Applying machine learning to CALICE data

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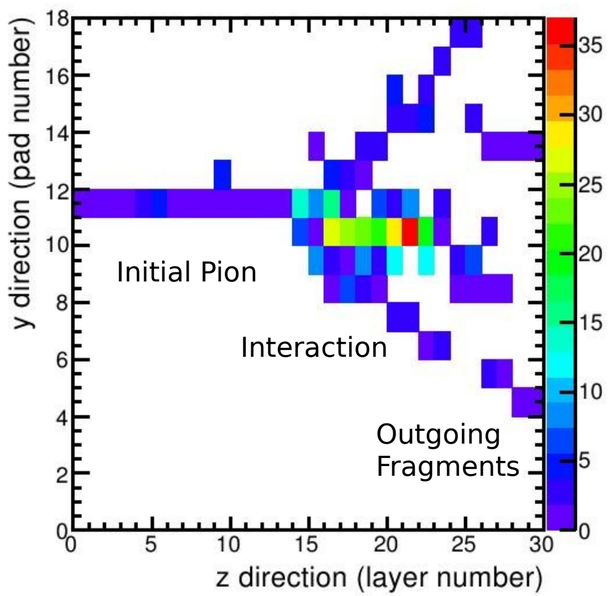
Objectives

- Improve jet reconstruction in the eCal (hCal)
  - energy resolution
  - assigning each pixel (energy deposit) to an incoming particle: jet separation

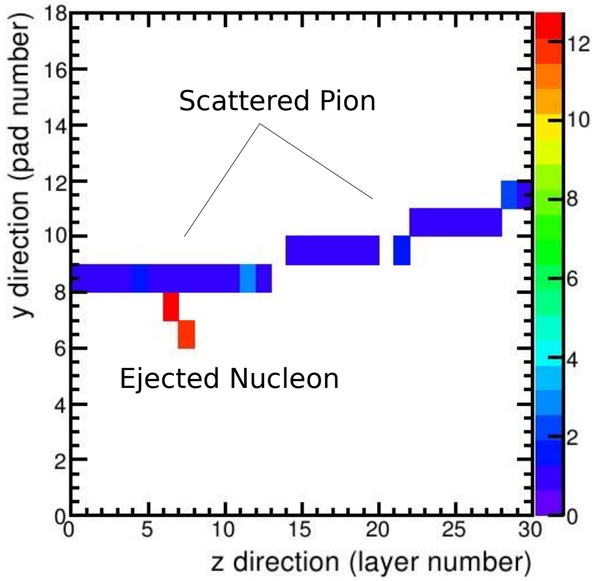
Granularity and hadronic cascades
(Start of) Hadronic showers in the SiW Ecal

Complex and impressive



Inelastic reaction in SiW Ecal

Simple but nice



Short truncated showers

Outline

- Mainly a plan at this point
- The generative approach
  - Parametrizing GEANT4 (model reduction)
  - Fitting the models on calorimeter data
  - EM or MCMC to handle mixtures
- The direct approach
  - Train neural nets/BDTs for the inverse function
  - Engineer features or use deep learning
  - How to handle overlapping jets?

The generative approach

- x: observables: pixels
- y: parameters to infer:
  - e.g: incoming geometry, energy, type
- but also nuisance parameters that can be "read out" from GEANT4

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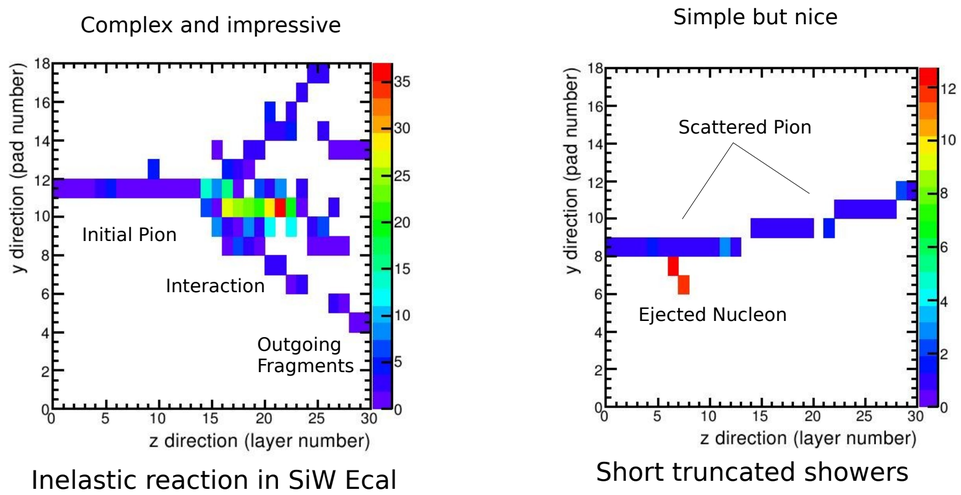


$$p(y \mid x) \sim p(x \mid y) \times p(y)$$

posterior likelihood prior

The generative approach

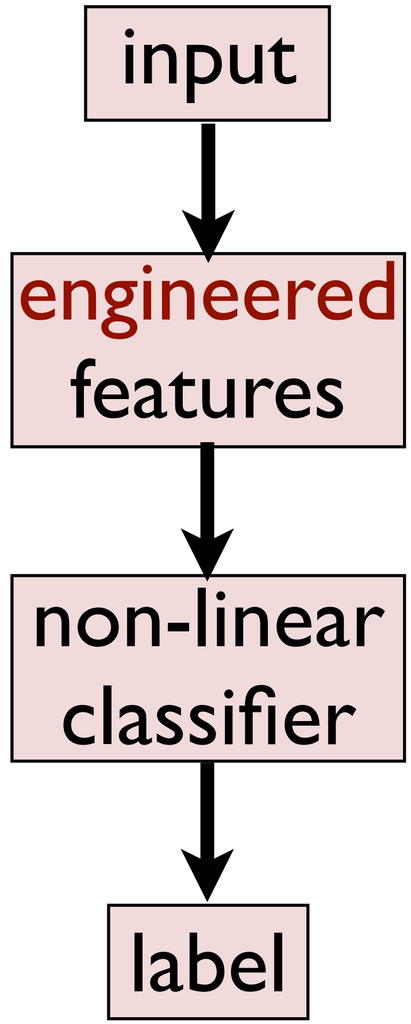
- $p(x \mid y)$ (likelihood)
  - parametrize GEANT4
  - at what granularity? computational and statistical issues
  - existing solutions for mixtures: $p(x \mid y) = \Sigma_i \alpha_i\, p(x \mid y_i)$: EM, MCMC
- natural handling of model dependence, controlled use of simulators
- conceptually neat but computationally heavy: zillions of calls to the likelihood

The direct approach

- model directly the posterior p(y | x)
  - x: pixels, y: elastic/non-elastic label
  - no neat (physical) parametrization: nonparametric approach
  - black box (neural net or boosted decision tree), trained on a sample generated by GEANT4, only end-to-end setup
  - not completely clear how to handle mixtures: similar to image segmentation
  - standard technology
  - computationally fast inference
  - recent advances in deep learning (training multi-layer neural nets) to be harvested

The direct approach

- The classical setup
  - image, speech, text, etc.
  - domain knowledge goes into features
  - not fully automatic but flexible



The direct approach

- The features
  - the front image
  - the lateral vector
  - the lateral discrete derivative
  - covariance and correlation structure of the front image
- The classifier
  - AdaBoost + decision trees

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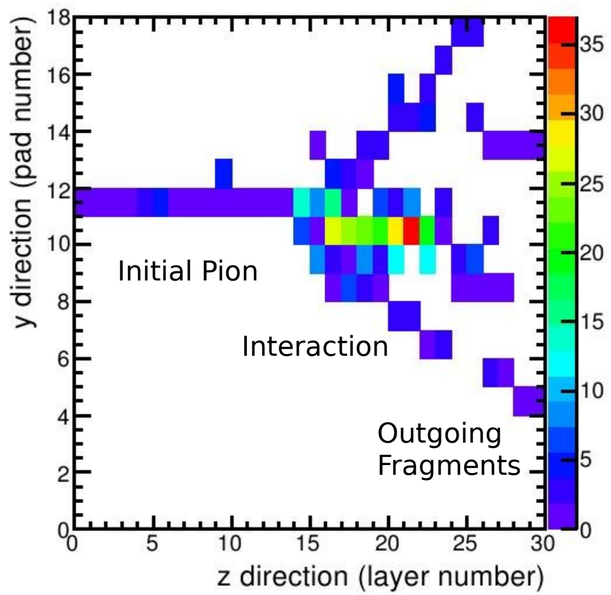

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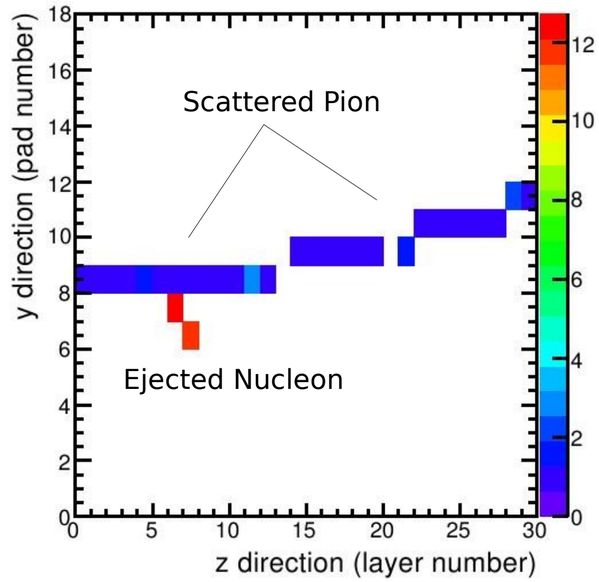
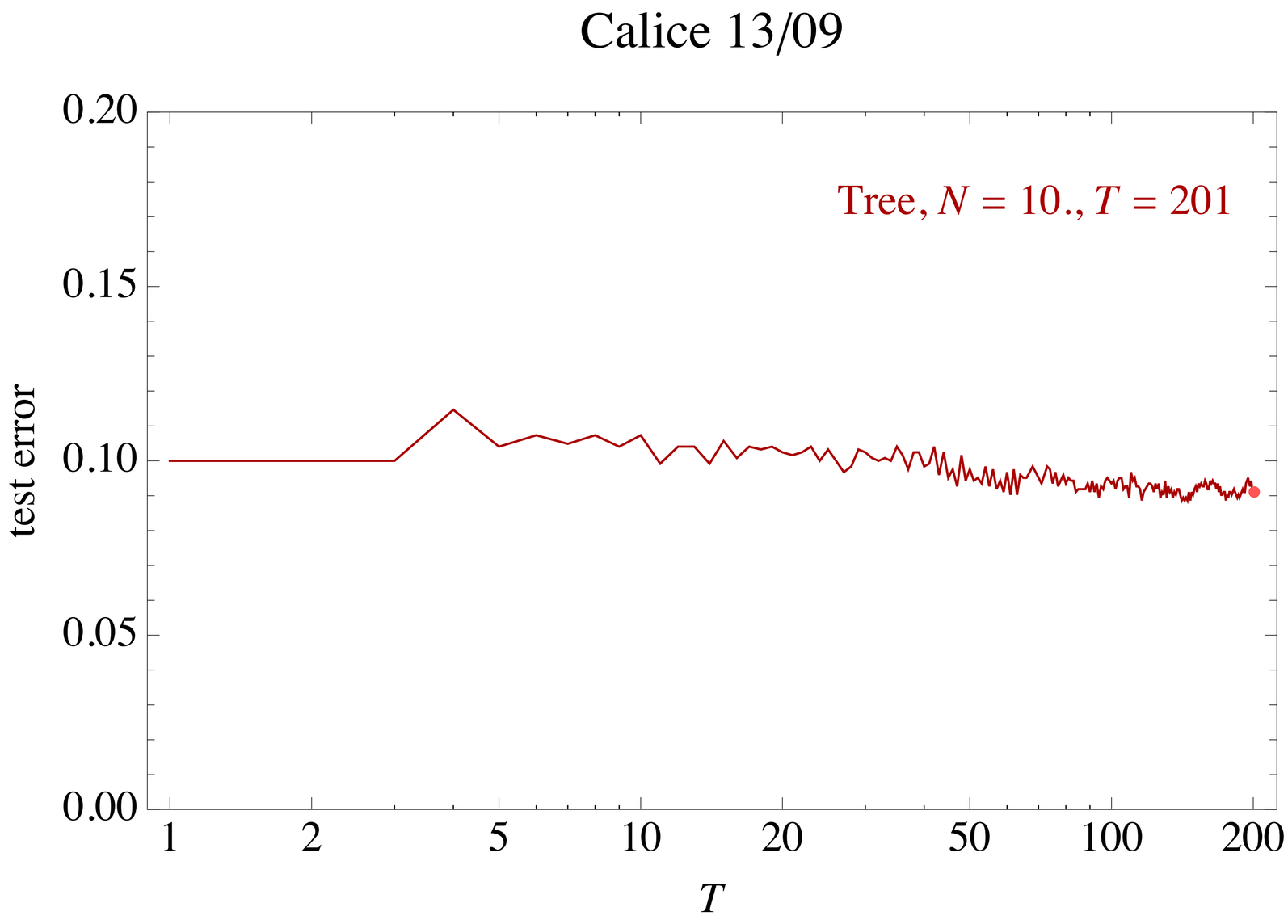


Short truncated showers

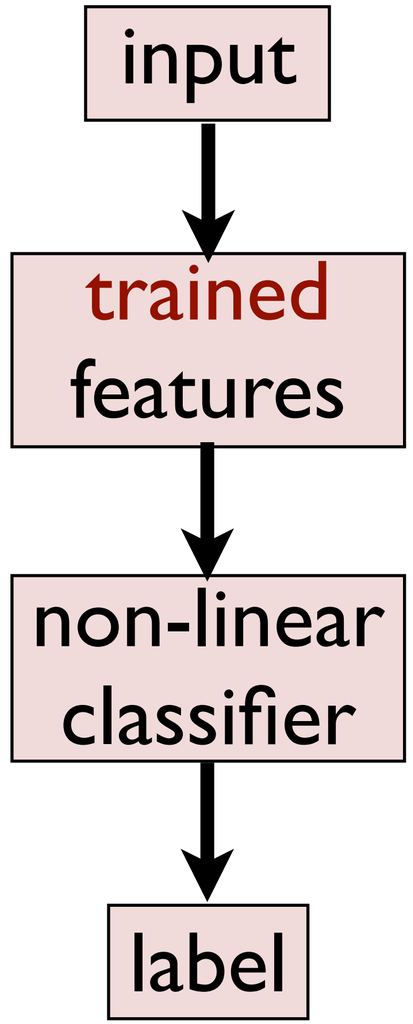
The direct approach

- The learning curve with engineered features



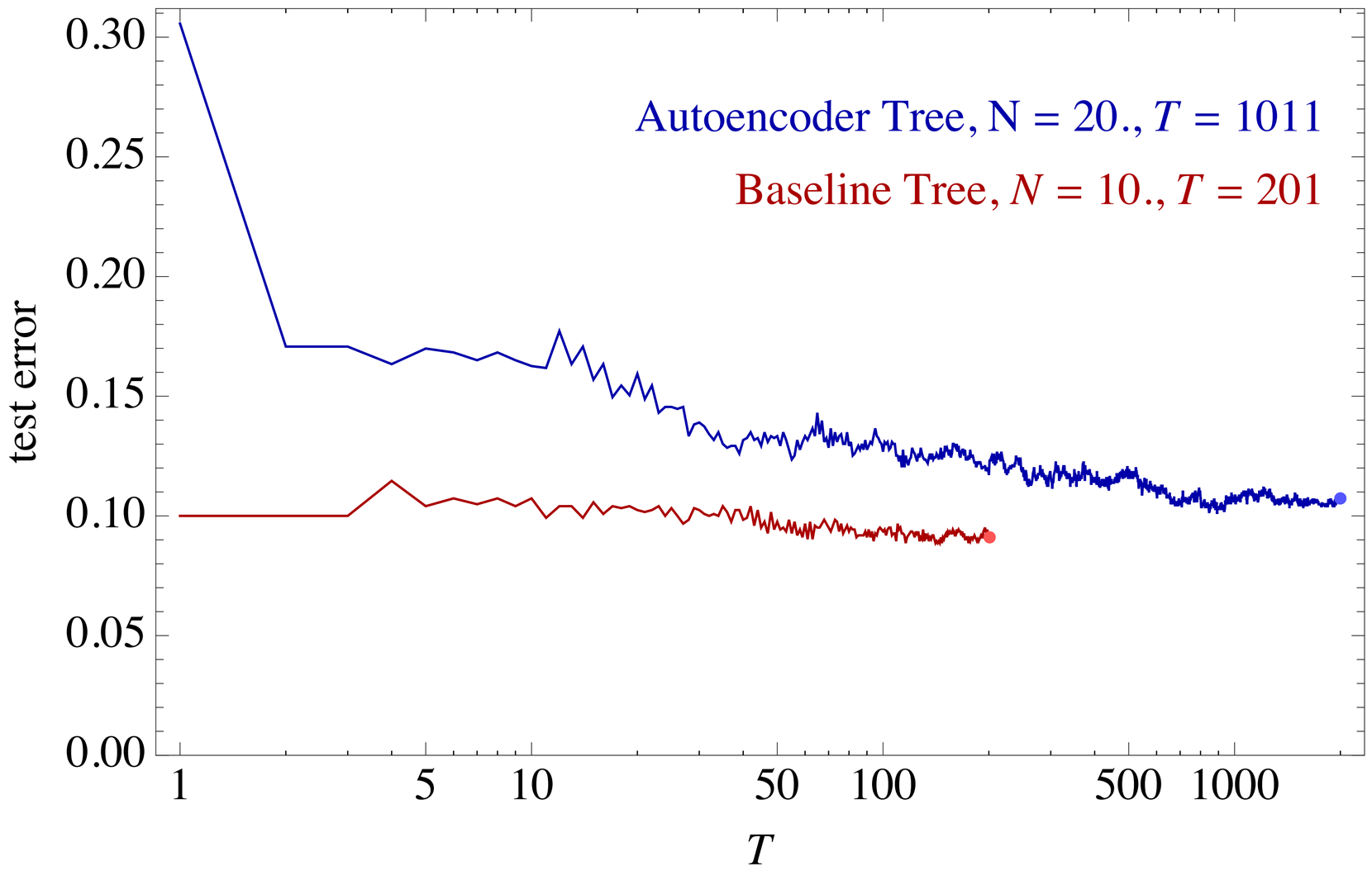
The direct approach

- The deep learning setup
  - unsupervised pre-training (stacked autoencoder)
  - supervised training of a giant network (convolutional net)
- revolutionized speech and image recognition in the last five years



The direct approach

- The learning curve with trained features (autoencoder)



Conclusions

- Feasibility testing of different inference and learning approaches
  - generative or direct?
  - engineered or trained features?
  - how to handle mixtures and pixel assignment?
  - long road ahead