

# Optical Communications: 64-QAM Classification with Neural Networks

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## Contextualization

### Quadrature Amplitude Modulation

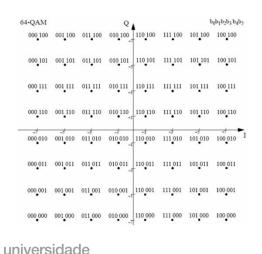
- A modulation scheme conveys data by changing some aspect of a carrier signal, or carrier wave, (usually a sinusoid) in response to a data signal
- In the case of QAM, the carrier wave is the sum of two sinusoidal waves of the same frequency, 90 degrees out of phase with each other ("I" and "Q" components)
- Each component wave is amplitude modulated

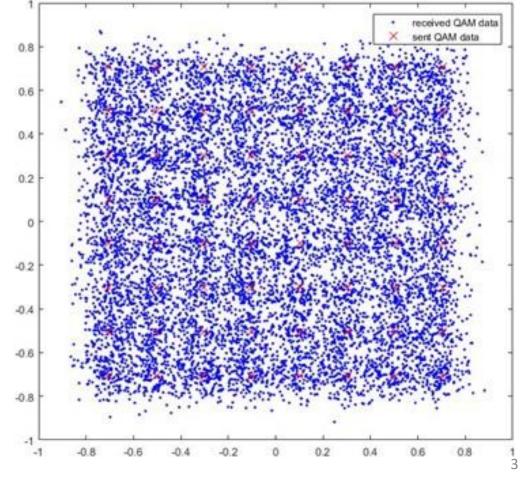


## Contextualization

Constellation Diagram

- 64 points
- separately encode all 64 combinations of 6 bits
- can transmit 6 bits per sample





## Contextualization

### Inter-Symbol Interference

- The transmitted signal is decoded by a demodulator. His function is to classify each sample as a symbol
- The performance of the fiber optic communication channels is limited by a phenomenon known as dispersion, giving rise to intersymbol interference (ISI)
- The demodulator may misidentify a sample as other symbol, resulting in a symbol error
- Dispersion compensation is an increasingly important issue



## Challenge Addressed

- Research teams are now looking for a viable answer to the demands of proper symbol identification by the demodulator
- Our goal for this project was to apply ML methods to compensate the inter-symbol interference and correctly decode the symbols transmitted
- We focused on the approach of considering the channel equalization as a classification problem with 64 classes and building a reliable classifier – Artificial Neural Network Classifier



• How can an ANN consider 64 classes in a feasible and efficient manner?

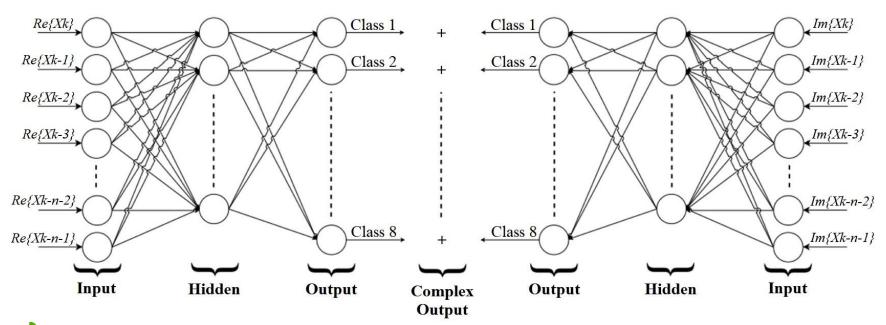
• What can the best input parameters be?

 How can the best values for the ANN's hyperparameters be found in the minimum amount of time?



#### Neural Networks Architecture

dividing the problem in two Neural Networks





#### Data Nature

- Taking in consideration that the data consisted in a stream of symbols where the current symbol is somehow related with the previous ones
- Purposes: search for good way to predict the symbols' classes;
  find out if the symbols of the stream close to the current one had any effect on its class;

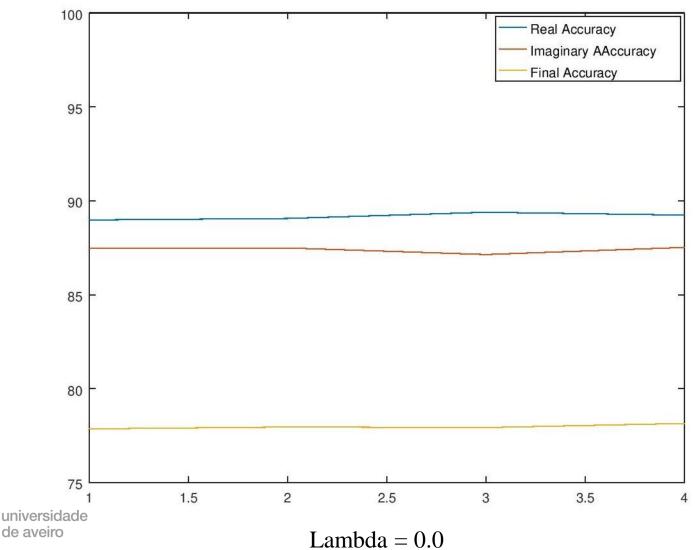


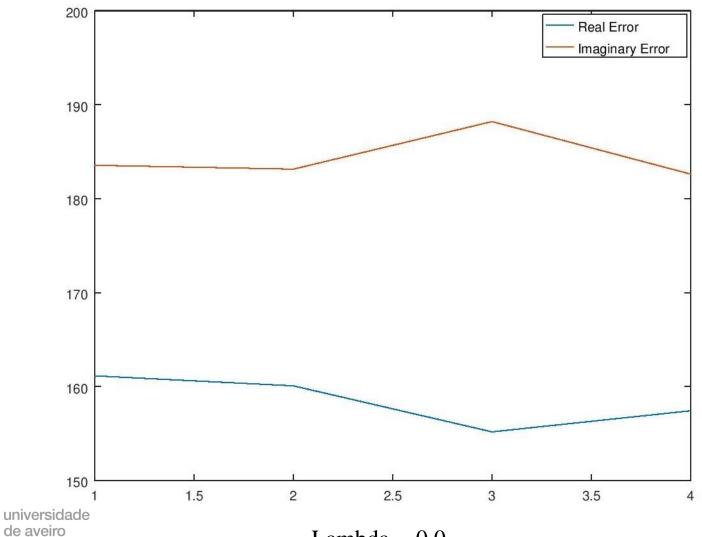
### Hyperparameter Weights

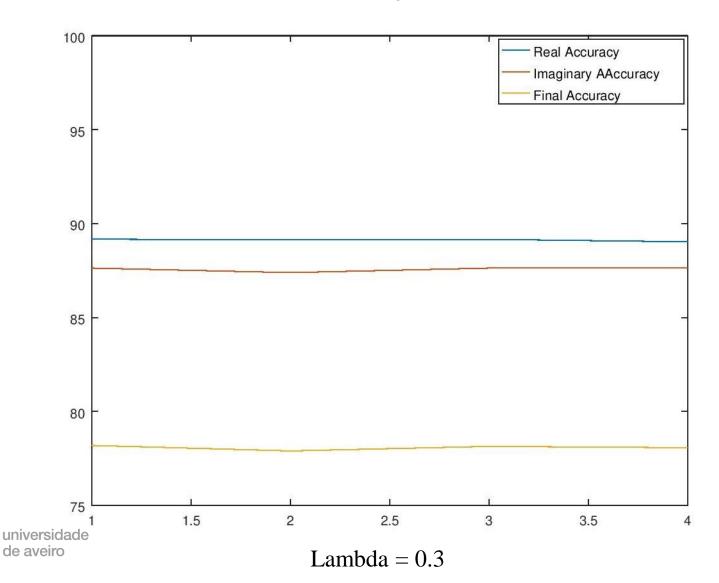
- Hyperparameters involved:
  - number of features of each ANN
  - learning rate (Lambda)
  - number of hidden layer neurons
  - number of Epochs
- Compromise the variations of values of each (due to shortage of time)

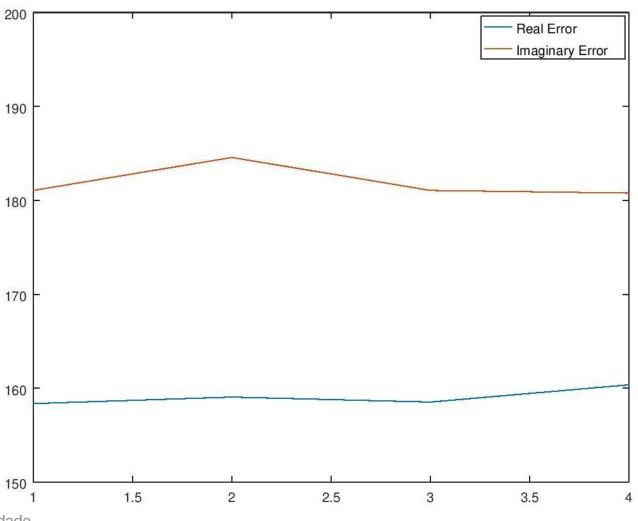
# Features	Lambda	# ANN Neurons	# Epochs
1	0	10	100
2	0	10	100
3	0	10	100
4	0	10	100
1	0.3	10	100
2	0.3	10	100
3	0.3	10	100
4	0.3	10	100





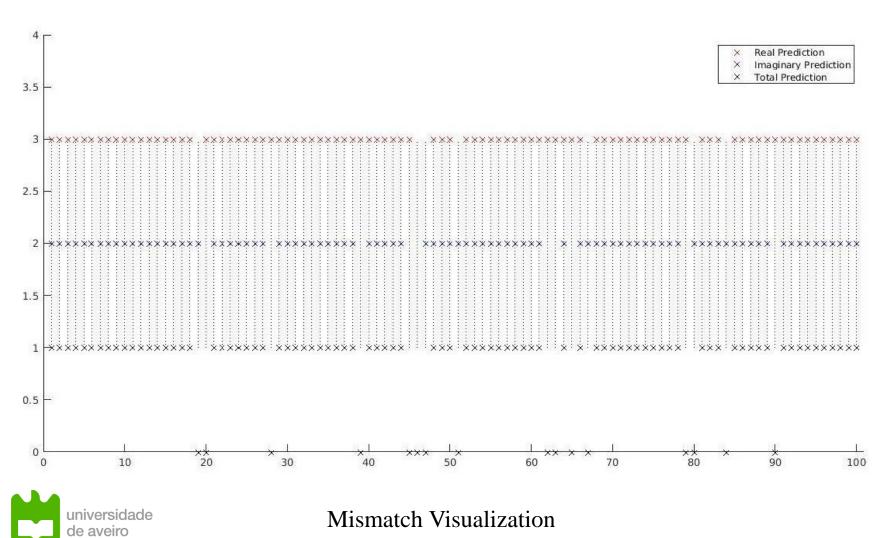








Lambda = 0.3



## **Best Solution**

- Improving the capabilities of the system using the best found values for the ANNs
- Validating the final stage of the system using the testin data and calculating the predictions based on the new and improved theta values

Real Error	Imag. Error	Real Accuracy	Imag. Accuracy	Total Accuracy
158.0394	172.6481	89.1958	88.2049	78.7817



## **Conclusions & Future Work**

- The overall results of our research were bellow the expectations
- The assumption that other symbols on the signal stream could influence the class of the symbol being classified might be partially incorrect, or at least their weights may be of little effect
- The next step could be to adopt a new strategy for the ANNs' features
- Considering a class as isolated and calculating the distances between the received signal (with ISI) and all the real classes



The collected knowledge made it clear that Neural Networks can be one future solution for this big challenge and are today one step closer to finding it.

