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).

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

**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.

**Signal**

- t-channel
- Single top
- W+jets

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

- 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 (transfer learning)**

- 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.

**Deep CNN trained from scratch**

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

- An 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?

- CNNs (images)
- XGBoost (kin. variables)

We expect that CNNs can learn physics!!

- 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.

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

**Advantages**

- 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".

**Disadvantages**

- This different shape in MET is learnt by the CNN.

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

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

**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
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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.

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Visual recognition is based on Convolutional Neural Networks (CNNs).

José Enrique García Navarro, María Moreno Llácer and Adrián Rubio Jiménez (speaker)

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<td>16</td>
<td>16,3</td>
<td>8,7</td>
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**Deep CNN trained from scratch**

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

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

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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. It looks so! And transfer learning seems to be a suitable option. Another example with more complex final states tt+X (X=tt,H,W) has also been studied.