Machine Learning meets particle physics

Overview & examples

Troels C. Petersen

With contributions from Stefan Hasselgren, Lukas Ehrke, Frederik Faye, Benjamin Henckel, and Daniel Nielsen

Niels Bohr Institute

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Outline

Outline of talk:
• In the beginning: b-jet tagging in ALEPH
• HEP data and why it is exciting for Machine Learning (ML)
• Going large scale: Electrons and photons in ATLAS
  – Data samples, variables, and selections
  – Electron PID and Energy Reconstruction (ER)
  – Discussion of performance measures (loss functions)
• Looking at the future: v-reconstruction in IceCube

Purpose of talk:
• Show Machine Learning cases in science.
• Present HEP data, and why it is great (but also cumbersome!)
• Open up for possible inspiration/collaboration

In the following, all numbers and plots are “Not Even Preliminary”, and should in not be used elsewhere.
A word about particle physics

We search for MANY different things, typically rare (1:10^9) with complex decays.

Candidate:
Higgs → ZZ* → 4 leptons (e or μ)
Particle physics data and simulation

To make sure that we understand our experiment we use simulation extensively:
- Detector optimisation (before experiment)
- Reconstruction design/optimisation (before/during experiment)
- Selection optimisation (during experiment)
- Signal efficiency estimates (during experiment)

The simulation is done in three steps: Event generation, Simulation, and Digitisation.

The total CPU time needed for one event is about 20-30 minutes, and we have now simulated about a billion events (using 0.5M cores).

The simulation is done from first principles, and there are therefore (smaller) differences between simulation and data (maybe a point of interest to fix?).
Aim of this project

Electrons and photons play a central role in the ATLAS physics programme, in particular in **Higgs physics**, where they dominate the two golden channels. Current methods use likelihood approach (PID) and simple ML (Energy).

Given the cost of running, we would be satisfied, if we could add 10% to each of these in terms of statistics, knowing this would also benefit many other analysis.
In the beginning: b-jet tagging in ALEPH
ALEPH b-jet tagging

25 years ago, particle physics was actually at the forefront of using Machine Learning. We had large computers and much data fit for ML usage.

At the time, LEP was searching for the Higgs boson at lower masses, where its decay was almost always to b-quarks.

For this reason, many resources were used to get the best possible b-jet tagging in place.
ALEPH b-jet tagging

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For this reason, many resources were used to get the best possible b-jet tagging in place.

Both lifetime (displaced vertices), jet shape, and lepton pT was used, but none of these by themselves provide a good way to select b-jets.

Impact parameter significance:

Figure 3.5: Impact parameter significance ($\delta/\sigma_\delta$) distributions for (a) fragmentation or tracks from uds events, (b) tracks from weakly decaying c hadrons, (c) tracks directly from b hadron decay, (d) tracks from the cascade decay of a c hadron from the decay of a b hadron.
ALEPH b-jet tagging

However, using one of the very first ML algorithms (JetNet 3.4), six variables were put together in a neural network with two hidden layers each with 10 neurons:

• Light quark (uds) jet probability from track impact parameter significance.
• Difference in Chi2 from search for secondary vertices in jet.
• Transverse momentum of (possible) electron/muon in jet.
• Boosted sphericity of jet.
• Energy flow multiplicity (scaled by jet energy).
• Sum of transverse momenta (with respect to the jet axis) squared.

The neural network was trained on 400,000 simulated events, and though I haven’t been able to find the exact time used for this training, colleagues have told me “many hours, sometime days”.

Interestingly, my students now code the setup in about an hour, and get results in minutes.
ALEPH b-jet tagging

The result of these labours was a very nice b-jet tagging variable, which allowed ALEPH to get the most out of their data.
ALEPH b-jet tagging

A more “modern” plot could look like this:

Btags of signal and different types of backgrounds

- Gluons
- b quarks
- c quarks
- l quarks
- Signal

Benjamin Henckel
Going large scale: e/γ PID & ER in ATLAS
Overview

Currently in ATLAS, electrons and photons are identified using a likelihood approach:

$$d_L = \frac{\mathcal{L}_S}{\mathcal{L}_S + \mathcal{L}_B}, \quad \mathcal{L}_S(x^i) = \prod_{i=1}^{n} P_{s,i}(x_i)$$

The likelihood is composed of 22 variables, for which 1D histograms are used to compute the likelihood value.

To minimise correlations, the likelihood is divided into regions of $E_T$ and $\eta$.

This makes for a very transparent approach, which at the same time performs well.

The question is, if there is more information to be gained, and thus a more powerful PID to be gotten.

Enter Machine Learning (ML)…

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hadronic leakage</td>
<td>Ratio of $E_T$ in the first layer of the hadronic calorimeter to $E_T$ of the EM cluster (used over the range $</td>
<td>\eta</td>
</tr>
<tr>
<td>Hadronic leakage</td>
<td>Ratio of $E_T$ in the hadronic calorimeter to $E_T$ of the EM cluster (used over the range $0.8 &lt;</td>
<td>\eta</td>
</tr>
<tr>
<td>Back layer of EM calorimeter</td>
<td>Ratio of the energy in the back layer to the total energy in the EM accordion calorimeter</td>
<td>$f_2$</td>
</tr>
<tr>
<td>Middle layer of EM calorimeter</td>
<td>Lateral shower width, $\sqrt{(\Sigma E_{i,\eta})/\Sigma E_{i}} - (\Sigma E_{i,\eta})/\Sigma E_{i}$, where $E_i$ is the energy and $\eta_i$ is the pseudorapidity of cell $i$ and the sum is calculated within a window of $3 \times 5$ cells</td>
<td>$W_{\text{cal}}$</td>
</tr>
<tr>
<td>Middle layer of EM calorimeter</td>
<td>Ratio of the energy in $3 \times 3$ cells over the energy in $3 \times 7$ cells centered at the electron cluster position</td>
<td>$R_p$</td>
</tr>
<tr>
<td>Middle layer of EM calorimeter</td>
<td>Ratio of the energy in $3 \times 7$ cells over the energy in $7 \times 7$ cells centered at the electron cluster position</td>
<td>$R_\eta$</td>
</tr>
<tr>
<td>Strip layer of EM calorimeter</td>
<td>Shower width, $\sqrt{(\Sigma E_{i,\eta})/\Sigma E_{i}}$, where $i$ runs over all strips in a window of $\Delta \eta \times \Delta \phi = 0.0625 \times 0.2$, corresponding typically to 20 strips in $\eta$, and $i_{\text{max}}$ is the index of the highest-energy strip</td>
<td>$w_{\text{cal}}$</td>
</tr>
<tr>
<td>Strip layer of EM calorimeter</td>
<td>Ratio of the energy difference between the largest and second largest energy deposits in the cluster over the sum of these energies</td>
<td>$E_{\text{ratio}}$</td>
</tr>
<tr>
<td>Strip layer of EM calorimeter</td>
<td>Ratio of the energy in the strip layer to the total energy in the EM accordion calorimeter</td>
<td>$f_1$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Number of hits in the B-layer (discriminates against photon conversions)</td>
<td>$n_{\text{layer}}$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Number of hits in the pixel detector</td>
<td>$n_{\text{pix}}$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Number of total hits in the pixel and SCT detectors</td>
<td>$n_{\text{hit}}$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Transverse impact parameter</td>
<td>$d_0$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Significance of transverse impact parameter defined as the ratio of $d_0$ and its uncertainty</td>
<td>$\sigma_{d_0}$</td>
</tr>
<tr>
<td>Track quality</td>
<td>Momentum lost by the track between the perigee and the last measurement point divided by the original momentum</td>
<td>$\Delta p/p$</td>
</tr>
<tr>
<td>TRT</td>
<td>Total number of hits in the TRT</td>
<td>$n_{\text{trt}}$</td>
</tr>
<tr>
<td>TRT</td>
<td>Ratio of the number of high-threshold hits to the total number of hits in the TRT</td>
<td>$F_{\text{trt}}$</td>
</tr>
<tr>
<td>Track-cluster matching</td>
<td>$\Delta \eta$ between the cluster position in the strip layer and the extrapolated track</td>
<td>$\Delta \eta_l$</td>
</tr>
<tr>
<td>Track-cluster matching</td>
<td>$\Delta \eta$ between the cluster position in the middle layer and the extrapolated track</td>
<td>$\Delta \eta_m$</td>
</tr>
<tr>
<td>Track-cluster matching</td>
<td>Defined as $\Delta \eta_2$, but the track momentum is rescaled to the cluster energy before extrapolating the track to the middle layer of the calorimeter</td>
<td>$\Delta \eta_2$</td>
</tr>
<tr>
<td>Track-cluster matching</td>
<td>Ratio of the cluster energy to the track momentum</td>
<td>$E/p$</td>
</tr>
<tr>
<td>Conversions</td>
<td>Veto electron candidates matched to reconstructed photon conversions</td>
<td>$n_{\text{conv}}$</td>
</tr>
</tbody>
</table>
Electron PID - on MC
Reweighing
Reweighing

The background is reweighed to look like signal in $E_T$, $\eta$ and $\langle \mu \rangle$ using GBReweighter (https://arogozhnikov.github.io/hep_ml/reweight.html). This is a general issue to be solved in physics involving simulations.
Electron PID performance

The electron PID performance is generally much improved with ML:

We train the Machine Learning (ML) algorithm (LightGBM) with a mix of backgrounds, and then see how well it performs on each.

We compare to the current ATLAS LH, not to boast our results, but as a solid reference, which helps us getting the most performant & general results.

Lukas Ehrke
Electron PID performance

The electron PID performance is generally much improved with ML:

The ML performance clearly improves with number of variables. From the 18 (LLH) variables to 26 and 29 variables, performance increases a lot... after that it only grows very slowly.

Q: Should we aim at 26-29 variables?
Where do we improve (most)?

The improvements are NOT uniform in energy and angle. We gain most in the "crack" and forward direction.

**Hadron acceptance LHV LValue / LGBM at 98% electron efficiency**
Electron PID feature importance

The importance of each PID input variable is shown below (https://github.com/slundberg/shap).

![SHAP Value Ranking Chart](https://example.com/shap-chart.png)
Electron PID feature importance

The importance of each PID input variable is shown below (https://github.com/slundberg/shap).

The ML approach can easily incorporate more input variables, also those which describe environment more than PID in itself (e.g. energy, direction, pile-up, etc.).
Status of efforts - DATA
Zee candidates are selected with Tag&Probe (T&P).

**Purity: 45-95%**

**Tag electron**
identification applied ensures readout of data

**Probe electron**
no identification applied used for training/testing
Electron PID on data

Applying ML PID trained on MC to data naturally gives lesser results.

Also, the shown improvement is a lower bound, as signal in the background lowers (apparent) performance.

Stefan Hasselgren
Master thesis finished (link below)
(defend end of December 2018)
Impact in data

ML electron PID on probe side yields **in data** more Zee events (same background):

While the gain is modest (4.5%), it is doubled, when also applied to the tag side. Better energy reconstruction can also contribute…
In real data we don’t have perfect labelling. The selections for signal and background have a few percent of label confusion each, depending on energy and detector part hit.

It turns out, that Random Forests (RF) perform better than Boosted Decision Trees (BDT) given this label confusion, as one might expect.

Malte Algren
Electron Energy Reconstruction - on MC
We started to work on **electron energy reconstruction (ER)** using scalar variables combined with a BDT approach, just like ATLAS does. However, we are now exploring to use a Convoluted Neural Network (CNN) for the task, as this “naturally” fits the problem, when considering the calorimeter cells as images. Naturally, there are still scalar variables to add to the regression:

<table>
<thead>
<tr>
<th>BDT scalar variables</th>
<th>CNN scalar variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>p_eAccCluster</td>
<td>p__eta</td>
</tr>
<tr>
<td>p_f0Cluster</td>
<td>p__deltaPhiRescaled2</td>
</tr>
<tr>
<td>p_R12</td>
<td>pX__deltaPhiFromLastMeasurement</td>
</tr>
<tr>
<td>p__etaCluster</td>
<td>pX__deltaPhiRescaled0</td>
</tr>
<tr>
<td>p_cellIndexCluster</td>
<td>pX__deltaEta2</td>
</tr>
<tr>
<td>p__etaModCalo</td>
<td>pX__deltaEta3</td>
</tr>
<tr>
<td>p__phiModCalo</td>
<td>p__charge</td>
</tr>
<tr>
<td>p_fTG3</td>
<td>BC__distanceFromFront</td>
</tr>
<tr>
<td>p_dPhiTH3</td>
<td>BC__filledBunches</td>
</tr>
<tr>
<td>p__pt_track</td>
<td>p__pt_track</td>
</tr>
<tr>
<td>averageInteractionsPerCrossing</td>
<td>averageInteractionsPerCrossing</td>
</tr>
<tr>
<td>NvtxReco</td>
<td>NvtxReco</td>
</tr>
</tbody>
</table>

- **Blue** are used by the current $E$ calib
- **No ECAL variables**
The photon energy reconstruction performance is shown here (for $Z \rightarrow e e \gamma$ sample):

**Photon ER performance**

**Z-value for trained models**

- ATLAS
- LGBM126
- LGBM100
- LGBM50
- LGBM35
- LGBM15
Photon ER performance

The photon energy reconstruction performance is shown here (for \(Z \rightarrow ee\gamma\) sample):

<table>
<thead>
<tr>
<th>Key</th>
<th>MAE(Z)</th>
<th>MSE(Z)</th>
<th>ICE(5)</th>
<th>ICE(25)</th>
<th>Lower5</th>
<th>Upper5</th>
<th>Median</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATLAS</td>
<td>0.0501</td>
<td>0.0075</td>
<td>0.0726</td>
<td>0.0384</td>
<td>-0.117</td>
<td>0.122</td>
<td>0.0019</td>
<td>0.0021</td>
</tr>
<tr>
<td>LGBM126</td>
<td>0.0410</td>
<td>0.0071</td>
<td>0.0560</td>
<td>0.0320</td>
<td>-0.093</td>
<td>0.091</td>
<td>-0.0000</td>
<td>0.0012</td>
</tr>
<tr>
<td>LGBM100</td>
<td>0.0420</td>
<td>0.0077</td>
<td>0.0571</td>
<td>0.0325</td>
<td>-0.095</td>
<td>0.093</td>
<td>0.0000</td>
<td>0.0014</td>
</tr>
<tr>
<td>LGBM50</td>
<td>0.0421</td>
<td>0.0073</td>
<td>0.0581</td>
<td>0.0326</td>
<td>-0.096</td>
<td>0.095</td>
<td>-0.0001</td>
<td>0.0011</td>
</tr>
<tr>
<td>LGBM35</td>
<td>0.0428</td>
<td>0.0069</td>
<td>0.0595</td>
<td>0.0332</td>
<td>-0.099</td>
<td>0.097</td>
<td>-0.0000</td>
<td>0.0011</td>
</tr>
<tr>
<td>LGBM15</td>
<td>0.0506</td>
<td>0.0095</td>
<td>0.0715</td>
<td>0.0393</td>
<td>-0.117</td>
<td>0.118</td>
<td>-0.0000</td>
<td>0.0021</td>
</tr>
</tbody>
</table>
The great thing is that for each cell we don’t just have the energy, but also the time (rejecting out-of-time pile-up), gain, and cell noise level (gauging the energy precision).
However, these are not same units, so combined with gate (not concatenation).
Using Angular Variables
to disentangle
$H \rightarrow ZZ^* \rightarrow eee$?

CNN architecture

We use a $3 \times 3$ convolution matrices for all layers.

Each convolution layer is followed by a batch normalisation and activation.

For all $i > 1$, block begins with downsampling and the number of feature maps is doubled.

A worry is, that the scalar variables “drown” in the many feature map outputs. To be investigated further.
However, we know that scalar variables improve performance as it is!

Images containing time are treated differently…
Using Angular Variables
to disentangle

\[ H \rightarrow Z^* \rightarrow eee \]

CNN results

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>IQR(Z)</th>
<th>rMAE</th>
<th>rIQR(Z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E calib.</td>
<td>1.753</td>
<td>0.041</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>LGBM(9)</td>
<td>1.726</td>
<td>0.040</td>
<td>1.016</td>
<td>1.014</td>
</tr>
<tr>
<td>LGBM(12)</td>
<td>1.685</td>
<td>0.039</td>
<td>1.040</td>
<td>1.047</td>
</tr>
<tr>
<td>CNN</td>
<td>1.562</td>
<td>0.037</td>
<td>1.122</td>
<td>1.100</td>
</tr>
<tr>
<td>CNN(s)</td>
<td>1.548</td>
<td>0.036</td>
<td>1.132</td>
<td>1.124</td>
</tr>
<tr>
<td>CNN(s,t)</td>
<td>1.533</td>
<td>0.036</td>
<td>1.144</td>
<td>1.138</td>
</tr>
</tbody>
</table>

\[ Z = \frac{E_{\text{pred}} - E_{\text{truth}}}{E_{\text{truth}}} \]
CNN results

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\[ Z = \frac{E_{\text{pred}} - E_{\text{truth}}}{E_{\text{truth}}} \]
CNN results

Using Angular Variables
to disentangle

$H \rightarrow ZZ^* \rightarrow eee$
CNN results

Using Angular Variables
to disentangle $H \rightarrow ZZ^{*} \rightarrow eee$?
Using Angular Variables to disentangle $H \rightarrow ZZ^*$ from CNN results.
Electron Energy Reconstruction - on MC... latest development!
FiLM = Feature wIse Linear Modulation

$$\text{FiLM}(x) = \gamma(z) \odot x + \beta(z).$$

Frederik Faye

Results from FiLM

\[ Z = \frac{E_{\text{pred}} - E_{\text{truth}}}{E_{\text{truth}}} \]

- E calib.
- CNN
- CNN(s→FiLM)

Frequency/0.004
Looking at the future: ν-reconstruction in IceCube
Ideen für die Zukunft

The IceCube detector is a less “classic” particle physics detector. Here, 86 strings with about 5000 Digital Optical Modules (DOMs) in total are put in the ice at the South Pole, and used to detector neutrinos (and involuntarily cosmic muons) interact in the ice.

The detector is triggered by coincidences of several adjacent DOMs, and then read out.

Each DOM provides a measurement in time and size of signal. However, there is a significant amount of noise and also effects such as after-pulses, which makes the data less clean.
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The detector is triggered by coincidences of several adjacent DOMs, and then read out.

Each DOM provides a measurement in time and size of signal. However, there is a significant amount of noise and also effects such as after-pulses, which makes the data less clean.

The bottleneck is the event reconstruction!

This is based on the minimisation of a likelihood including ray tracing and ice properties.
Ideas for the future

Neutrinos and cosmic muons interact in the ice, and leaves signals to be reconstructed.
Neutrinos and cosmic muons interact in the ice, and leaves signals to be reconstructed.

Problem 1: Which hits belong to the event and which are noise?
Ideas for the future

Neutrinos and cosmic muons interact in the ice, and leaves signals to be reconstructed.

Problem 1:
Which hits belong to the event and which are noise?

Problem 2:
Given a list of hits, how to determine the direction, energy, type, etc.?
And… how to do it in a “reasonable” amount of time?
Currently t(reco) = 30 min.
Ideas for the future

Neutrinos and cosmic muons interact in the ice, and leaves signals to be reconstructed.

Problem 1: Which hits belong to the event and which are noise?

Problem 2: Given a list of hits, how to determine the direction, energy, type, etc.? And... how to do it in a "reasonable" amount of time?

A student of mine (Andreas Søgaard) tried to see, if he could get an ML algorithm to do the reconstruction. It didn’t perform very well (yet!), but $t({\text{reco}}) = 0.01$ sec. Currently $t({\text{reco}}) = 30$ min.
Conclusions

I think that there is a lot of prospect in Machine Learning for physics.
• New algorithms see the light of day almost daily.
• In some cases, it may simply give a more performant data analysis.
• However, in some cases, it makes all the difference.
• Particle physics data is well suited for ML as we have “accurate” simulation.

The data requires collaboration, as there are several “particle physics tricks” needed to evaluate performance in real data.

There are many areas to try ML on:
• Transformation of simulation to match data better (challenge: extrapolation).
• Simulation using GANs and VAEs (already started in ATLAS).
• Reconstruction in the IceCube experiment

I’ve been surprised by the speed with which students “pick up” ML, once you give them an introduction to it. The challenge is often to find data “suitable” for the algorithms given. We - in HEP - tend to actually have that!
Bonus slides

Event as seen by the TRT detector. The occupancy is near 100%, rendering reconstructing void!
Signal/background selection

- DAOD production: mixture of EGAM1, EGAM3, EGAM7, EGAM8 and EGAM9 including cells and bunch crossing information
- $Z \rightarrow ee$ Tag and Probe
  - Tag
    - $p_T > 24.5$ GeV
    - Tight ID
    - Loose Isolation
    - Crack veto and Central
    - Pass HLT_e26_lhtight_nod0_ivarloose
    - Has track particle and vertex
    - Pass object quality cut
  - Probe
    - $p_T > 4.5$ GeV
    - Pass object quality cut
    - $|\eta| < 4.9$
  - Combined
    - $dR > 0.4$ for tag and probe
    - $M_{ee} > 50$ GeV
- Dijet, $W^{\pm} \rightarrow \ell^{\pm} \nu$ ($\ell = e, \mu$), $Z \rightarrow \mu\mu$ samples background selection
  - Missing transverse energy (MET) < 25 GeV
  - $p_T > 4.5$ GeV
  - pass Object Quality
  - Z veto: Match with any other medium electron, $|M_{ee} - m_{Z^0}| < 20$ GeV
  - W veto: Match with MET, transverse mass < 40 GeV
- $Z(\gamma) \rightarrow ee$ (Drell-Yan), $Z \rightarrow \ell\ell\gamma, \gamma +$ jet
  - EGamma truth particles

More complete documentation [https://twiki.cern.ch/twiki/bin/viewauth/AtlasProtected/EgammaMachineLearning](https://twiki.cern.ch/twiki/bin/viewauth/AtlasProtected/EgammaMachineLearning)
The electron probe purities for both signal and background are far from ideal!
Comparison of Combination

**Eff(bkg) @ 92% Eff(sig):**
- ATLAS Likelihood: 0.40%
- ML(Calo)+ML(Trk): 0.12%
- ML(Calo+Trk): 0.09%

Note that the ML(Calo+Trk) can not be trained on real data, as one quantity (ML(Calo) or ML(Trk)) is required in order to get a clean sample for the other to be trained on.

**Improvement by factor 3.3 (in MC)**
Using Angular Variables to disentangle Performance of all methods

Eff(bkg) @ 92% Eff(sig):
ATLAS Likelihood: 2.2%
ML(Calo)+ML(Trk): 0.78%

Improvement by factor 2.8 (in DATA)
Electron PID on data

Performance is best in the forward region at high energies.

However, the later statement might be a result of determining performance with impure data (more so at lower energies).
What is a CNN?

CNNs are a type of neural network, which works well with spatially dependent data (typically images). CNNs use parameter/weight sharing.

Multi-layered images (e.g. RGB or ATLAS calorimeter) are handled naturally.

A CNN works by sliding (small) filter across the image, outputting the convolution (inner product) of the filter and pixels covered.
What is a CNN?

CNNs are a type of neural network, which works well with spatially dependent data (typically images). CNNs use parameter/weight sharing.

Multi-layered images (e.g. RGB or ATLAS calorimeter) are handled naturally.

A CNN works by sliding (small) filter across the image, outputting the convolution (inner product) of the filter and pixels covered.
Zee candidates are selected with Tag&Probe (T&P).

Purity: 30-90%
The Idea: Extended Tag&Probe

1) Zee candidates are selected with Tag&Probe (T&P). **Purity: 30-90%**

2) The probe electron is “divided” into three independent (?) parts: **Track, Calo, Isolation**
The Idea: Extended Tag&Probe

1) Zee candidates are selected with Tag&Probe (T&P).

**Purity: 30-90%**

2) The probe electron is “divided” into three independent (?) parts:
   - Track
   - Calo
   - Isolation

3) When considering one part of the probe electron, the other two can be used to further purify probes:

**Purity: 99-99.9%**