

# Plans for ML Applications in AMPEL

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# HEIBRiDS program



- *Helmholtz Einstein International Research School in Data Science*
- Joint graduate program between the Einstein Center Digital Future (ECDF) together with the Helmholtz Association
- Cooperation between 3 Berlin universities, Charité and 6 Helmholtz centers
- Interdisciplinary program for training scientists in Data Science and other scientific disciplines at the same time
- Supervisors: Prof. Johann-Christoph Freytag and Prof. Marek Kowalski



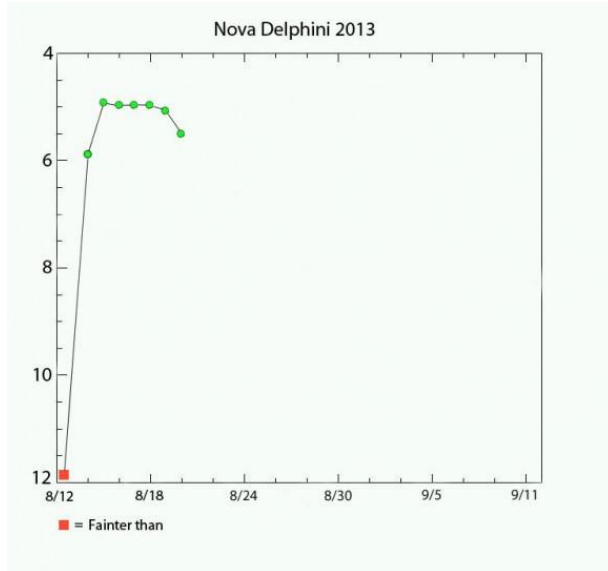
# Why use ML in AMPEL?



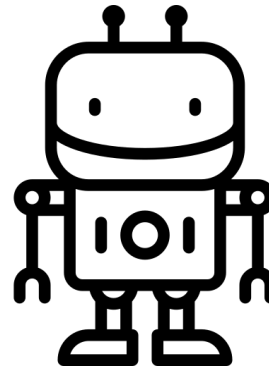
- New telescopes like LSST will greatly increase transient detection capabilities.
- However, spectroscopic follow up capabilities of these sources has not increased at the same rate.
- ML automatization of the detection process from photometric data is a good solution for this problem.
- Supernova cosmology surveys with LSST should provide a large amount of samples for ML model training.



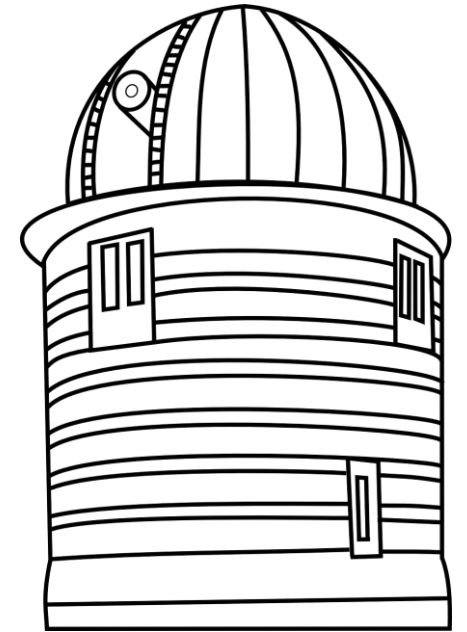
# Use cases of ML in AMPEL



Identify early if a light curve doesn't belong to a known class



Trigger a photometric and spectroscopic follow up of this unusual object



If the classification done by the model is correct enough, then we can use the model directly to identify objects by their photometric data without the need for spectroscopic follow up.

# Use cases of ML in AMPEL

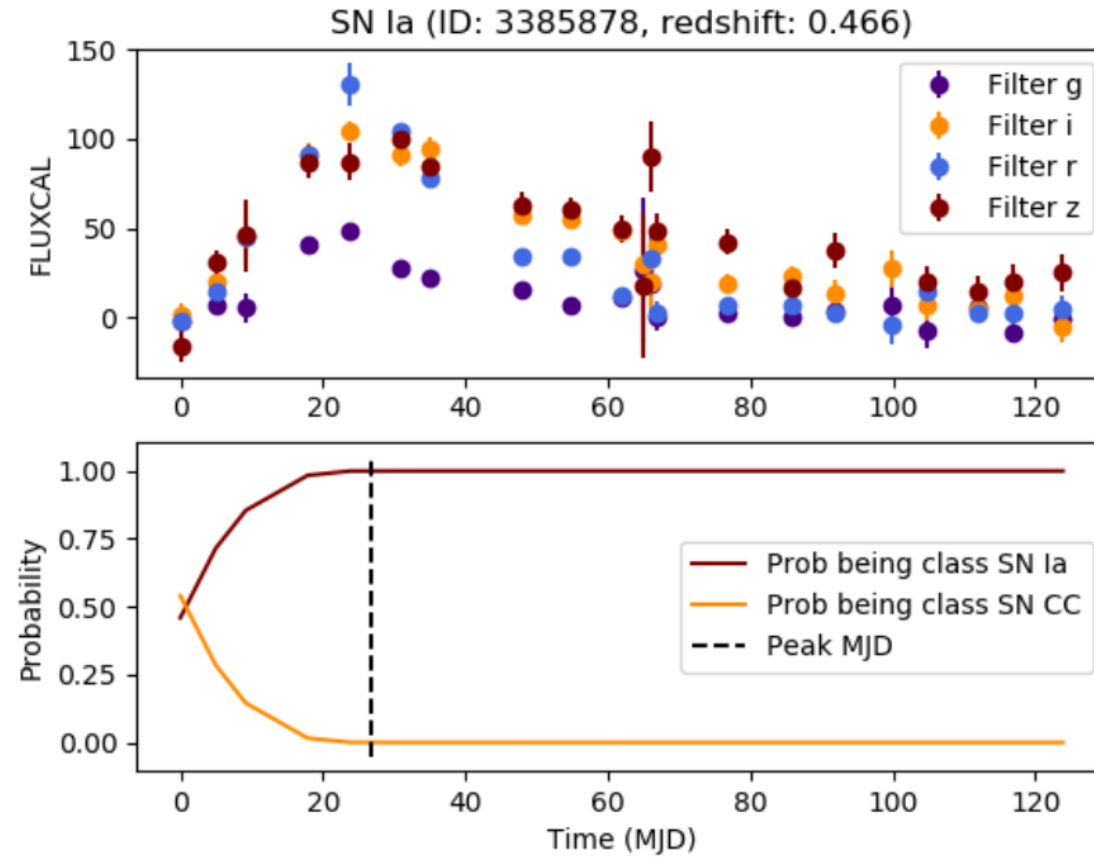
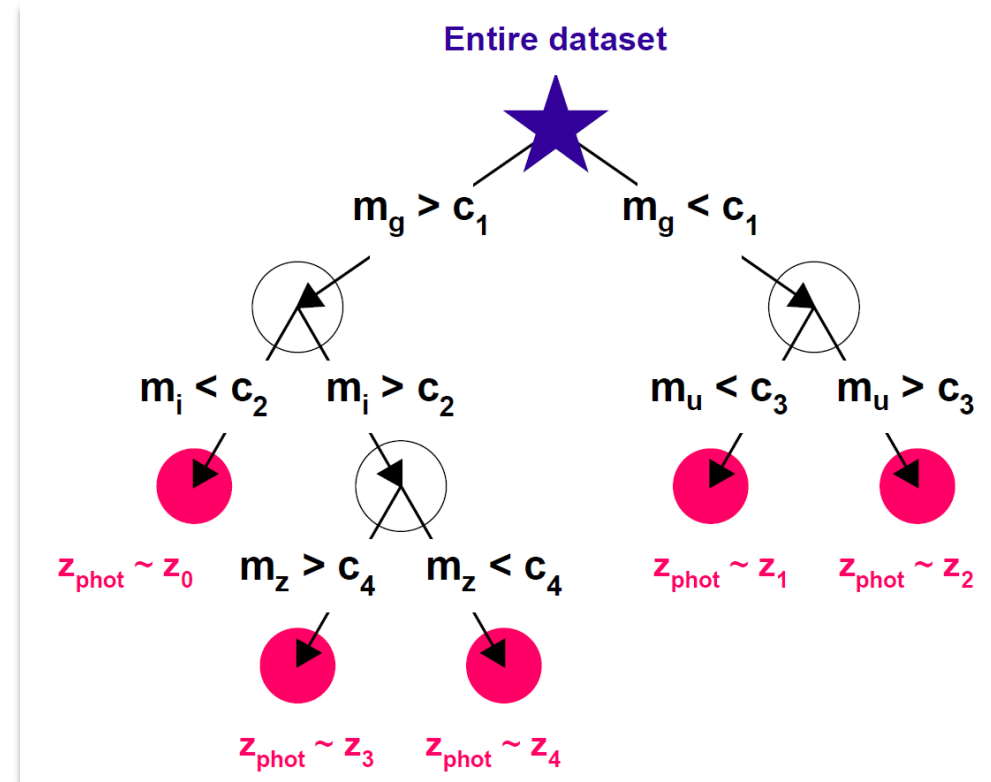
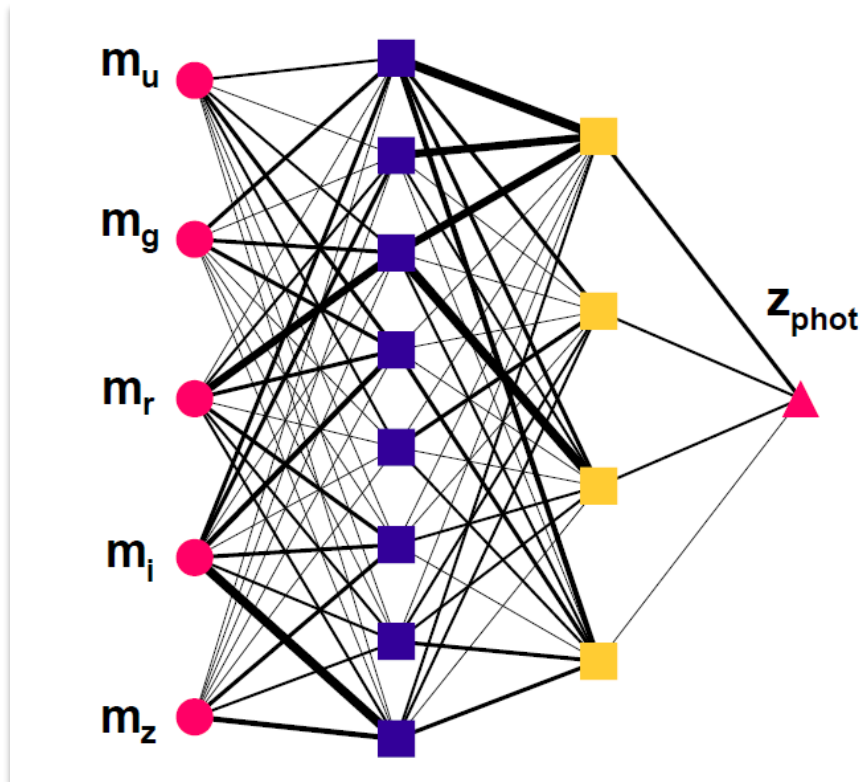


Image credits: [Anais Möller](#), [Thibault de Boissière](#) (2019)

# Current use of ML in AMPEL: ANNz2

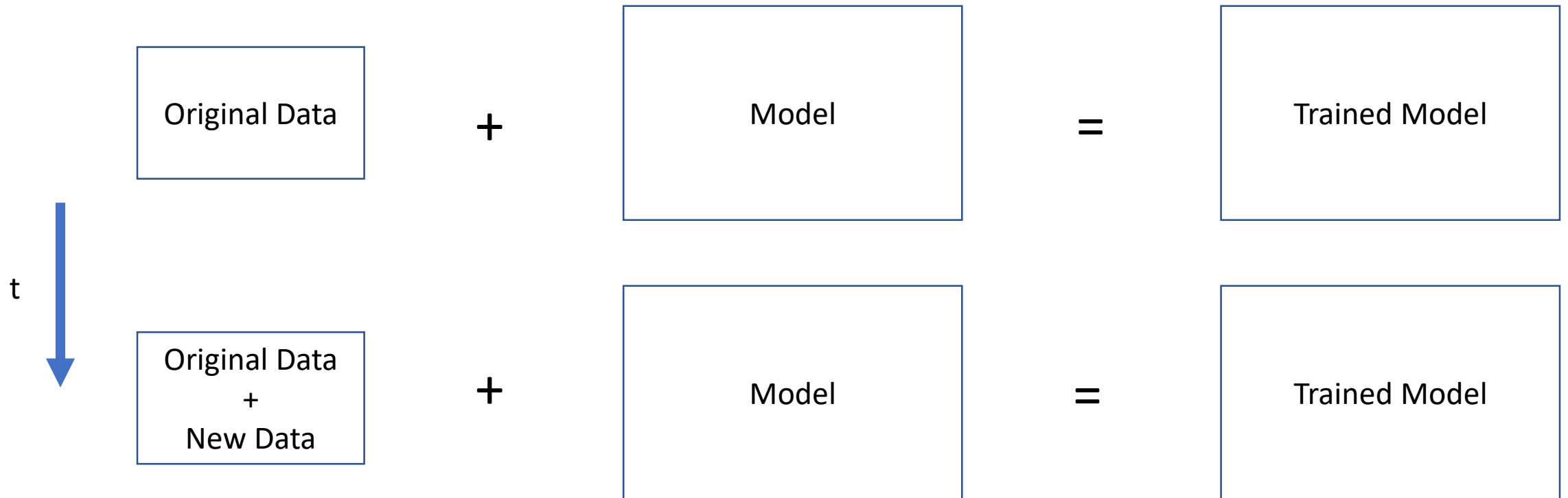


# Future applications: ML and streams

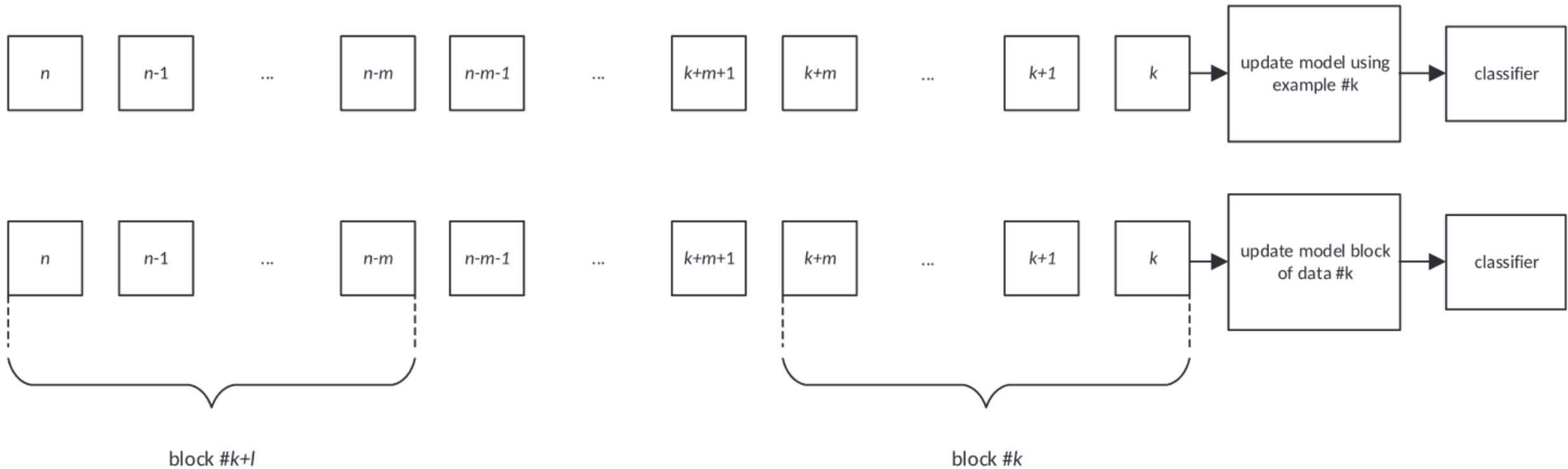
- The most direct and information-rich way to interpret astronomical transient data is as alert streams.
- This would imply giving a ML model dynamic data as input, instead of a set of static data.
- Training a model in this setup becomes the challenge.
  - One could “un-stream” the data after receiving and saving it, and later treat it as if were static training data.
  - However, it would be desirable to train a model directly over the data stream by using a process which involves incremental learning.



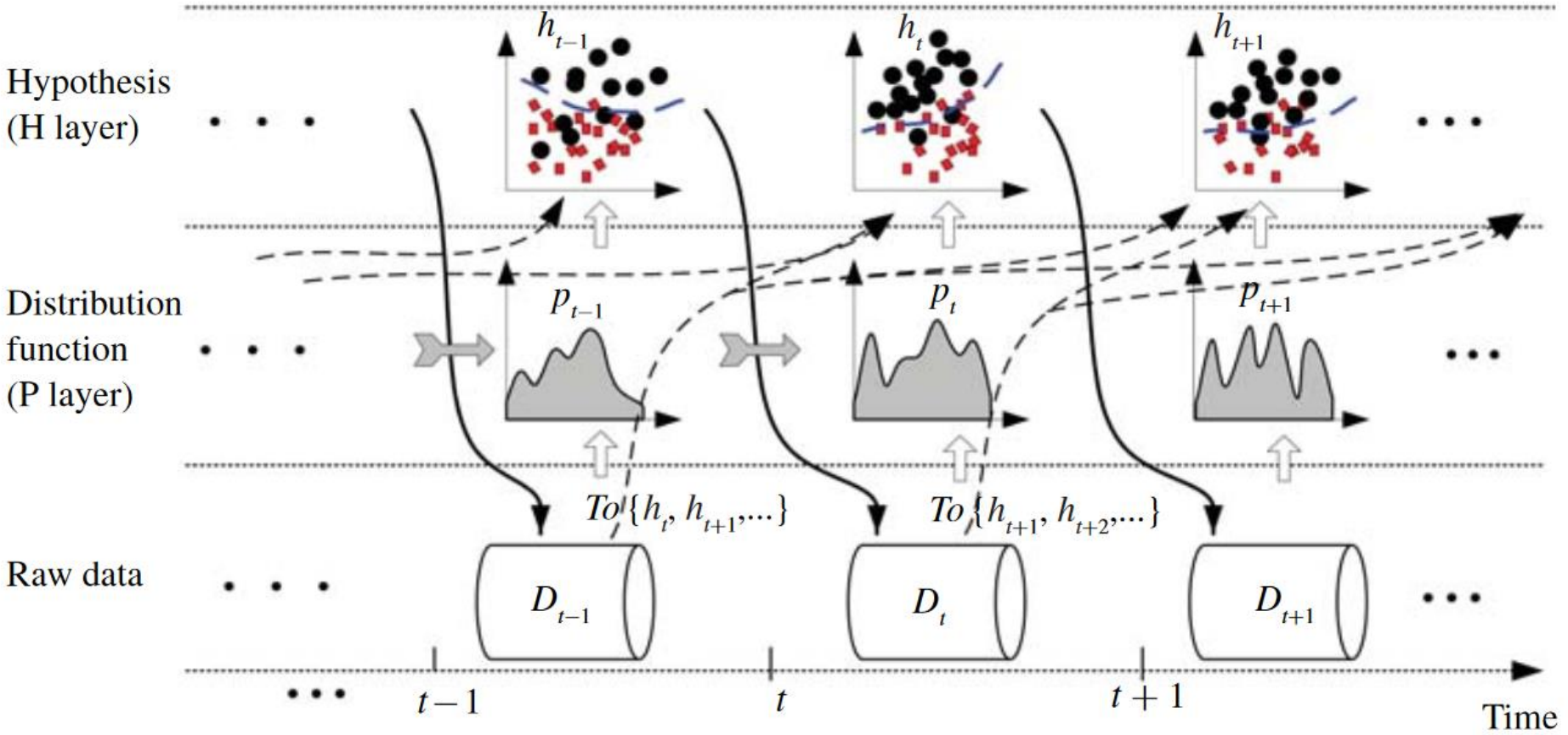
# Naïve approach for ML training with streams



# ML and streams: batch vs example



# ML and streams: ADAIN



# Future steps



- Set up a benchmark of classification results (scores) with commonly used ML models over static light curve feature data.
  - For this we are planning to use Redshift Completeness Factor (RCF) real light curve data as a training set.
  - Fit and estimate parameters of transients with appropriate tools (e.g. MOSFIT).
- Adapt the current models for running as part of an incremental learning framework that receives transient alert data as input.
- Compare the results between the original benchmark and running the models over the same training set in a streamed form.
- Integrate the model to the AMPEL system and evaluate its performance.

# References

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