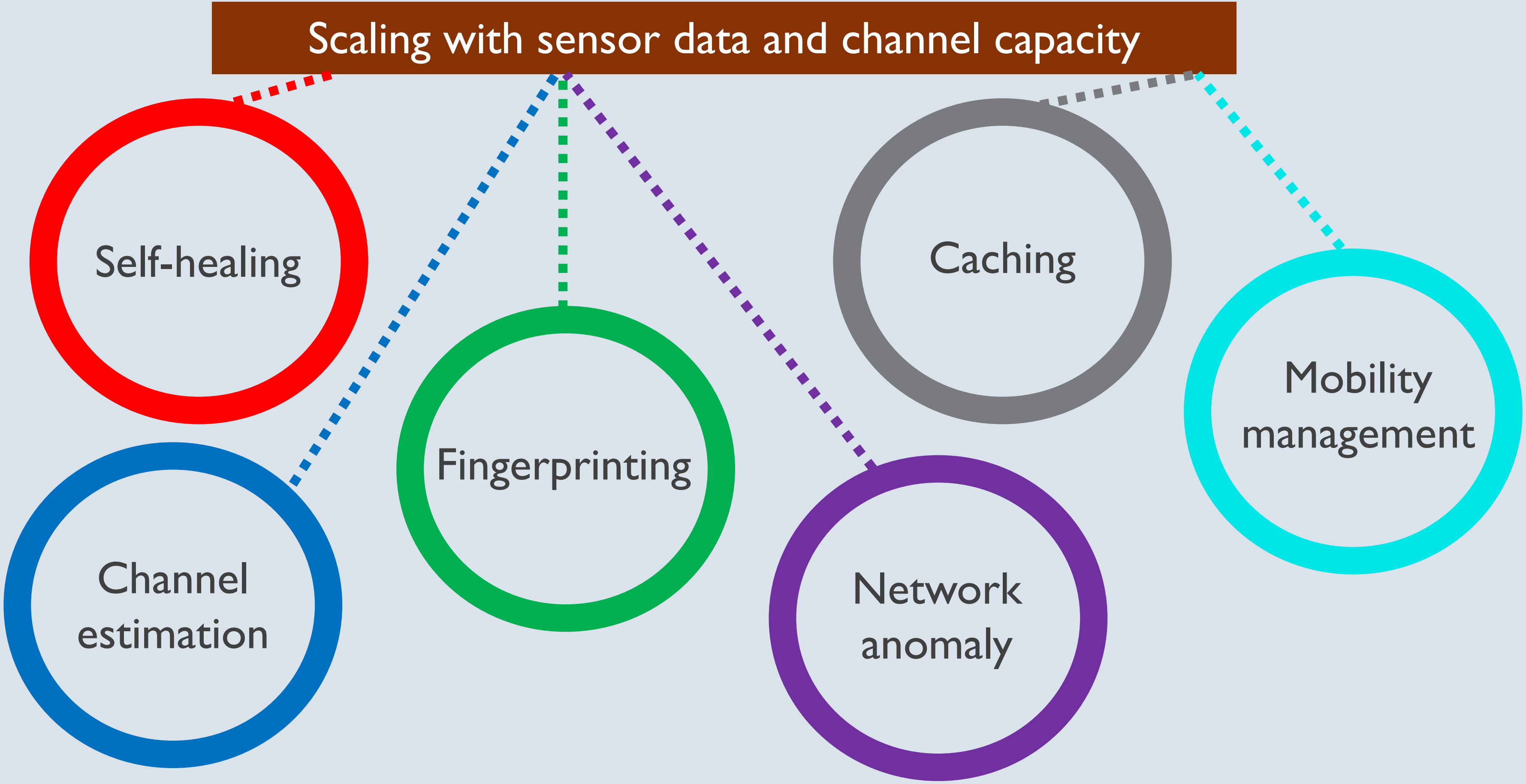


Different sensors can be attached to a tower in conjunction with the antennas

ML can help exploit sensor information to aid communication

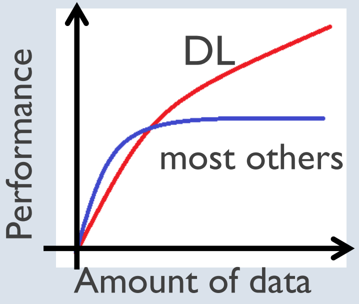
N. González Prelcic, Anum Ali, Vutha Va and R. W. Heath, Jr., ``Millimeter Wave communication with out-of-band information,'' IEEE Communications Magazine, vol. 55, no. 12, pp. 140-146, Dec. 2017.

Other applications of machine learning in communications



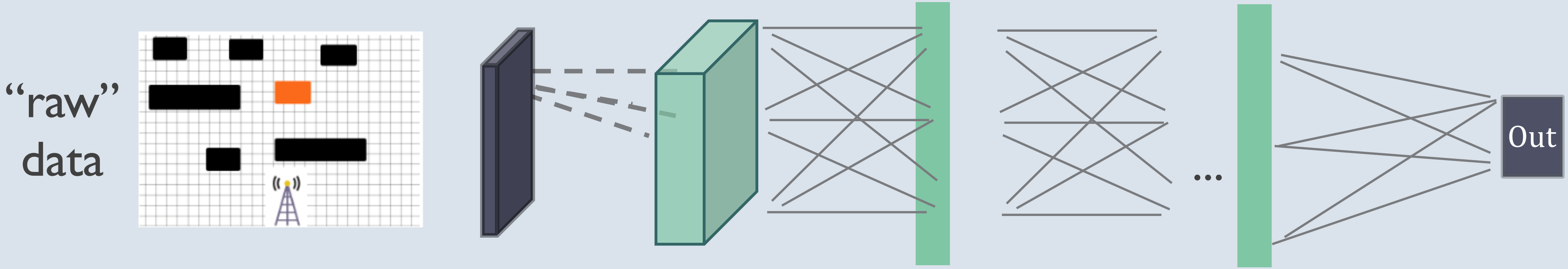
Thank you!

Deep machine learning



DL key characteristics:

- Performance scales with amount of data
- Leverages on stochastic gradient descent (robustness, etc.)
- Efficient for supervised, unsupervised, reinforcement and new learning paradigms such as GANs
- May not require much feature engineering (e.g. conv nets can learn internal representations)



[1] Deep Learning-based Channel Estimation for Beamspace mmWave Massive MIMO Systems, H. He, C.-K. Wen, S. Jin, and G. Y. Li, 2018.
[2] Improving Massive MIMO Belief Propagation Detector with Deep Neural Network, X. Tan, W. Xu, Y. Be’ery, Z. Zhang, X. You, and C. Zhang, 2018