Applications of Machine Learning to particle physics

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What is machine learning?

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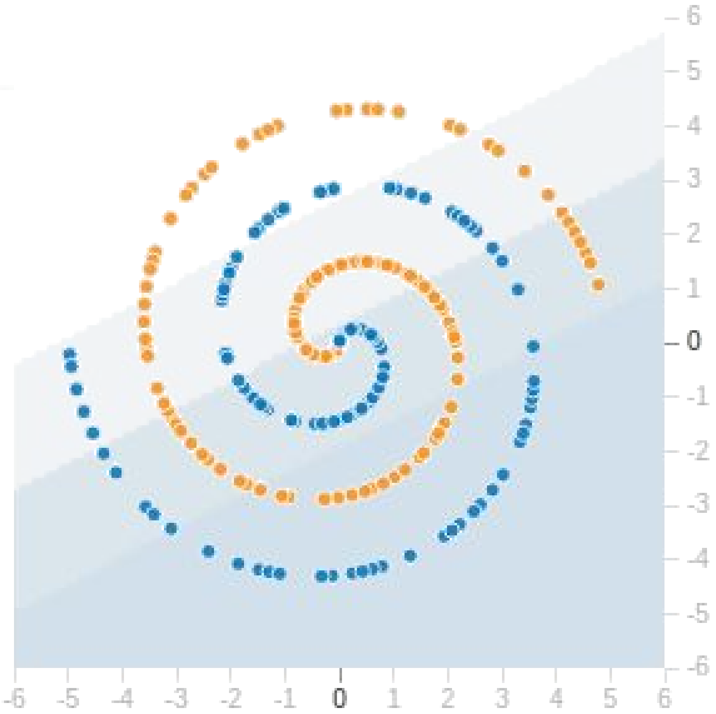
Automated model building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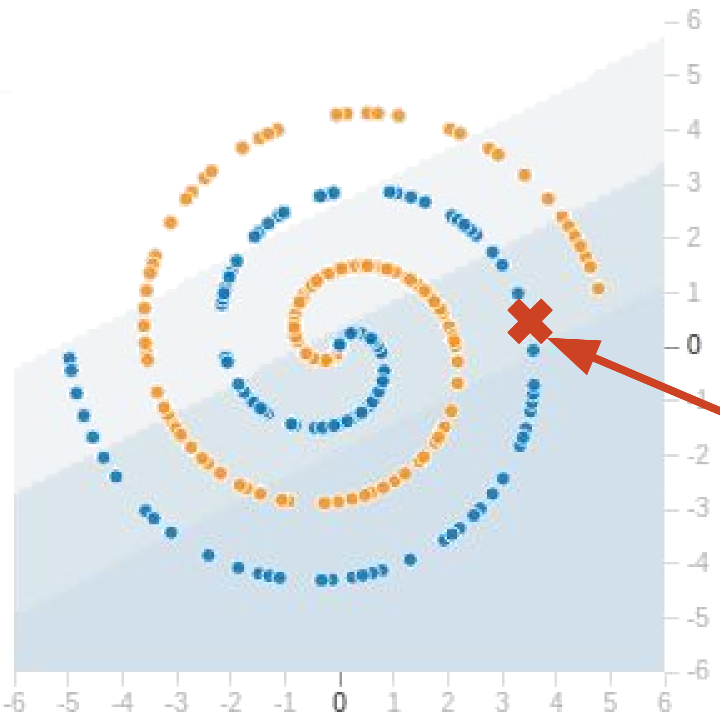
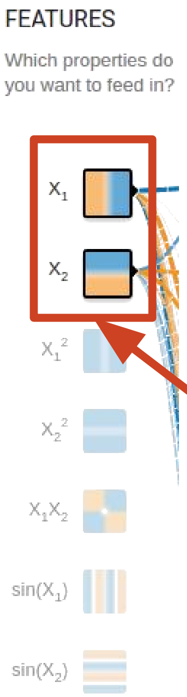
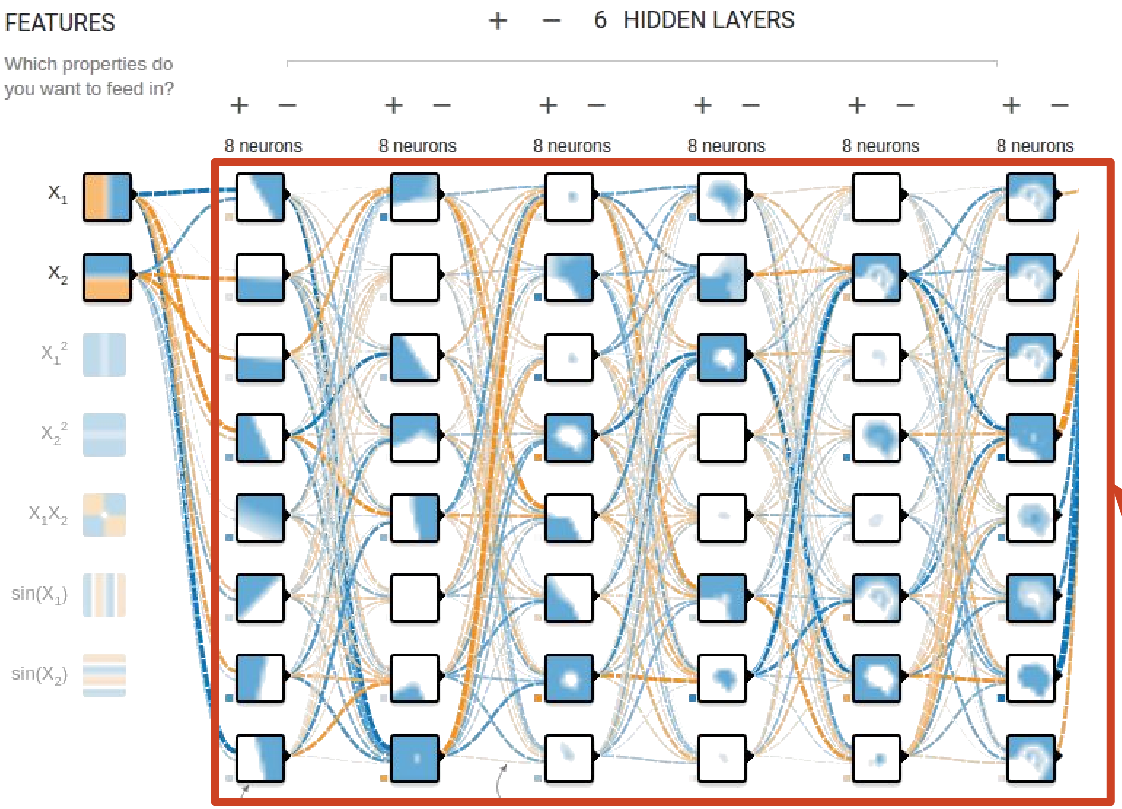


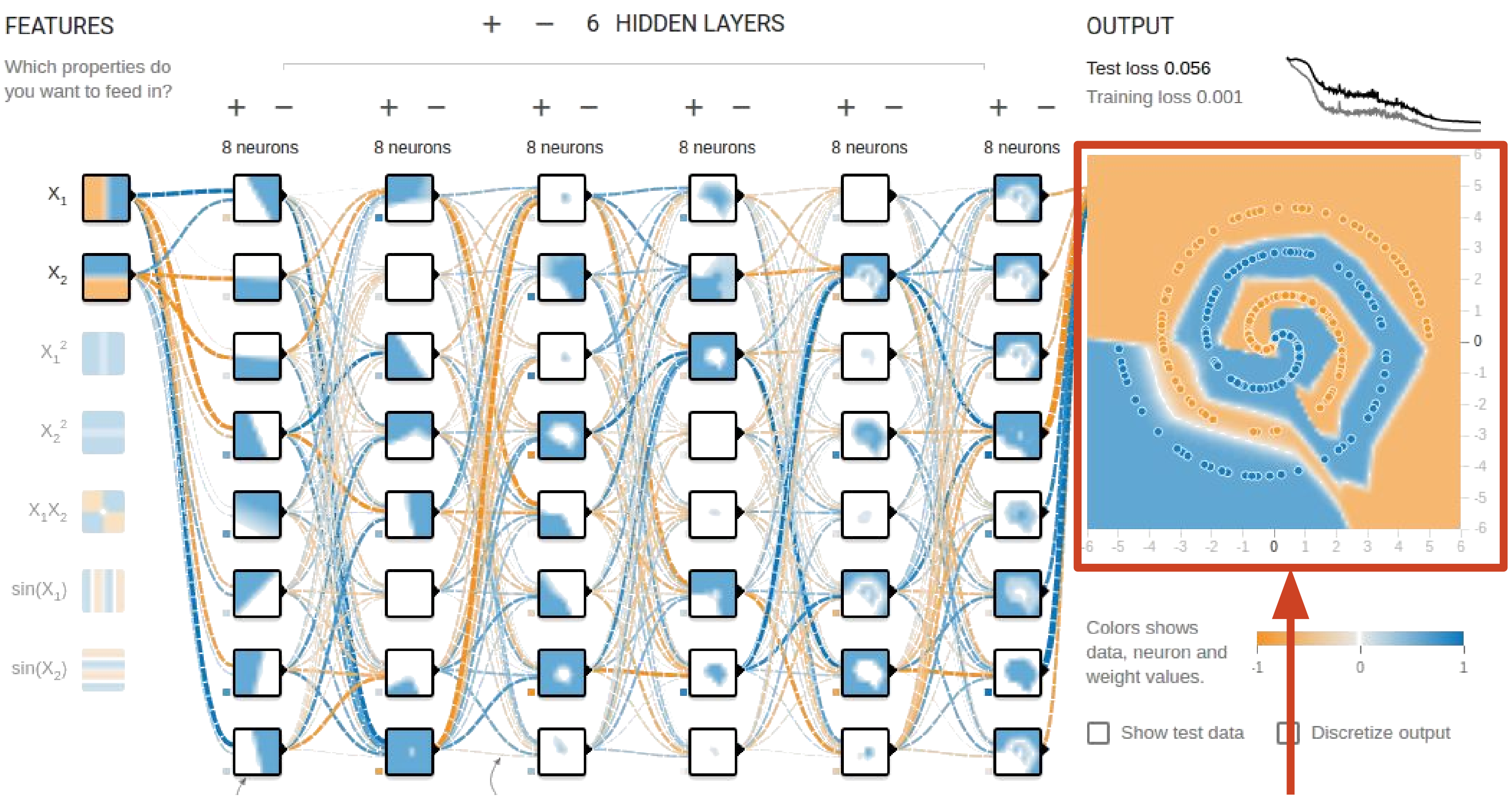
Is a point here
blue or orange?



Low-level information - X and Y coordinates



Flexible system to learn map between inputs and target function:
X, Y -> blue/orange



Train on example data

Simple example $\longrightarrow$ High-energy physics

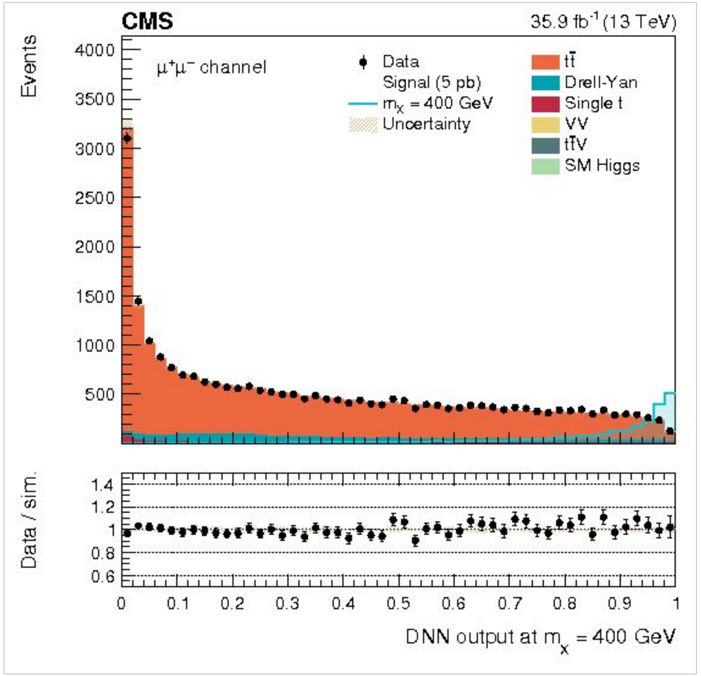
Simple example → High-energy physics

Data and desired outputs are more complex

Underlying principle is the same

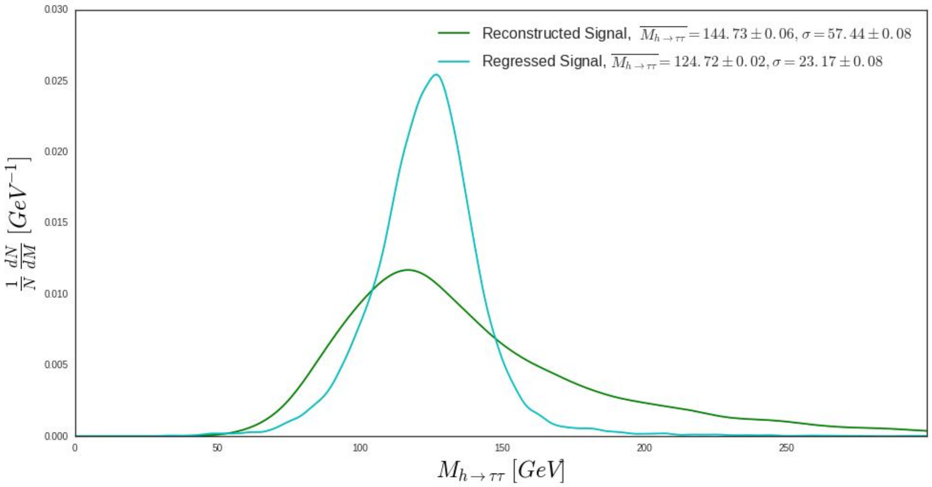
Event classification

- Search for rare processes by predicting what process occurs in a particle collision
- E.g. Di-Higgs production - [1708.04188]



Mass regression

- Predict the mass of a decayed particle from knowledge of its decay products
- E.g. Higgs to tau tau - [AMVA4NP:WP1-D1]



Reduce systematic uncertainties

- Use *adversarial training* to build classifiers which are immune to unknown model parameters
- Helps improve inference of other model parameters, e.g. cross-section of a particular process
- E.g. Learning to Pivot with Adversarial Networks and Adversarial learning to eliminate systematic errors: a case study in High Energy Physics

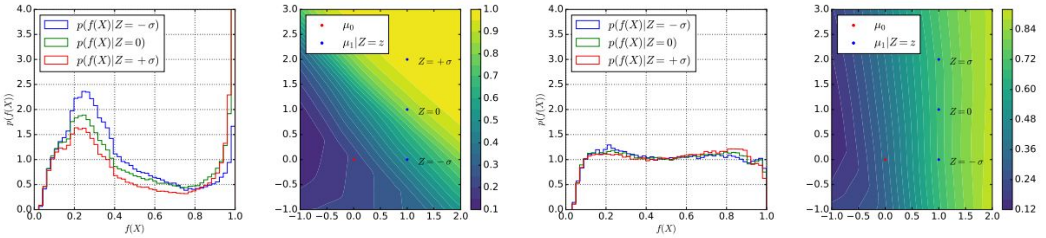


Figure 2: Toy example. (Left) Conditional probability densities of the decision scores at $Z = -\sigma, 0, \sigma$ without adversarial training. The resulting densities are dependent on the continuous parameter Z, indicating that f is not pivotal. (Middle left) The associated decision surface, highlighting the fact that samples are easier to classify for values of Z above σ, hence explaining the dependency. (Middle right) Conditional probability densities of the decision scores at $Z = -\sigma, 0, \sigma$ when f is built with adversarial training. The resulting densities are now almost identical to each other, indicating only a small dependency on Z. (Right) The associated decision surface, illustrating how adversarial training bends the decision function vertically to erase the dependency on Z.

Jet physics

- Use convolutional and recurrent networks to classify jets according to origin process: [DeepJet]
- Recluster event using QCD-aware recursive networks to provide jet embeddings: [QCD-Aware Recursive Neural Networks for Jet Physics]

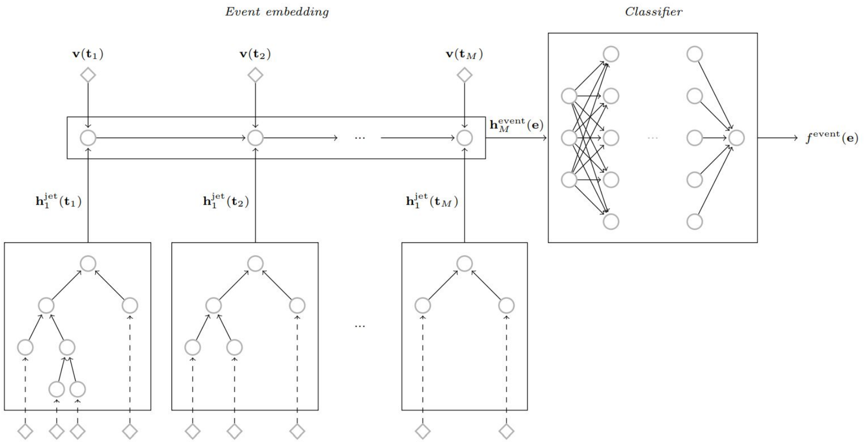


FIG. 2. QCD-motivated event embedding for classification. The embedding of an event is computed by feeding the sequence of pairs $(\mathbf{v}(\mathbf{t}_j), \mathbf{h}_1^{\text{jet}}(\mathbf{t}_j))$ over the jets it is made of, where $\mathbf{v}(\mathbf{t}_j)$ is the unprocessed 4-momentum of the jet $\mathbf{t}_j$ and $\mathbf{h}_1^{\text{jet}}(\mathbf{t}_j)$ is its embedding. The resulting event-level embedding $\mathbf{h}_M^{\text{event}}(\mathbf{e})$ is chained to a subsequent classifier, as illustrated in the right part of the figure.

Many possible applications

Jet tagging

Particle ID

Event classification

Event triggering

Kinematic regression

Simulation

Detector design

Inference

Further reading

- Play in browser: Tensorflow playground, gradient boosting playground
- Seminars and lectures: MLHEP-17, Karpathy, Hastie, HEP repository
- My resources: NN summary posts, example classifier