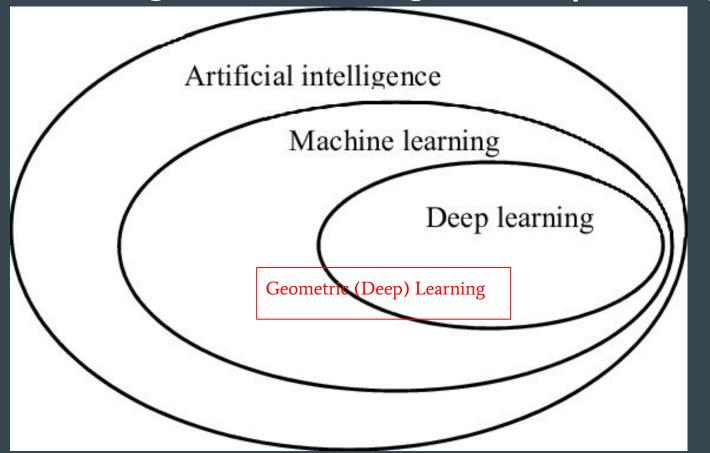
Graph Neural Networks

•••

Using Graph Neural Networks to classify or reconstruct events in KM3NeT

Gijs Vermariën 24-09-2020 - KM3NeT group meeting

Machine Learning/ Artificial Intelligence/ Deep Learning



Flavors of Machine Learning

- Supervised Learning \${x}, {y}\$
 - Support Vector Machines
 - Decision Trees
 - Linear Regression
 - Neural Networks
 - Vanilla Neural Networks
 - Convolutional Neural Networks
 - Graph (Convolutional) Neural Networks
- Unsupervised Learning \${x}\$
 - o (Deep) Reinforcement Learning
 - Clustering
 - Autoencoders
 - Generative Adversarial Networks

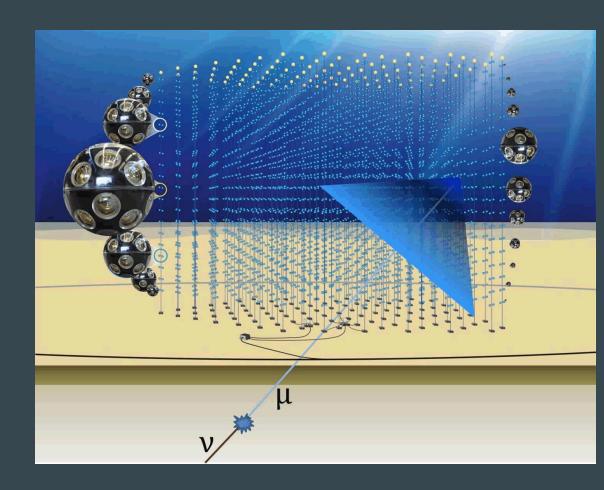
Vanilla to Convolutional to Graph

Neural	(2D) Convolutional	Graph Convolutional
$x \in \mathbb{R}^n, y \in \mathbb{R}^m$ $\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \rightarrow \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_m \end{bmatrix}$	$x \in \mathbb{R}^{m \times n}, y \in \mathbb{R}^{l}$ $\begin{bmatrix} x_{00} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots \\ x_{m0} & \cdots & x_{mn} \end{bmatrix} \rightarrow \begin{bmatrix} y_{0} \\ y_{1} \\ \vdots \\ y_{l} \end{bmatrix}$	$ \begin{cases} G = (\mathcal{V}, \mathcal{E}), \ \mathcal{V} \in \mathbb{R}^d, \mathcal{E} \in \mathbb{R}^{d \times d} \\ \left\{ \left\{ \begin{bmatrix} v_0 \\ \vdots \\ v_m \end{bmatrix} \right\}, \ \left\{ \begin{bmatrix} e_{00} & \cdots & e_{0n} \\ \vdots & \ddots & \vdots \\ e_{m0} & \cdots & e_{mn} \end{bmatrix} \right\} \right\} \rightarrow \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} $

where \rightarrow is many nonlinear transformations with (many) parameters

Benefits?

- Natural representation of data, no binning of data
- Sparsity
- More robust against curse of dimensionality
- Higher expressivity with lower number of parameters



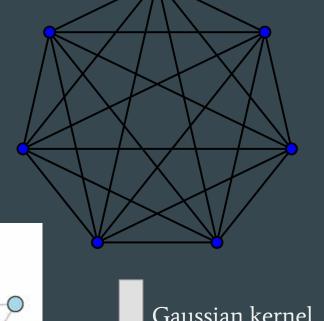
Data Architecture*

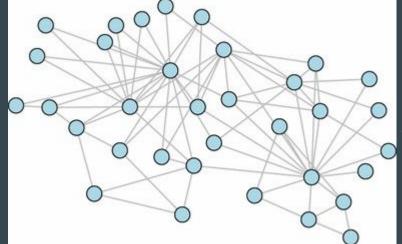
Simulated sensors (PMT) data:

One event ~1k rows:

- Spatial Features: x , y , z , dx , dy , dz
- Features:
 - o Time t
 - o Charge Q
 - o Rate v

Dense Graph





Gaussian kernel $d_{ij}=\exp(|\mathbf{r_i}-\mathbf{r_j}|^2/\sigma^2)$ Introduce sparsity

^{*} Prior work by me and Luuk Oudshoorn on Antares data

Current work within KM3NeT collaboration

- Michael Moser, Thomas Eberl: 4D CNN [1] development of OrcaSong and OrcaNet [2]
- Stefan Reck, Thomas Eberl: Implementation of EdgeConv [3] and contributions to Orca{Song,Net}
- Daniel Guderian: Research ORCA4 classification and reconstruction [3]
- Arumoy Shome, Brían Ó Fearraigh, Ronald Bruijn: Event classification in the KM3NeT pipeline [4]
- Other projects see [3]

Outside the collaboration:

- Graph Neural Networks for IceCube Signal Classification [5]
- [1] M. Moser, "Sensitivity Studies on tau neutrino appearance with KM3NeT/ORCA using Deep Learning Techniques," p. 113, 2020
- [2] https://git.km3net.de/{Ml.pages.km3net.de/{OrcaNet,OrcaSong} and https://ml.pages.km3net.de/{OrcaNet,OrcaSong}
- [3] https://indico.cern.ch/event/952545/
- [4] https://github.com/arumoy-shome/km3net
- [5] https://arxiv.org/abs/1809.06166

Outlook (work to be done)

O PyTorch

- implement the PyTorch Geometric Framework into Orcasong [1]
 - PyTorch backend
 - State of the art Graph Neural Network implementations (paper to first implementation sometimes on order of days)
 [2]
 - o CUDA support
- Compare PyG implementation to current work done by Daniel and Stefan

Possible science topics:

- Classifying Tau neutrino tracks in ORCA-6, that originate from neutrino flavor oscillations in the atmosphere from energetic cosmic beams (distinguish from NC and electron showers).
- Resolution and direction reconstruction of ARCA
- Use real background data on ORCA/ARCA and see how this compares to current MC simulations (Maarten de Jong came up with this idea) in the classifier/reconstruction
- High energy Tau neutrino identification
- [1] https://arxiv.org/abs/1903.02428 and https://github.com/rustyls/pytorch_geometric
- [2] https://twitter.com/mmbronstein/status/1255096720763113472