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Looking at New Physics using Visual recognition

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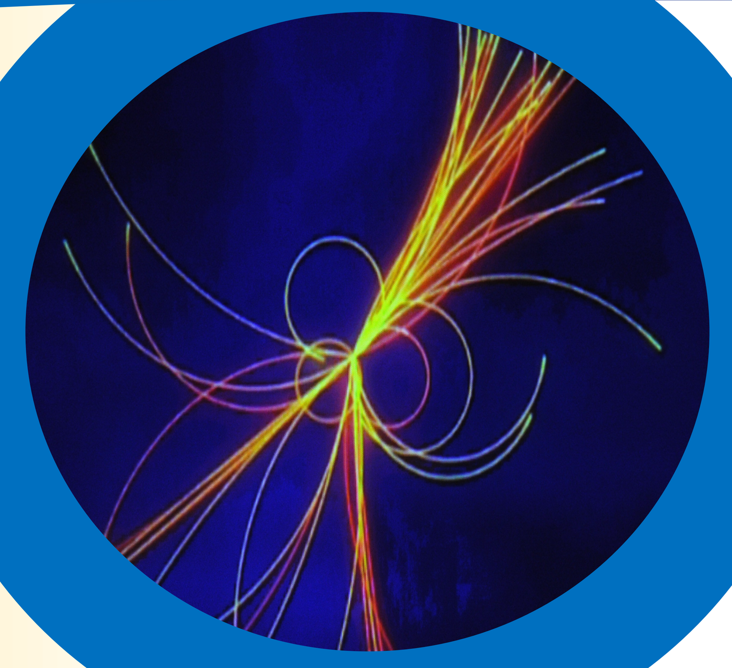
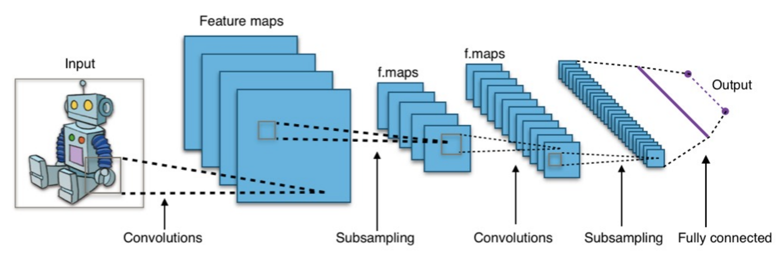
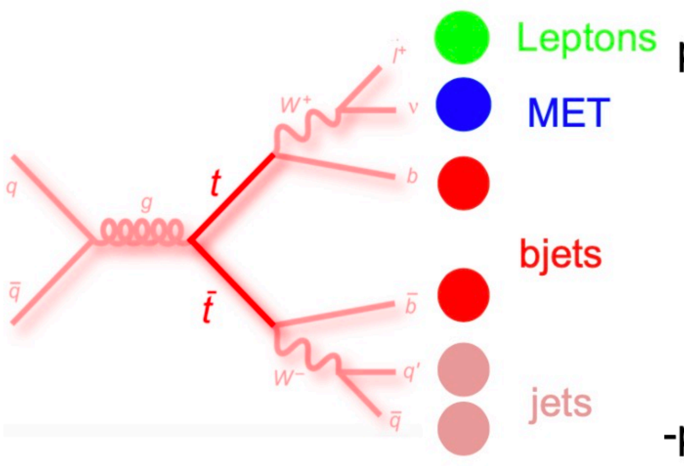
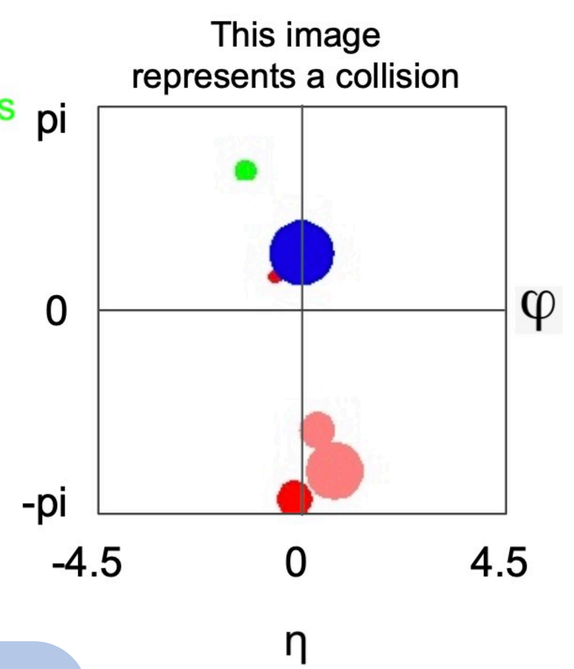


Visual recognition is based on Convolutional Neural Networks (CNNs)



Q1: How to codify the information of particle collisions in images?





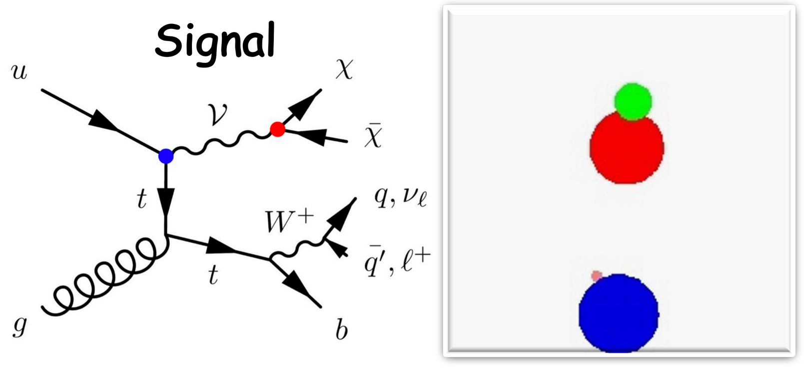
Despite different ways to represent a collision in an image can be imagined, this one is a very intuitive way in which every object corresponds to a coloured circle

For each object:
X-axis [-4.5,4.5]: **pseudorapidity**
Y-axis [-pi, pi]: **azimuthal angle**
Circle radius proportional to **transverse momentum** (non-linearly)

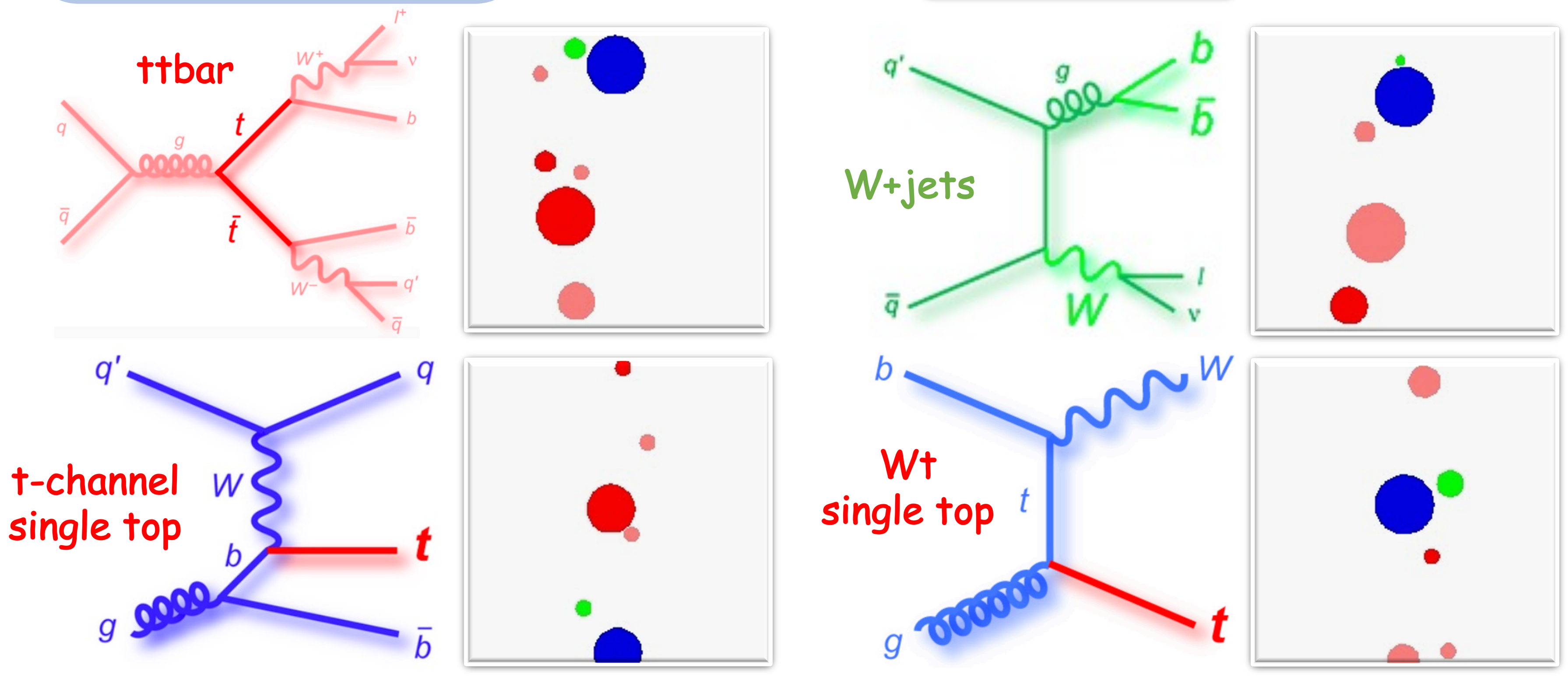
Much more underlying information:
- Angular distances between objects.
- Closest objects probably share a common origin (same parent decay).

We expect that CNNs can learn physics!!

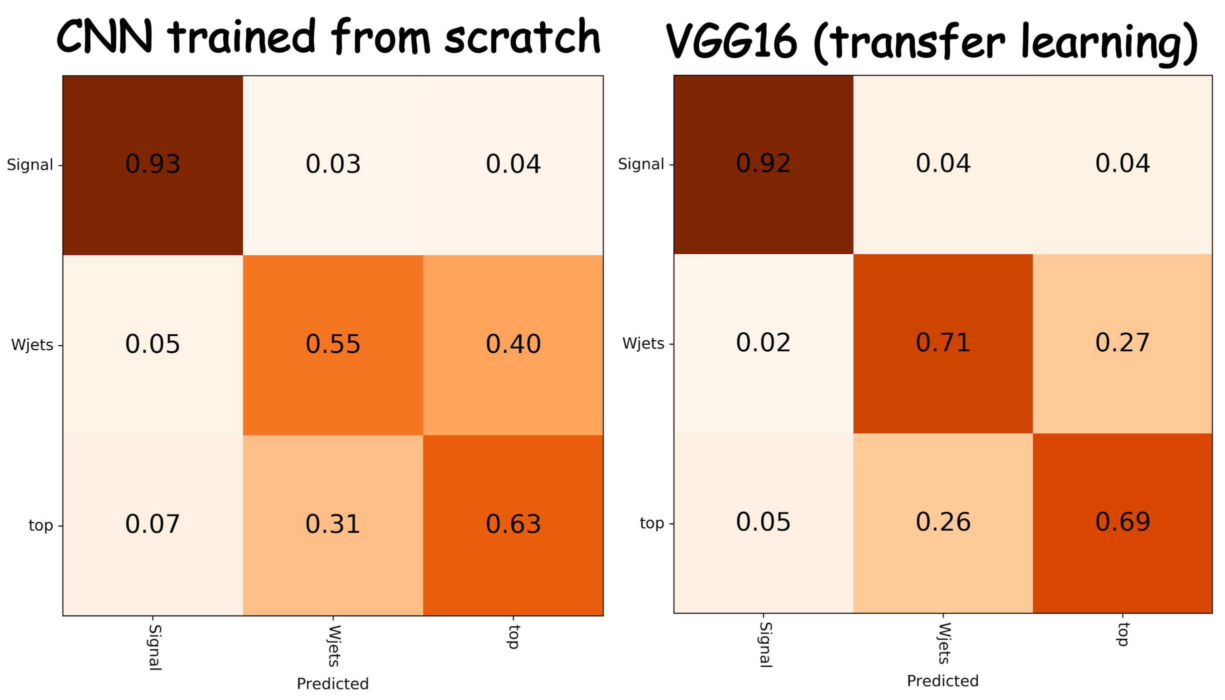
Search for Dark Matter using a mono-top process as signal. The background consists of W+jets, ttbar, t-channel and Wt single top (the latter three merged).



Selection
Exactly one lepton, at least one b-tagged jet and significant amount of MET.



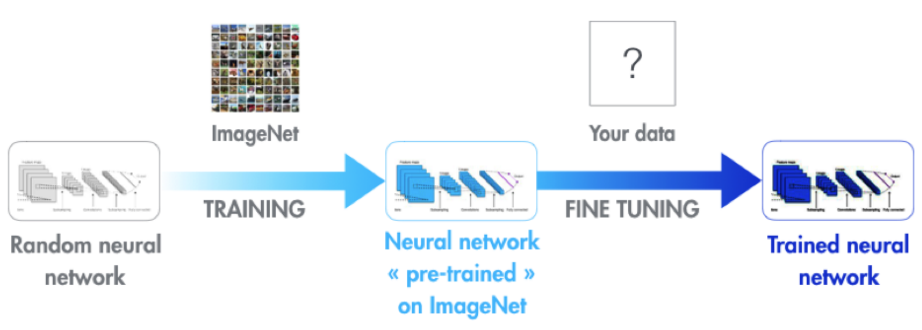
Q2: Could CNNs together with this image representation actually be used for event classification?



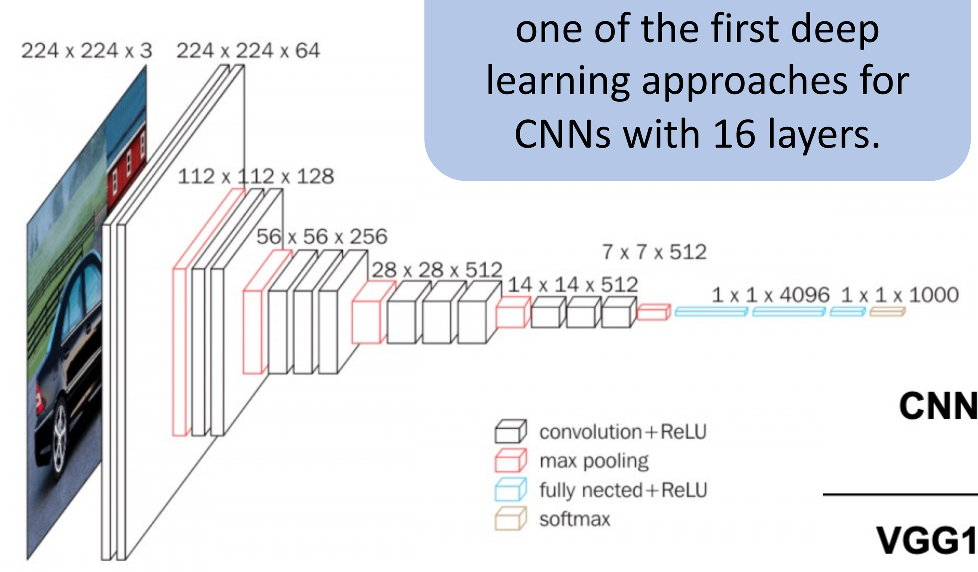
It looks so! And transfer learning seems to be a suitable option

Transfer learning is based on the idea that a good profit can be made of the power of a well-performing CNN with a previous training.

Thus, the "*feature extractor*" of VGG16 was already trained using the ImageNet dataset and only the "*classifier*" part has been tuned with our samples.



VGG16



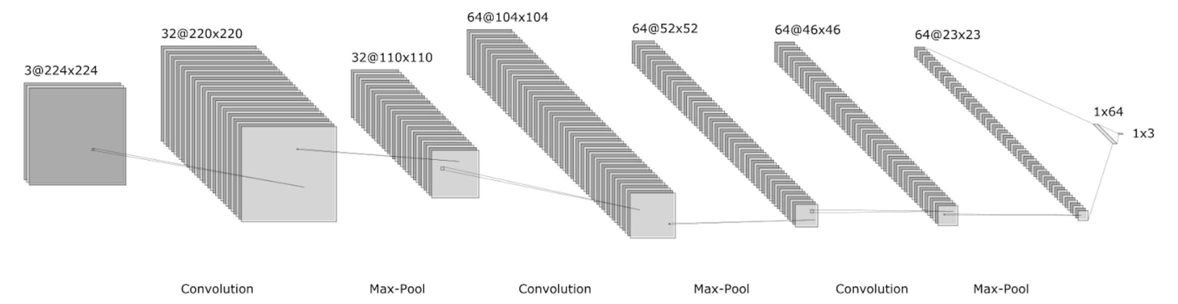
Based on AlexNet, this is one of the first deep learning approaches for CNNs with 16 layers.

Using transfer learning implies that not all the parameters will be trained.

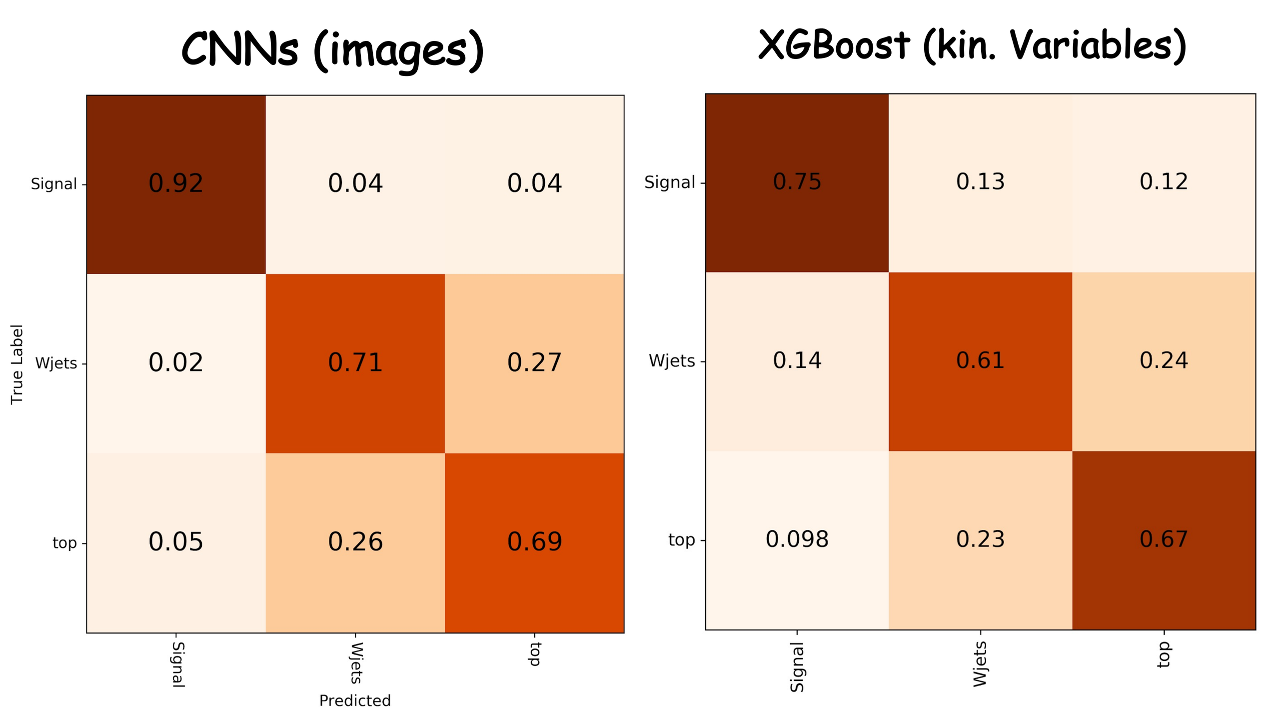
CNN	Number of layers	Total parameters ($x10^6$)	Trainable parameters ($x10^6$)
VGG16	16	16,3	8,7
Deep CNN	11	2,5	2,5

Deep CNN trained from scratch

A CNN with 11 layers has been built to train all its weights using our samples.

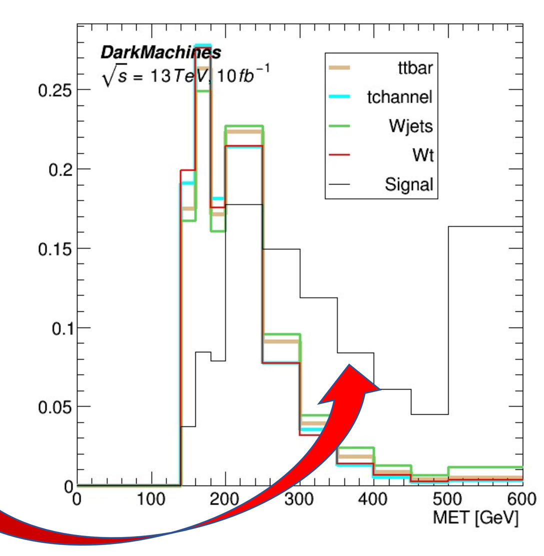


Q3: How well this technique (based on CNNs and images) performs in comparison to other techniques based on kinematic variables?



A very good performance is obtained, even better than a BDT in this case

Another example with more complex final states tt+X (X=tt,H,W) has also been studied.



The similar performance to the BDT shows that **the CNN is learning physics** instead of irrelevant details of the images.

This different shape in MET is learnt by the CNN

Advantages

No previous feature study is required, since most important information is in the images and "the CNN decides where to see".

This image representation makes the event information more intuitive also for humans.

Unlimited creativity can be applied for including additional features to the images.

Disadvantages

Creating these images introduces an additional step in the analysis chain, which is not required when using other techniques.

Study the features that the CNNs are learning is quite tedious, but still possible looking into intermediate layers.

Adding a new feature is not always as straightforward as adding a new "variable column".

References:
- Monte Carlo simulation samples from DarkMachines collaboration: https://www.phenomldata.org/
- Image representation based on previous study at IFCA: https://arxiv.org/abs/1708.07034
- VGG16: H. Ming and K. Xu. Surface Blemishes of Aluminium Material Image Recognition Based on Transfer Learning Journal of Physics: Conference Series, 1288:012016, 08 2019