Convolutional Neural Networks in High Energy Physics

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Convolutional Neural Networks

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- supervised learning algorithm (imitation of biological neural network),
- let T = ((x⁽¹⁾, y⁽¹⁾), ..., (x^(p), y^(p))), where p ∈ N is number of observations, j ∈ p̂ : x^(j) is input vector and j ∈ p̂ : y^(j) is labeled output, be a dataset,
- \mathcal{T} is further divided into training set, testing set and validation set (different techniques like *k*-fold cross-validation can be used),

 concept of neural networks is built upon universal approximation theorem

Most widely used architecture

• multilayer perceptron (MLP)

Figure: Multilayer perceptron with 4 inputs, 1 output and 1 hidden layer.



in each layer for each neuron : $z = f\left(\sum_{i=1}^{|\mathcal{I}|} w_i x_i + \theta\right)$ (1)

Optimization methods

- loss function measures the difference between output $\hat{y}^{(j)}$ produced by neural network (with input $x^{(j)}$) and labeled $y^{(j)}$ from \mathcal{T} ,
 - regression: mean squared error as $L = \frac{1}{p} \sum_{j=1}^{p} (y^{(j)} \hat{y}^{(j)})^2$,
 - classification:

cross-entropy for binary classification as:

$$L = -rac{1}{p}\sum_{j=1}^{p} y^{(j)} \log(\widehat{y}^{(j)}) + (1-y^{(j)}) \log(1-\widehat{y}^{(j)}),$$

cross-entropy for multi-class classification as:

$$L = -\frac{1}{\rho} \sum_{j=1}^{\rho} \sum_{i=1}^{\#\text{classes}} y_i^{(j)} \log(\widehat{y}_i^{(j)}),$$

• categorical cross-entropy = softmax (on $\widehat{y}^{(j)}$) + cross-entropy,

• goal is to find global minimum of L with respects to weights matrix W

- gradient descent,
- stochastic gradient descent (randomly selected samples to compute gradients) and its numerous modifications, e. g. Adam (Adaptive Moment Estimation; adaptive change of step length etc.),
- backpropagation algorithm,
- regularization to loss function:

• to loss function: e. g.
$$L = \underbrace{\frac{1}{p} \sum_{i=1}^{p} L_j}_{\text{data loss}} + \underbrace{\lambda \sum_{k} \sum_{l} W_{k,l}^2}_{\text{regularization loss}} (L_2 \text{ norm penalty}),$$

• in architecture: dropout (randomly excluding neurons)

Measures of classification goodness

- accuracy (simple correct predictions:all predictions on test set ratio)
- confusion matrix



Figure: Confusion matrix definition.

• F_1 score for binary classification, equals $2\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$, where Precision = $\frac{\text{TP}}{\text{TP} + \text{FP}}$ and Recall = True Positive Rate (TPR) = $\frac{\text{TP}}{\text{TP} + \text{FN}}$.

Measures of classification goodness

• receiver operating characteristic (ROC), area under curve (AUC)

Figure: ROC and AUC vizualization.



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Convolutional neural network

- specially effective with visual data, widely used in computer vision
- layers typical for CNN: convolution and pooling layers (and flatten)
- consists of feature learning and classification

Figure: Demonstration of CNN architecture.



Convolution layer

• 2D convolution with kernel K

$$(I * K)(i, j) = \sum_{m=-k}^{k} \sum_{n=-k}^{k} I(m, n) K(i - m, j - n)$$

- stride corresponds to pixel shift
- padding (e. g. zero padding) used for not lowering dimension (information loss prevention)





Pooling

- method for dimensionality reduction
- max pooling (most used), average pooling

Figure: Pooling.



Convolutional neural network architectures

- kernels in the first convolutional layer detect low-level features (edges and curves),
- kernels in higher layers encode more abstract features,
- by stacking several convolutional and pooling layers, higher-level feature representations could be gradually extracted,

Figure: Example of CNN architecture (AlexNET).



Convolutional neural network architectures

- benchmark datasets: MNIST, cifar10, ImageNet (ILSVRC challenge)
- breakthrough in 2012 (AlexNet)
- great successes in next years: LeNet (Inception), VGG, ResNet, ResNext; more in Mira's presentation



Figure: Different CNN architectures.

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Convolutional Neural Networks

- Liquid Argon Time Projection Chambers (LArTPC) experiment
- DUNE, protoDUNE: Fermilab, CERN collaboration
- dataset primarily focused on classification of electron, muon and tau neutrino; secondarily on other variables' classification (interaction type, number of particles in the process)
- optimizer: SGD
- binary cross-entropy (for binary classification of neutrino/antineutrino) and categorical cross-entropy (for multi-class classification for others)
- architecture: ResNet18 with primarily with one output layer, secondarily with seven output layers
- in Tensorflow 1.13.1, Python 3.6

Overall results by DUNE CNN team (accuracies in %) tested on protoDUNE Monte Carlo samples (MCC8.1):

- neutrino/antineutrino: 73.5,
- flavour: 90.3,
- interaction type: 71.5,
- # protons: 81.2 (0, 1, 2, 3+),
- # pions: 84.1 (0, 1, 2, 3+),
- # pizeros: 90.9 (0, 1, 2, 3+),
- # neutrons: 99.1 (0, 1, 2, 3+; but almost all the events have 0 neutrons)

Future goals:

- other metrics
- 3D convolutional neural network
- sparse convolutional network

Conclusion:

- we have given a brief introduction into neural network and its convolution aspects
- we have discussed protoDUNE experiment classification results

Thank you for your attention

- neutrino/antineutrino
- flavour: CC (charged current) ν_{μ} , CC ν_{e} , CC ν_{τ} , NC (neutral current),
- interaction type: CC quasi electric, CC Res, CC DIS, CC other
- # protons: 0, 1, 2, 3+,
- # pions: 0, 1, 2, 3+,
- # pizeros: 0, 1, 2, 3+,
- # neutrons: 0, 1, 2, 3+; but almost all the events have 0 neutrons