A Direction of Arrival Machine Learning approach for Beamforming in 6G

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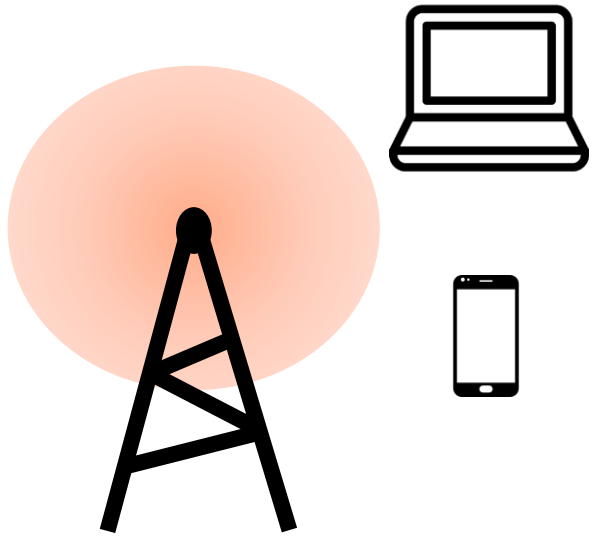
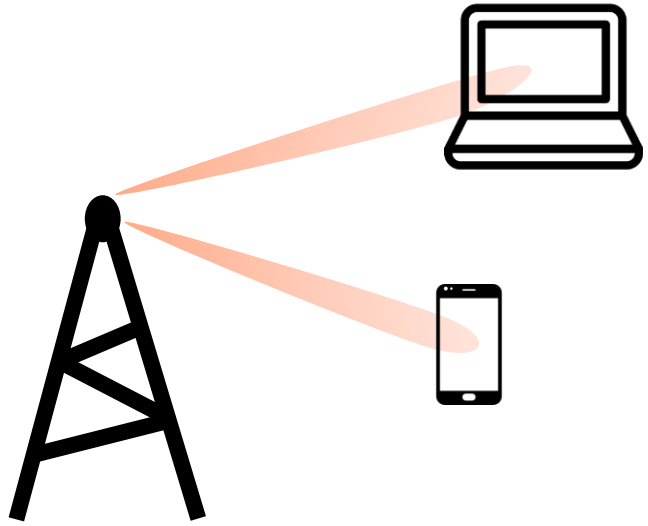
- Graduated in Telecommunications and Electronics Engineering from the Technological University of Havana, Cuba, in 2018.
- Currently studying a master's degree in Telecommunications at the National Telecommunications Institute of Brazil.
- Mainly interested in programming and Machine Learning.

Beamforming technique



Legacy network



Beamforming

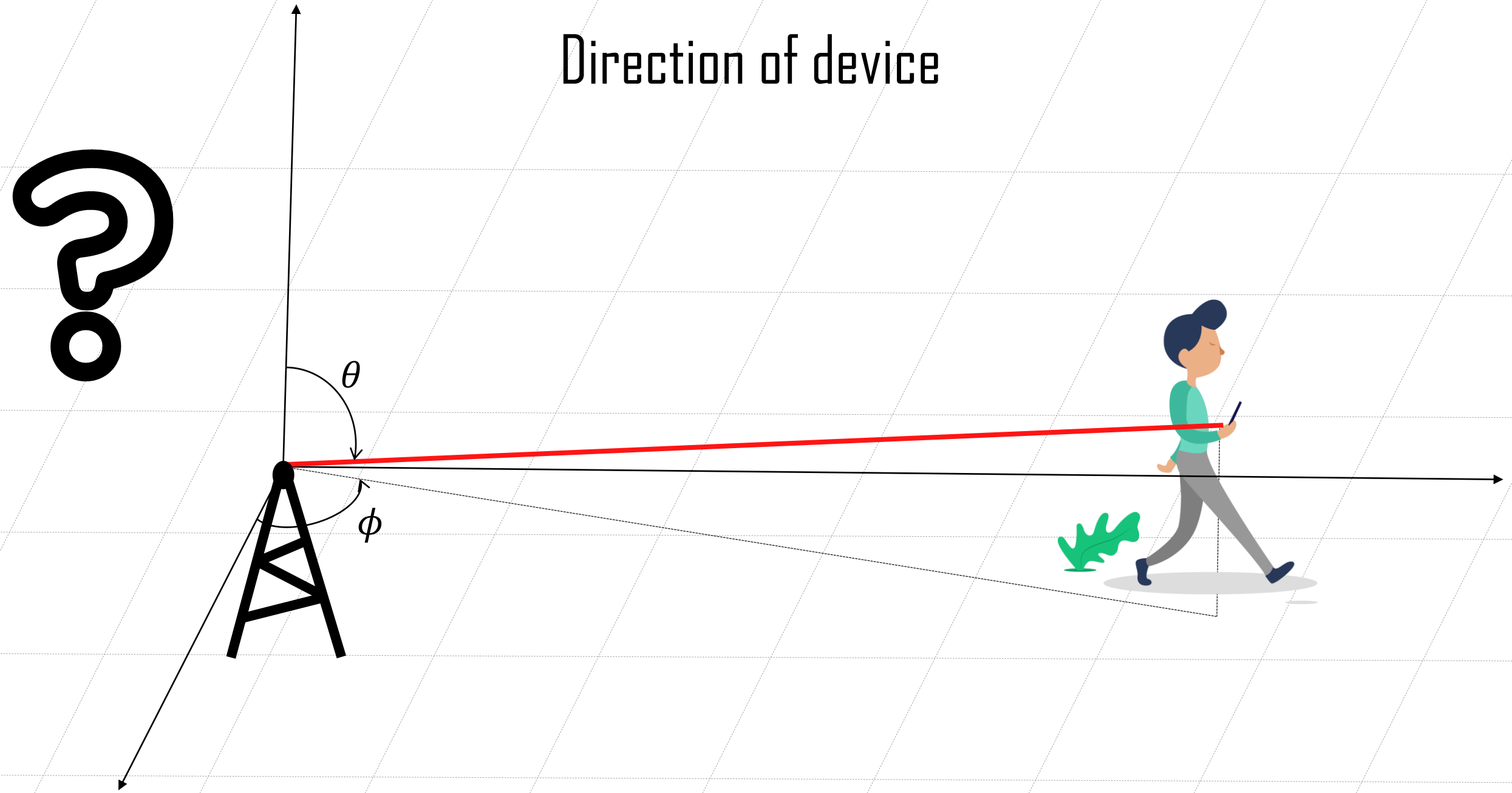
Autonomous

Reconfigurable

Adaptive

Fast responsive

Direction of device

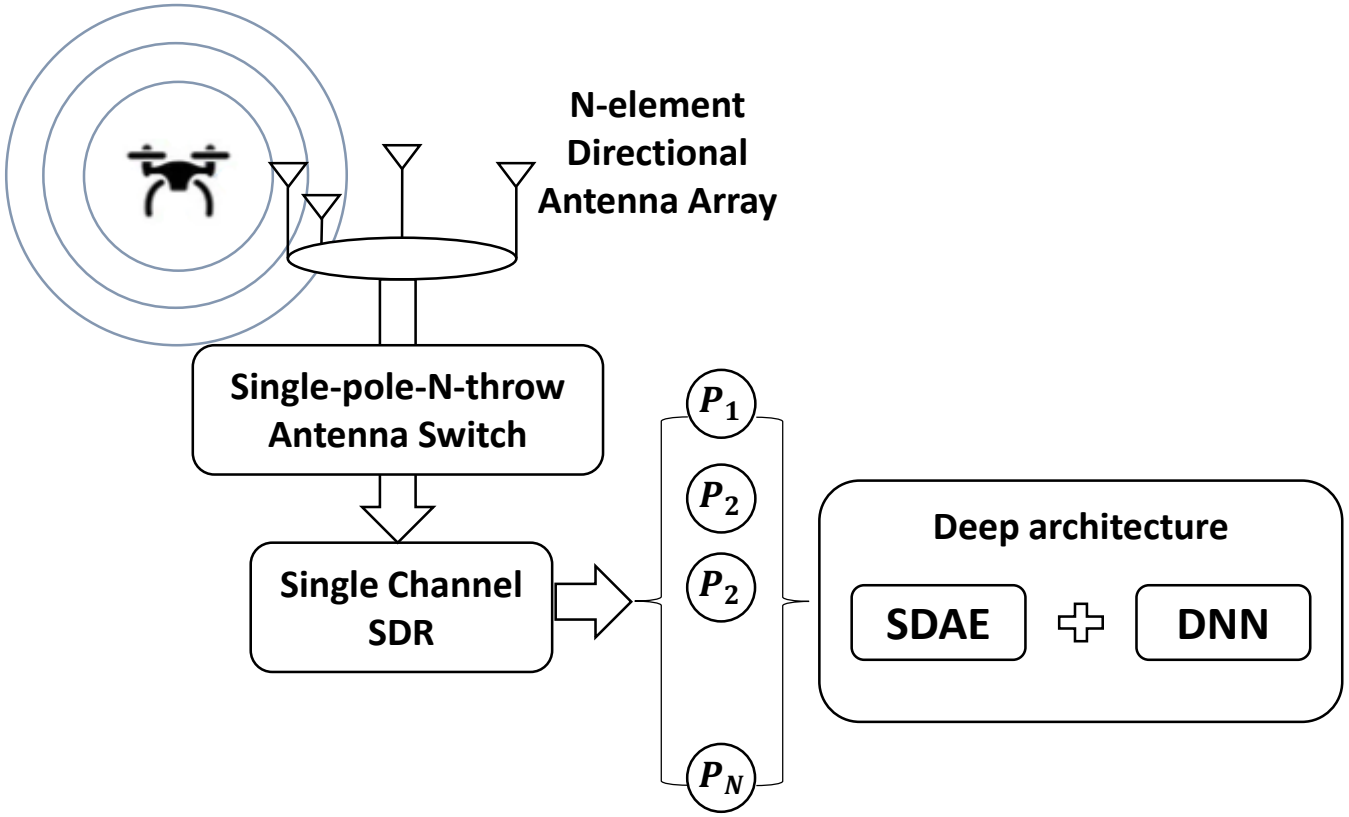


Direction of Arrival (DOA) methods

Estimates the **direction angle** of a source transmitting a signal to a receiver.

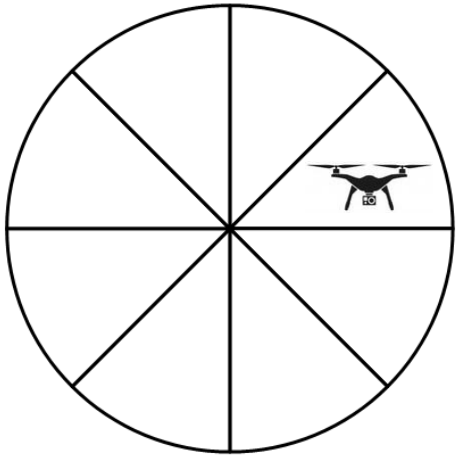
- Subspace Techniques (MUSIC, ROOTMUSIC, ESPRIT).
- Maximum Likelihood Estimator.
- Sparse Signal Reconstruction (SSR).
- Machine Learning (ML).

System model and Dataset



System model *(Abeywickrama et al. 2018)*

Training Field *(Abeywickrama et al. 2018)*



Direction Configuration *(Abeywickrama et al. 2018)*

P_1	P_2	P_2	P_4	ϕ_x

Abeywickrama, Samith, Lahiru Jayasinghe, Hua Fu, Subashini Nissanka, and Chau Yuen. 2018. "RF-Based Direction Finding of UAVs Using DNN." In *2018 IEEE International Conference on Communication Systems (ICCS)*, 157–61. Chengdu, China: IEEE. https://doi.org/10.1109/ICCS.2018.8689177.

Goal

- Proposes another ML method using the same dataset than in *(Abeywickrama et al. 2018)*.
- Show improvements in both the overall accuracy and the elapsed training time for DOA.

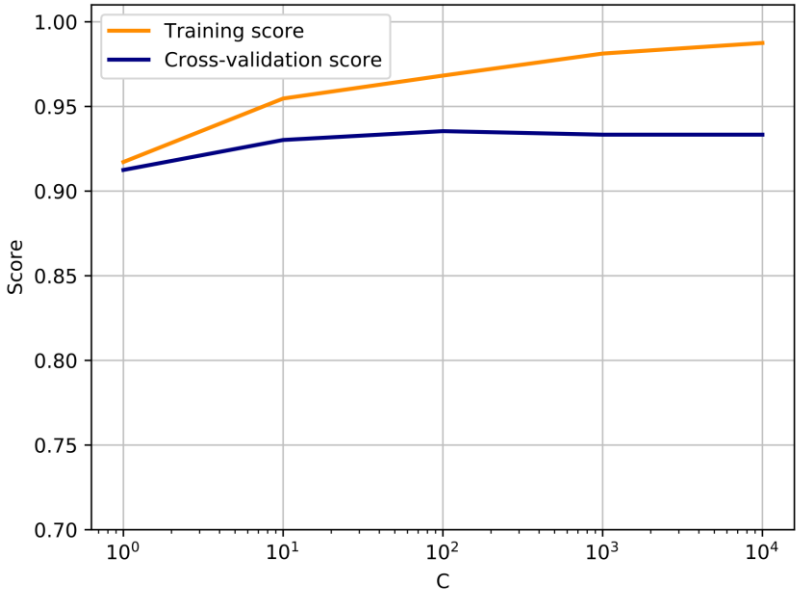
Abeywickrama, Samith, Lahiru Jayasinghe, Hua Fu, Subashini Nissanka, and Chau Yuen. 2018. “RF-Based Direction Finding of UAVs Using DNN.” In *2018 IEEE International Conference on Communication Systems (ICCS)*, 157–61. Chengdu, China: IEEE. https://doi.org/10.1109/ICCS.2018.8689177.

Classification model

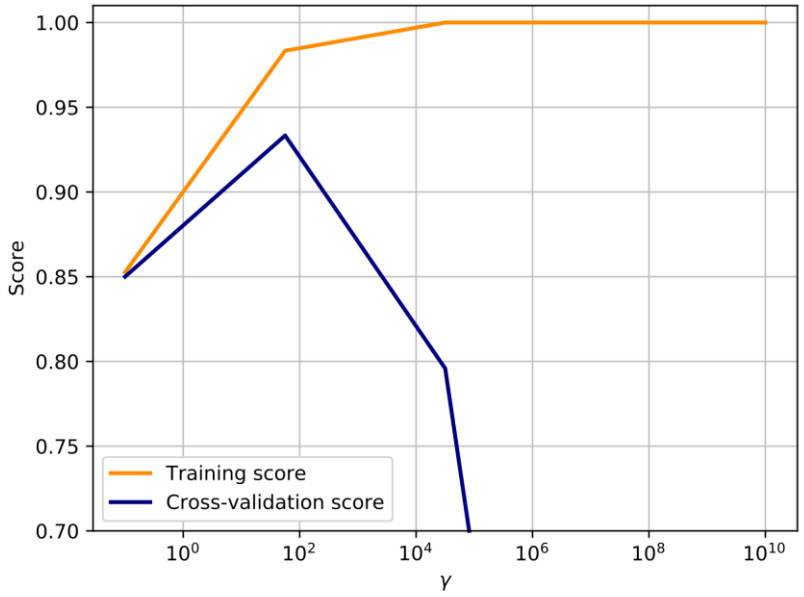
- Support Vector Classification (SVC)
- Decision Tree (DT)
- Bagging Classifier (BC)

Model	Parameters
SVC	kernel
	C
	gamma
DT	max_depth
BC	base_estimator
	n_estimators
	max_samples
	bootstrap
	n_jobs
	random_state

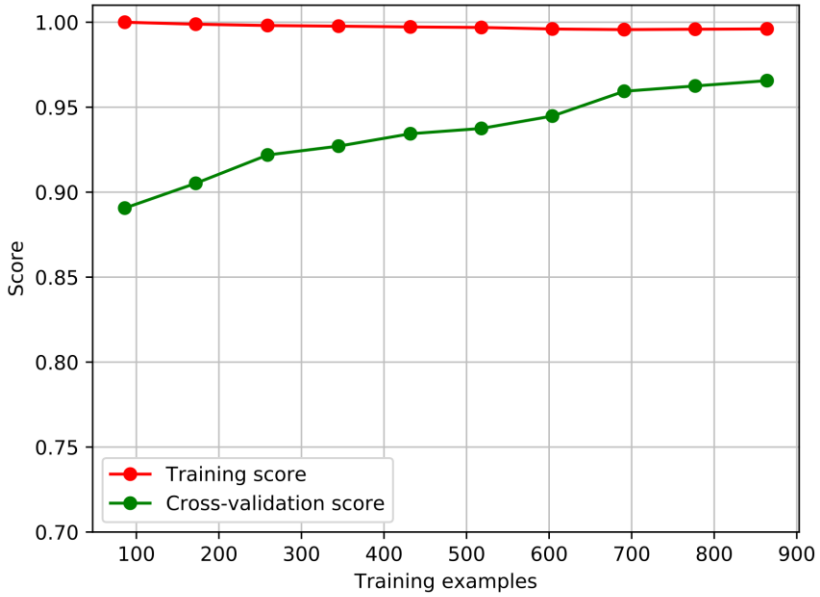
Validations curves and Learning curves of SVC



a. Validation Curve for the *C* parameter.



b. Validation Curve for the *gamma* parameter.

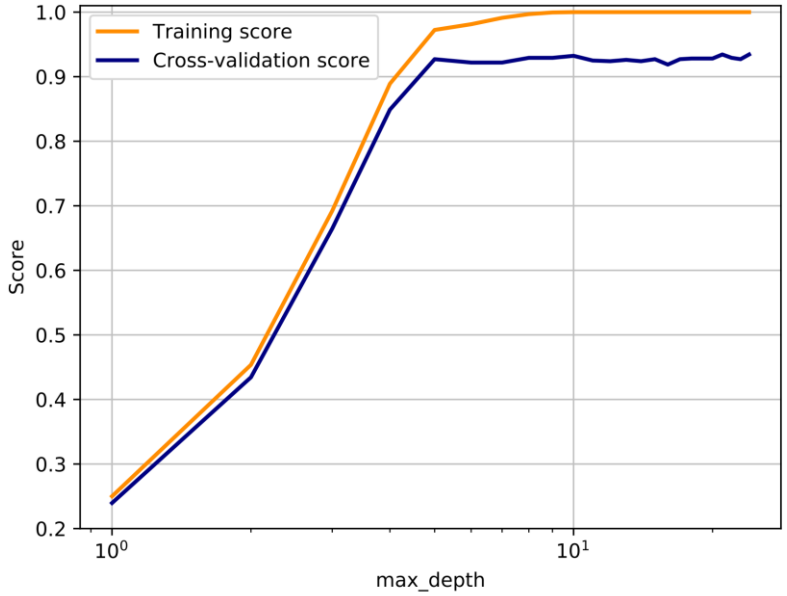


c. Learning Curve.

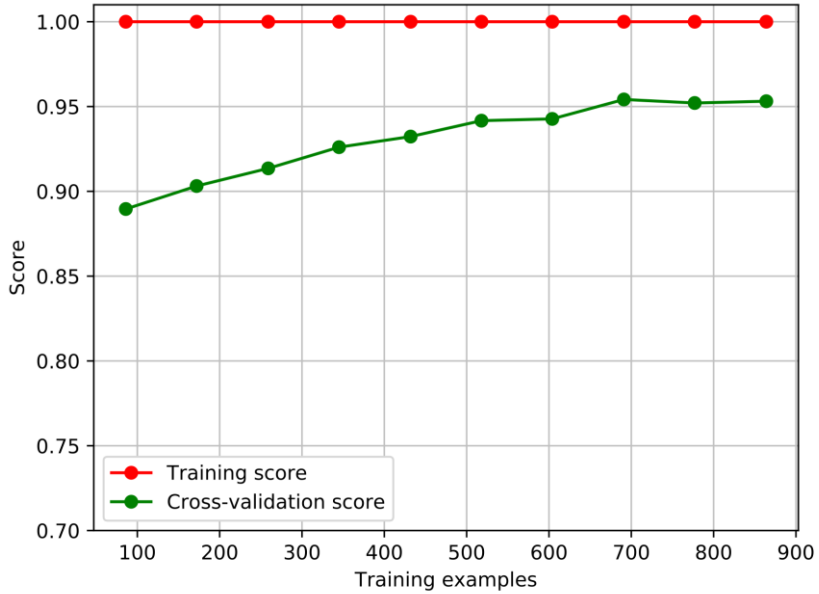
Parameters	Values
kernel	rbf
C	100
gamma	300

- *kernel*: Selects the type of hyperplane used to separate the data. It must be one of linear, poly, rbf, sigmoid, precomputed or a callable.
- *C*: Is the penalty parameter of the error term. It controls the trade off between smooth decision boundary and classifying the training points correctly.
- *gamma*: *Kernel* coefficient for rbf, poly and sigmoid.

Validations curves and Learning curves of DT



a. Validation Curve for the *max_depth* parameter.

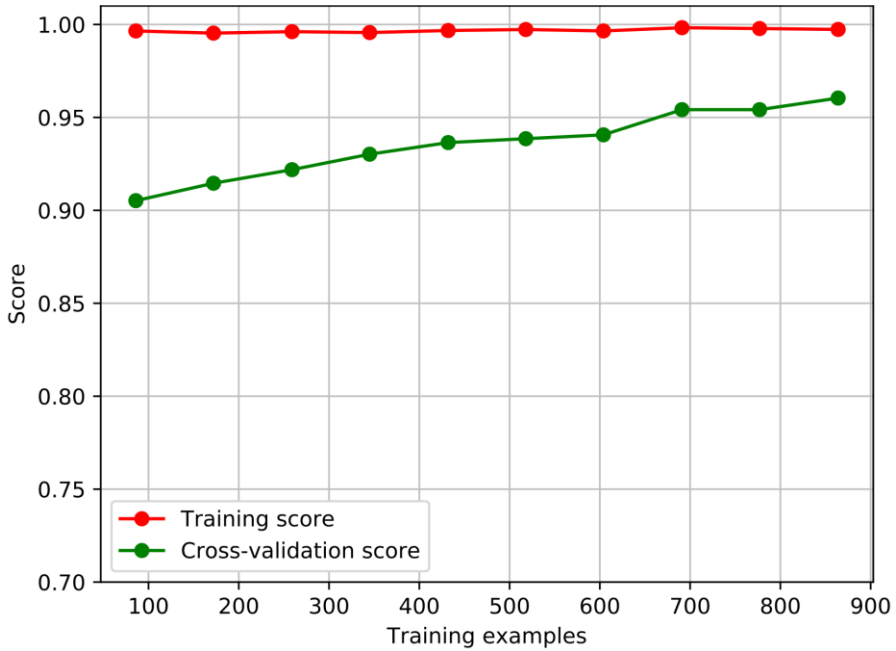


b. Learning Curve.

Parameters	Values
max_depth	16

- *max_depth: This indicates how deep the tree can be.*

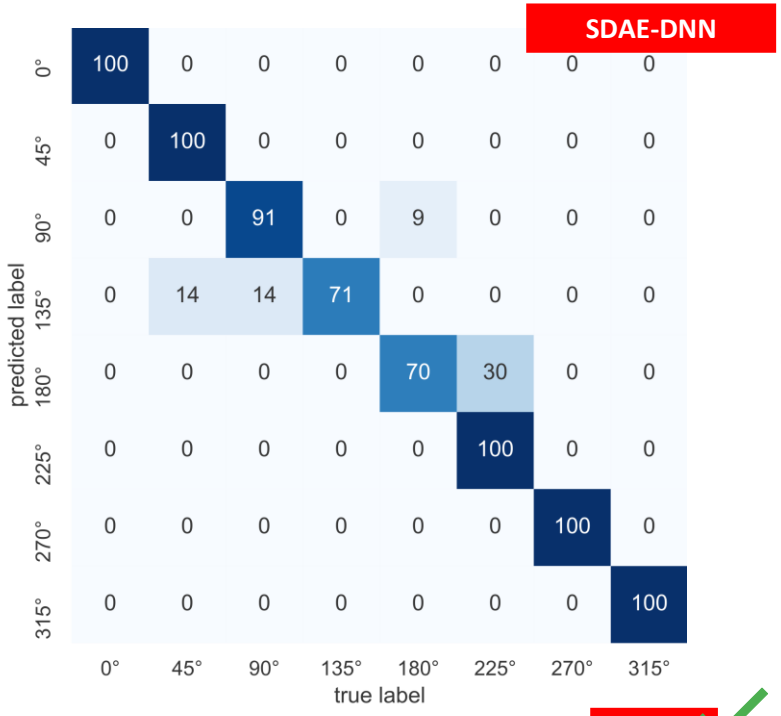
Learning curves of BC

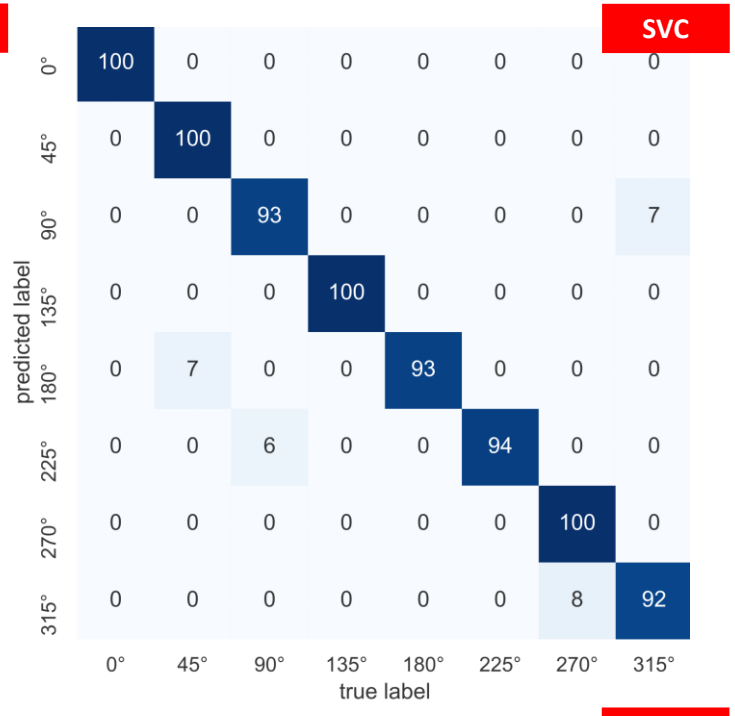


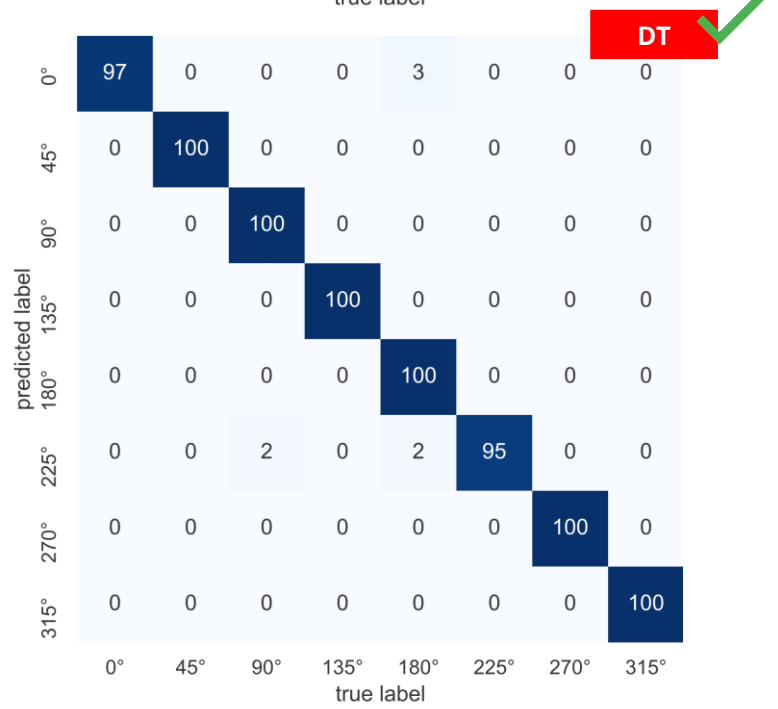
Parameters	Values
base_estimator	Decision Trees
n_estimators	300
max_samples	0.55
bootstrap	False
n_jobs	-1
random_state	42

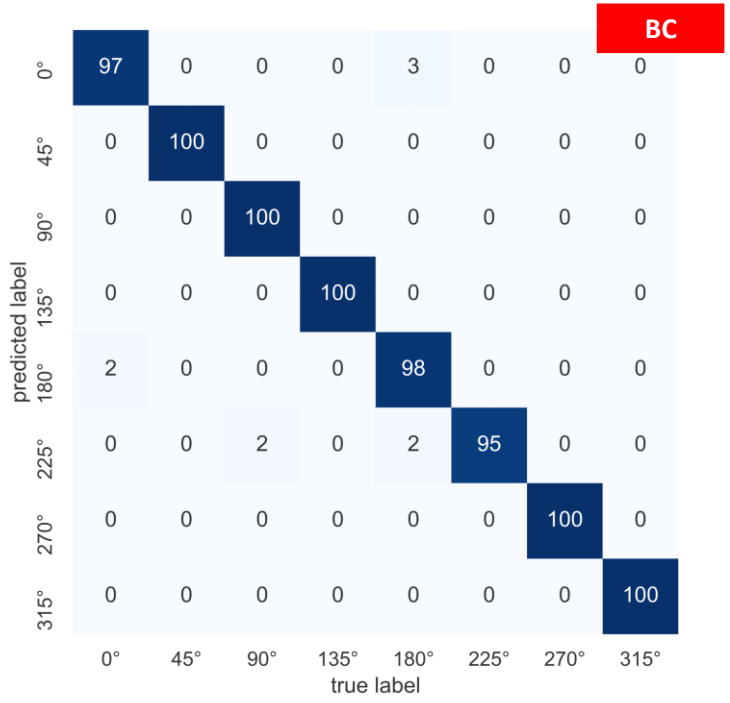
- *base_estimator*: Applied to random subsets of the dataset. The base classifier used was DT.
- *n_estimators*: The number of base estimators.
- *max_samples*: The number of samples to extract from the training data to train each base estimator.
- *bootstrap*: Defines whether samples are drawn with replacement. If False, sampling without replacement is performed.
- *n_jobs*: The number of CPU cores to use for training and prediction.
- random state: Provided to control the random number generator used.

Comparison between models









Model	Validation dataset size	Elapsed time	Accuaracy
SDAE-DNN	8.33 %	109.29s	96.25%
SVC	10%	0.02s	95.83%
DT	30%	0.0s	98.61%
BC	30%	5.23s	98.61%

Conclusions

- The necessity of having an intelligent system for DOA.
- These systems can integrate well-trained ML models to improve the robustness in performance.
- Different ML models were trained using a public dataset.
- The best results were obtained for the DT model.

Future works

- Include not only the azimuth angle for DOA but also the elevation angle.
- Offer results with better angle resolution.
- Evaluate by simulation results.