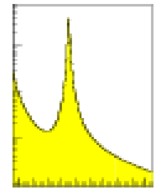

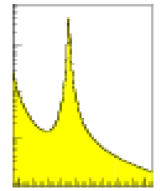

Event 4

# Using Machine Learning for Precision Measurements


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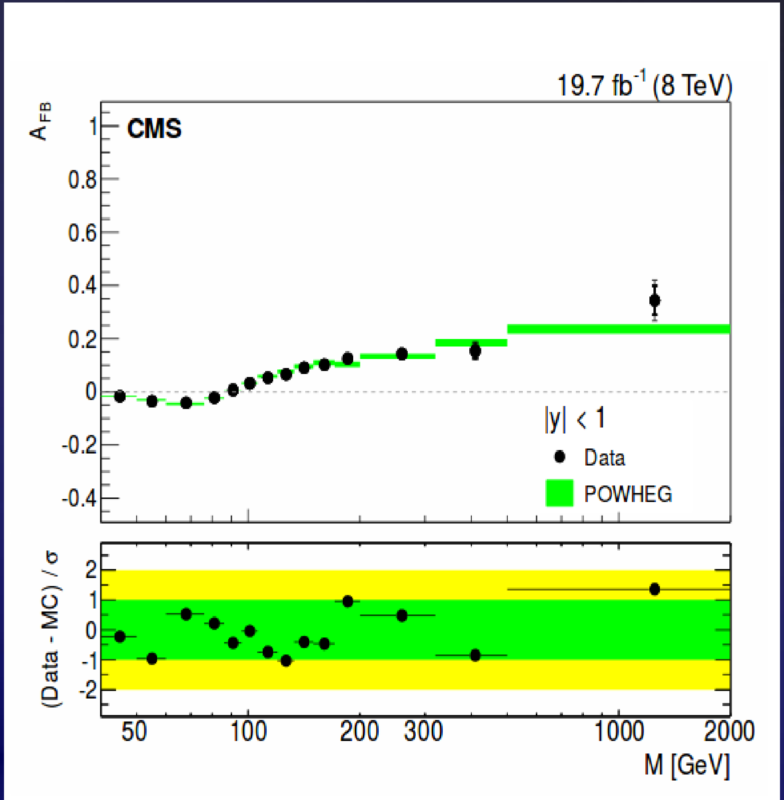
# Abstract

The use of machine learning techniques for classification is well established. They are applied widely to improve the signal-to-noise ratio and the sensitivity of searches for new physics at colliders. In this study I explore the use of machine learning for optimizing the output of high precision experiments by selecting the most sensitive variables to the quantity being measured. The precise determination of the electroweak mixing angle at the Large Hadron Collider using linear or deep neural network regressors is developed as a test study.

# Physics Motivation

- The forward-backward asymmetry $A_{FB}$ of lepton pairs at the LHC around the Z peak is sensitive to the electroweak mixing angle
- Traditionally it is measured from the cosΘ distribution in the Collins-Soper frame
- Can we extract $A_{FB}$ directly from the experimental measurements by applying ML techniques?

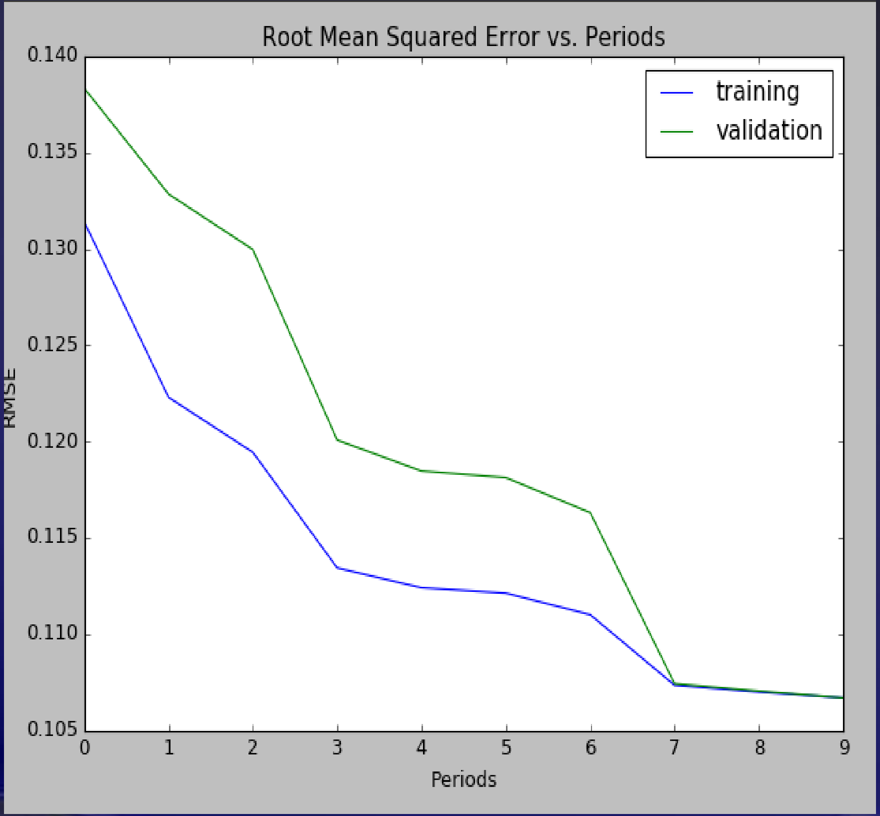


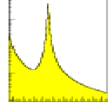
# Monte Carlo Simulations & Setup

- Generate events with PYTHIA 8.210 and CTEQ61 in the typical acceptance of a generic LHC detector @ 13 TeV at different masses (around 70, 91, 200 and 500 GeV)
- Split the samples in 3 independent parts:
  - ✓ 75% for training
  - ✓ 10% for validation
  - ✓ 15% for test
- Input variables: m (not used), $p_T$, y of the dilepton system, $\eta$, $p_T$, $\varphi$ for each decay lepton
- Target variable: observed $A_{FB}$
- Use linear or deep neural network regressors from Tensorflow to "learn" the $A_{FB}$ directly from data

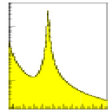
# Linear Regressor - Results

The linear regressor needs some help: by adding synthetic features like $|y|$ and $|\eta_1|$, $|\eta_2|$, well tuned to the symmetric nature of LHC (where the observed $A_{FB}$ is stronger when the dilepton system has higher boost), very good performance, as measured by the root mean squared error (RMSE), is reached

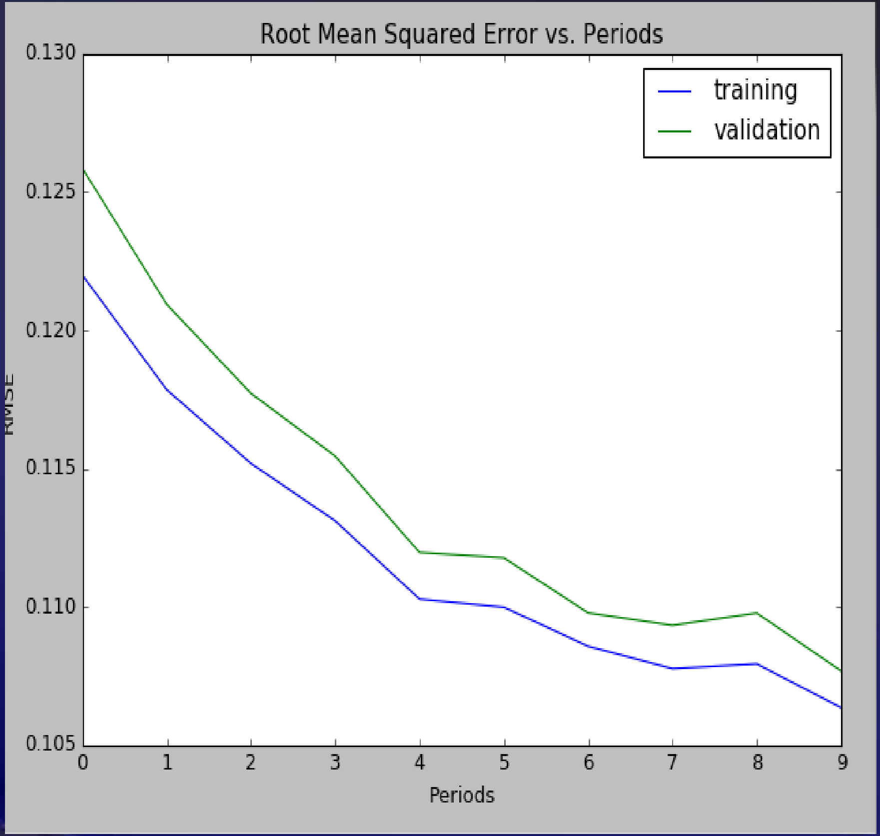




# DNN Regressor – Results I



- **Learn nonlinearities in the dataset and try to achieve better performance compared to the linear regressor**
- **Hyperparameters: 2 hidden layers with 10 nodes each, ReLu activation, batch size 100, 2000 epochs**
- **So far similar performance**

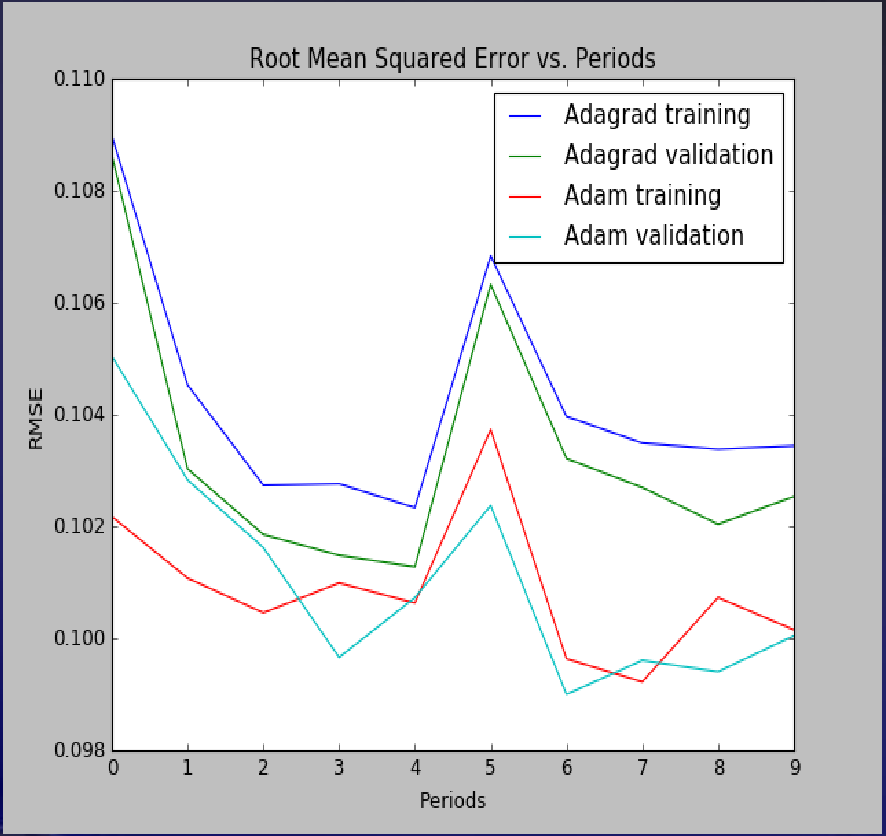


# DNN Regressor – Results II

Normalizing the input features and applying various optimization algorithms

Adagrad optimizer - great for convex problems

**Adam optimizer** - could be better for non-convex problems: best so far, **gaining ~ 8% in precision** compared to the linear regressor with synthetic features



# Outlook

- Machine learning techniques show interesting potential for precision measurements at the LHC
- Deep Neural Net regressors can outperform linear regressors with synthetic features
- Results preliminary, next steps:
  - Increase the size of the MC samples
  - Tune the hyperparameters of DNN for optimal performance