

Online deep learning for pulsed-signal data stream forecasting

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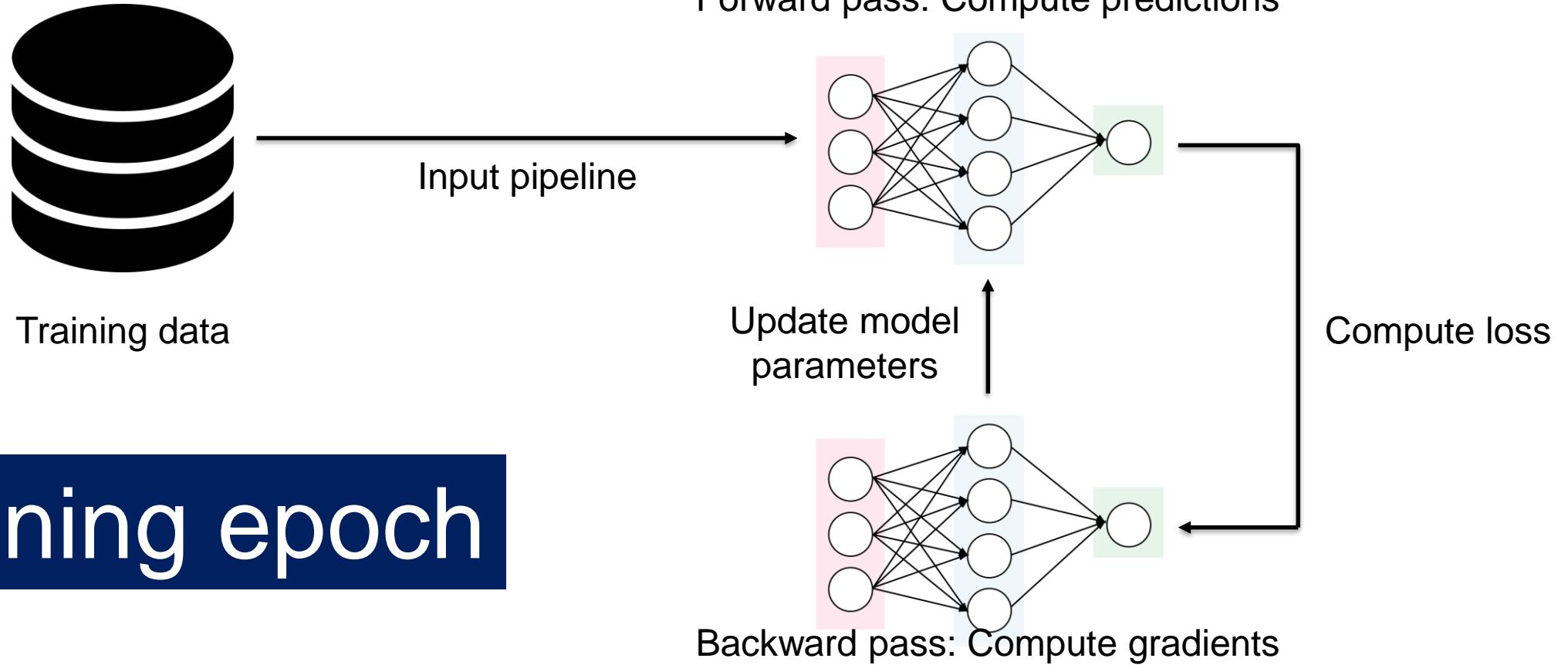
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Agenda

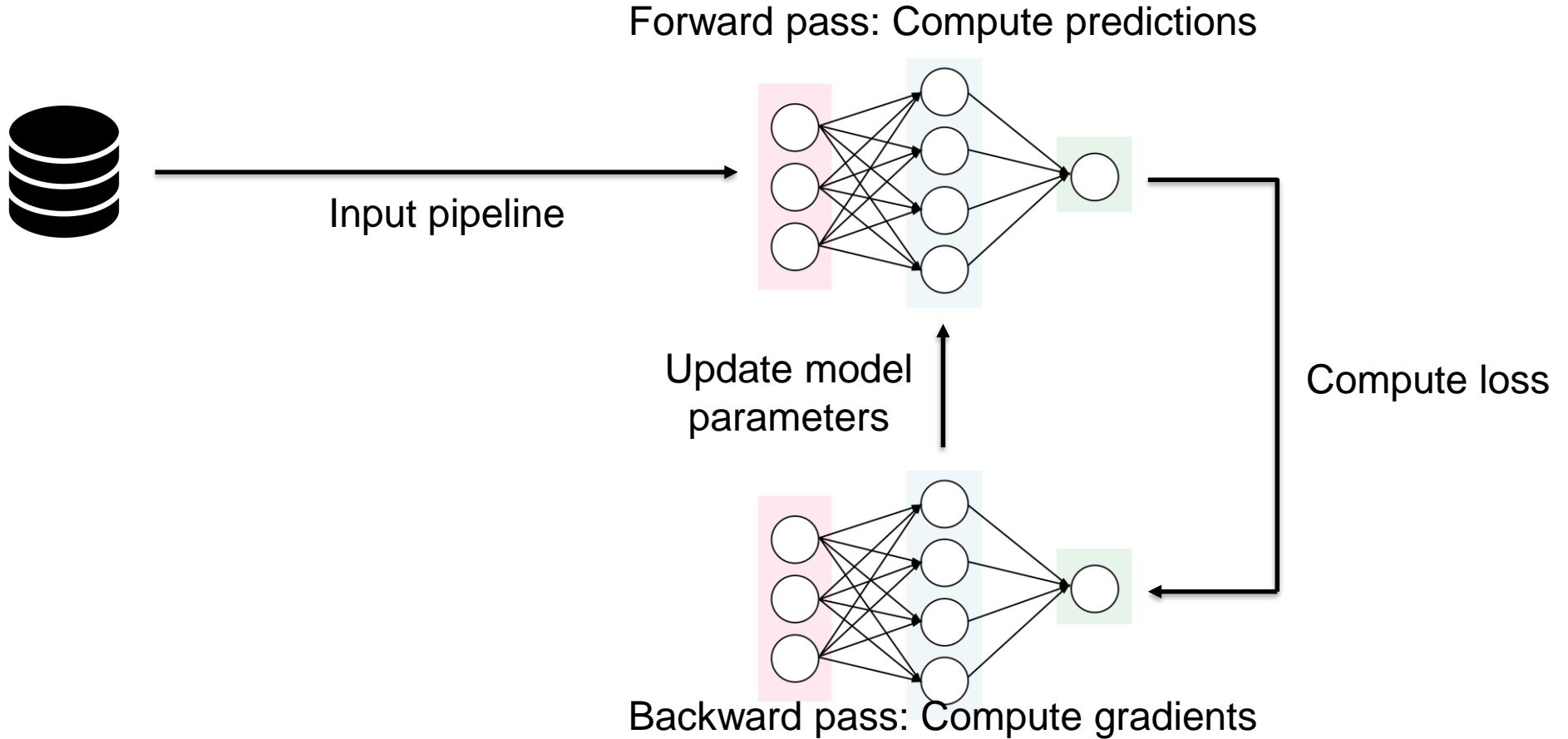


- Offline supervised deep learning
- Online deep learning
- Pulsed-signal forecasting
- Evolving stochastic optimisation algorithm
- Example: ECG forecasting
- Comparison with other methods
- Applications to HEP

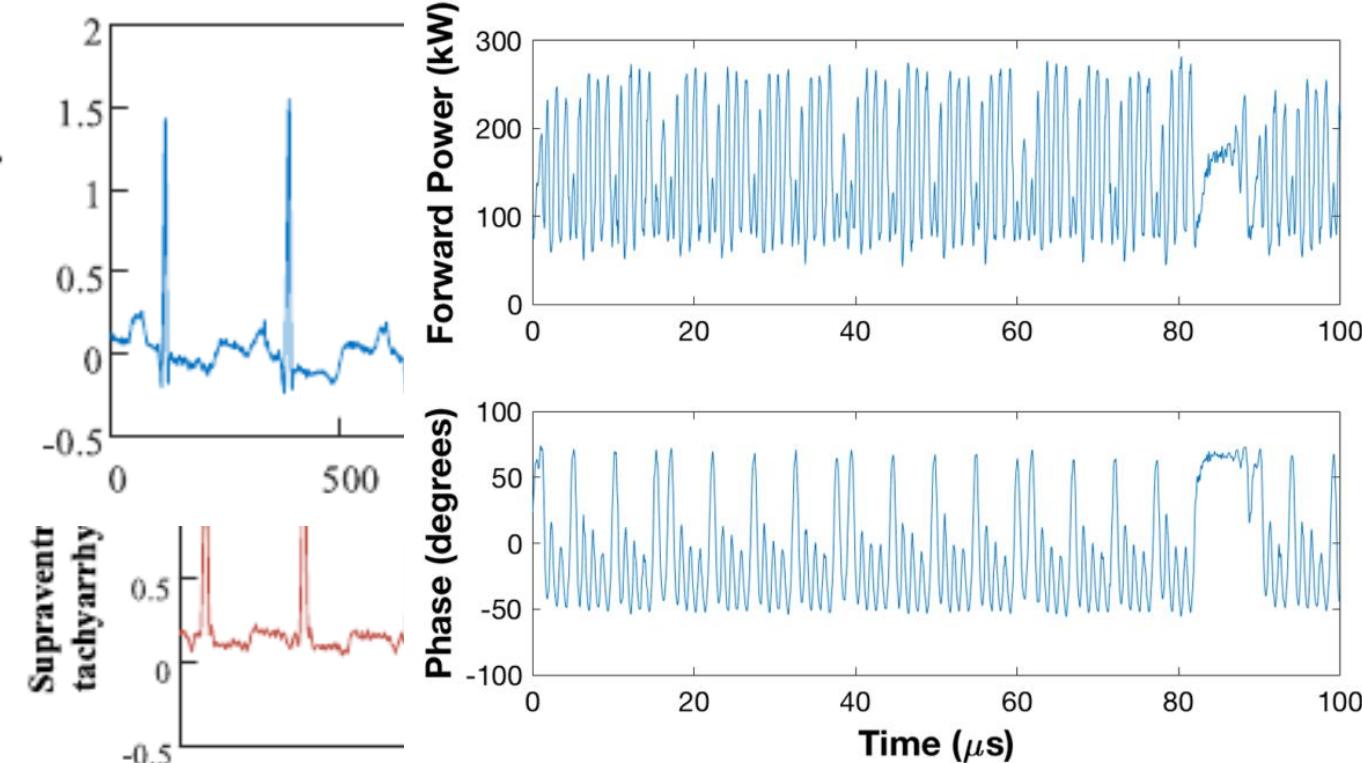
Offline supervised deep learning



Online supervised deep learning



Pulsed-signal forecasting



Yıldırım, Pławiak, Tan

FIG. 2. Klystron power with 2244 bunches, 1.2×10^{11} protons/bunch, 25 ns spacing, 6.5 TeV.

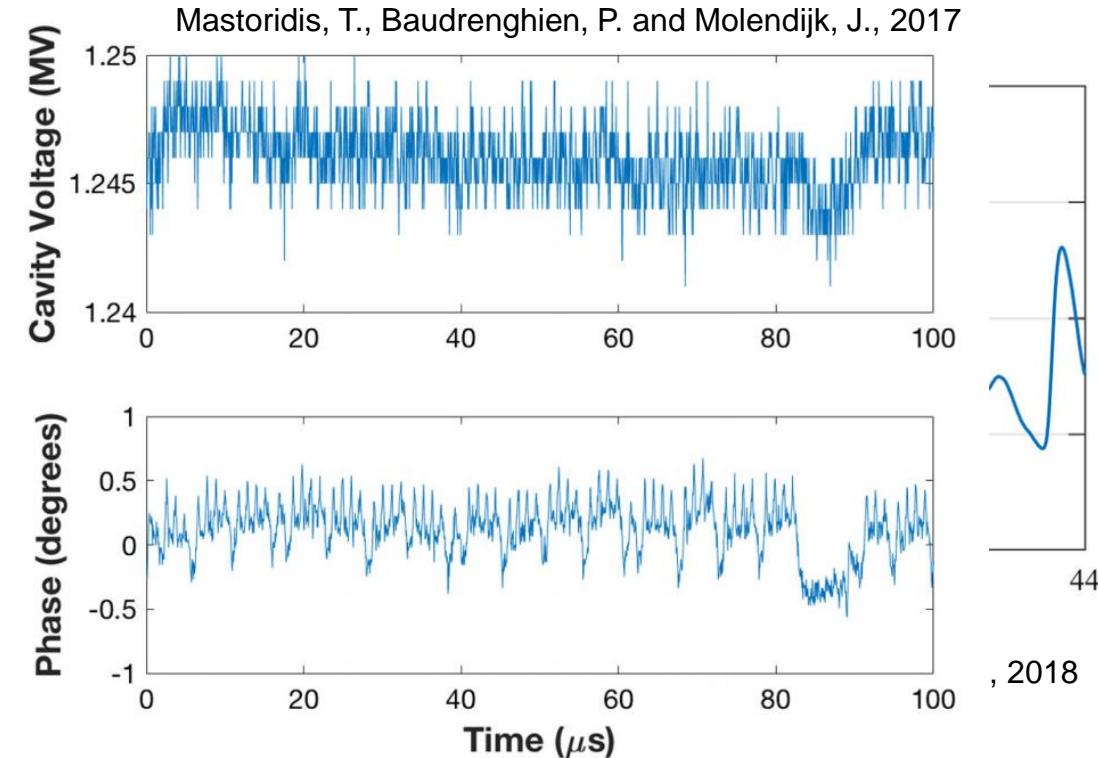


FIG. 1. Cavity voltage with 2244 bunches, 1.2×10^{11} protons/bunch, 25 ns spacing, 6.5 TeV.

Evolving stochastic optimisation



- Stochastic gradient descent (parallel)
- Natural selection
- Game-theoretic sequential decision-making
- Pure-exploration stochastic multi-armed bandit

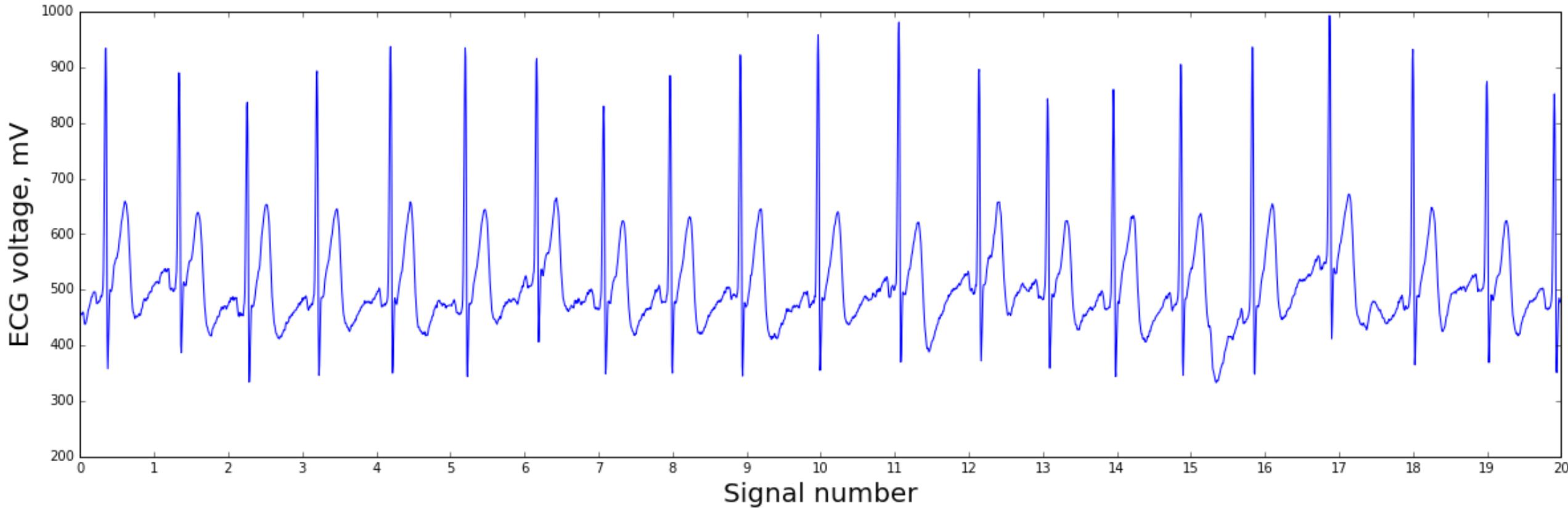
Evolving stochastic optimisation



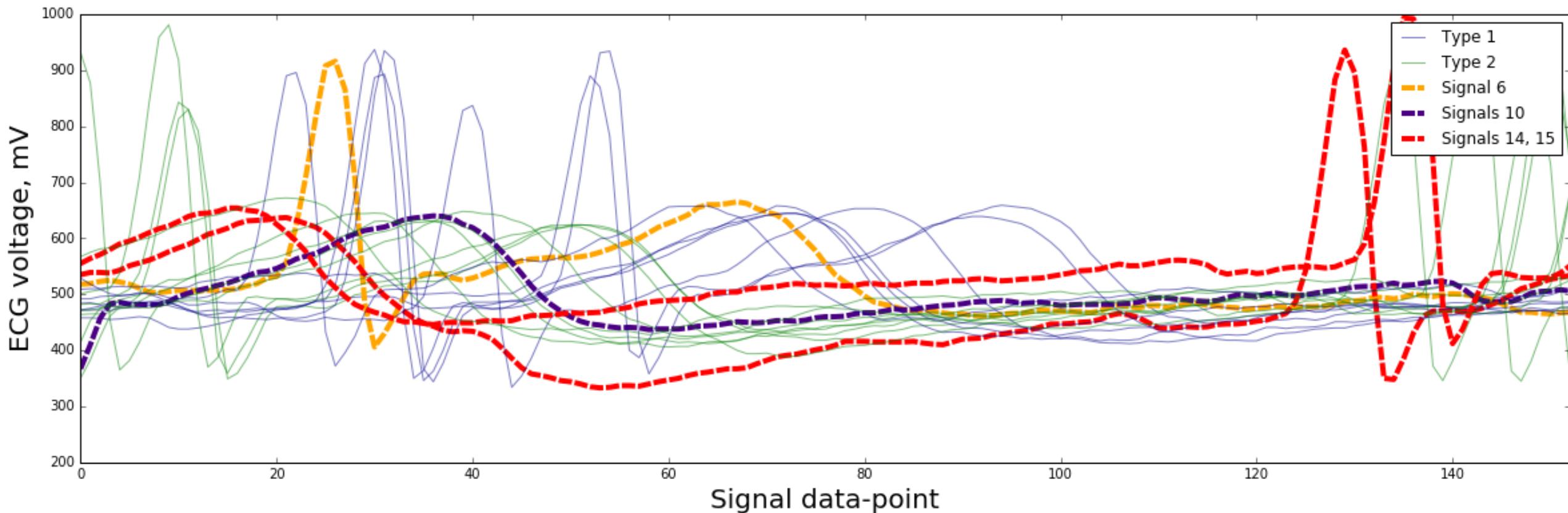
For $t = 1, \dots, T$

- Receive data stream signal, Z_t
- Draw n iid sub-sequences, $z_t(i) = (x_t(i), y_t(i)) \quad \forall i \in [n]$
- Compute losses $\ell_{i,t}(\hat{y}_t(i), y_t(i); w_t)$, for $\hat{y}_t(i) = f_t(x_t(i); w_t)$ in parallel
- Update weights $w_{i,t} = w_t - \eta_{i,t} \nabla_{w_t} \ell_{i,t}$ in parallel
- Re-index such that, $\ell_t(1) < \dots < \ell_t(n)$
- Let $w_t = \alpha w_t + (1 - \alpha) \frac{1}{p} \sum_{i=1}^p w_{i,t}$ for $p < n, \alpha \in [0,1]$
- Forecast $\hat{Z}_{t+1} = f_t(Z_t; w_t)$

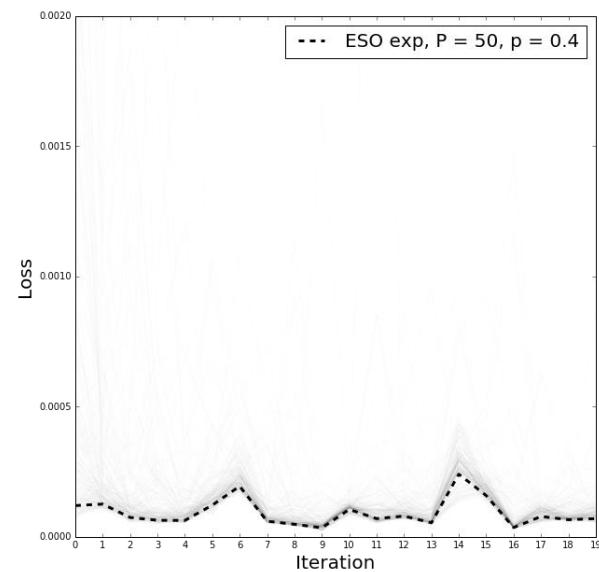
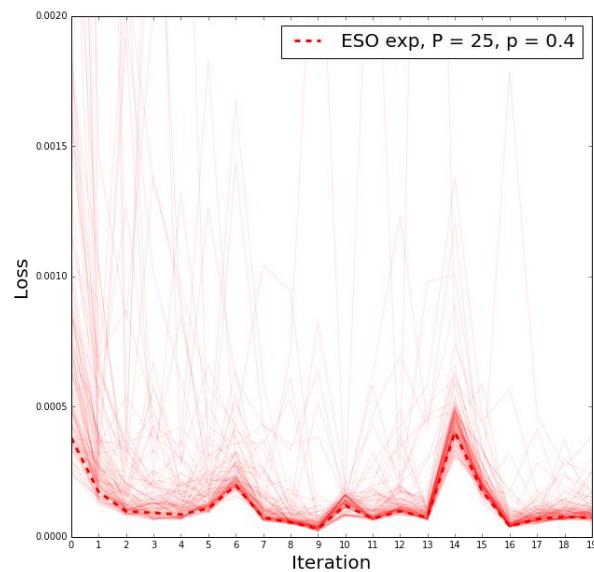
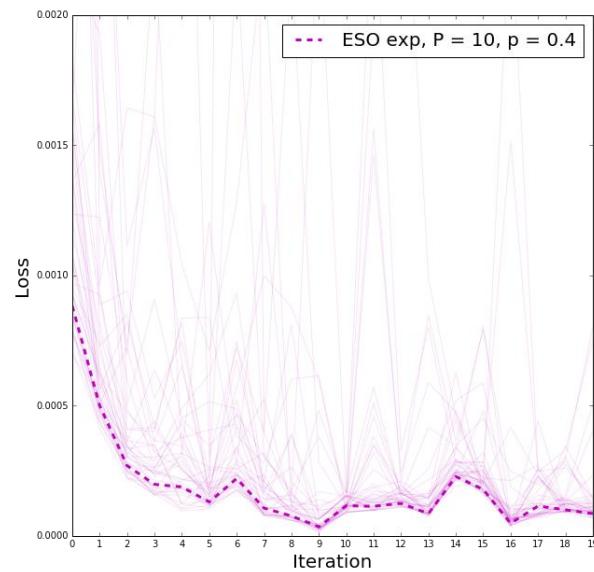
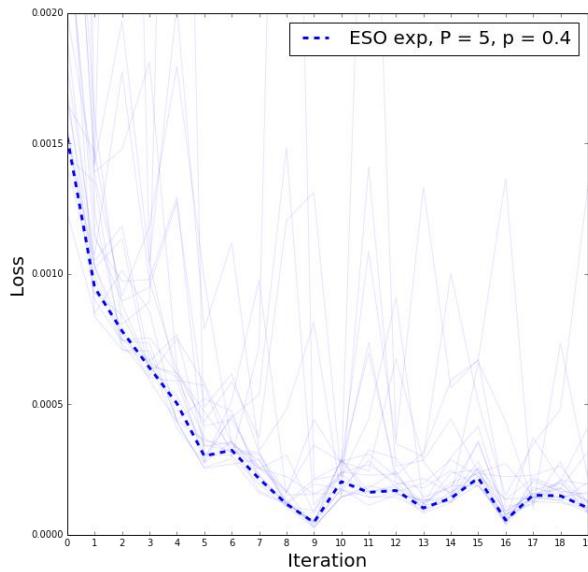
Example: ECG forecasting



Example: ECG forecasting

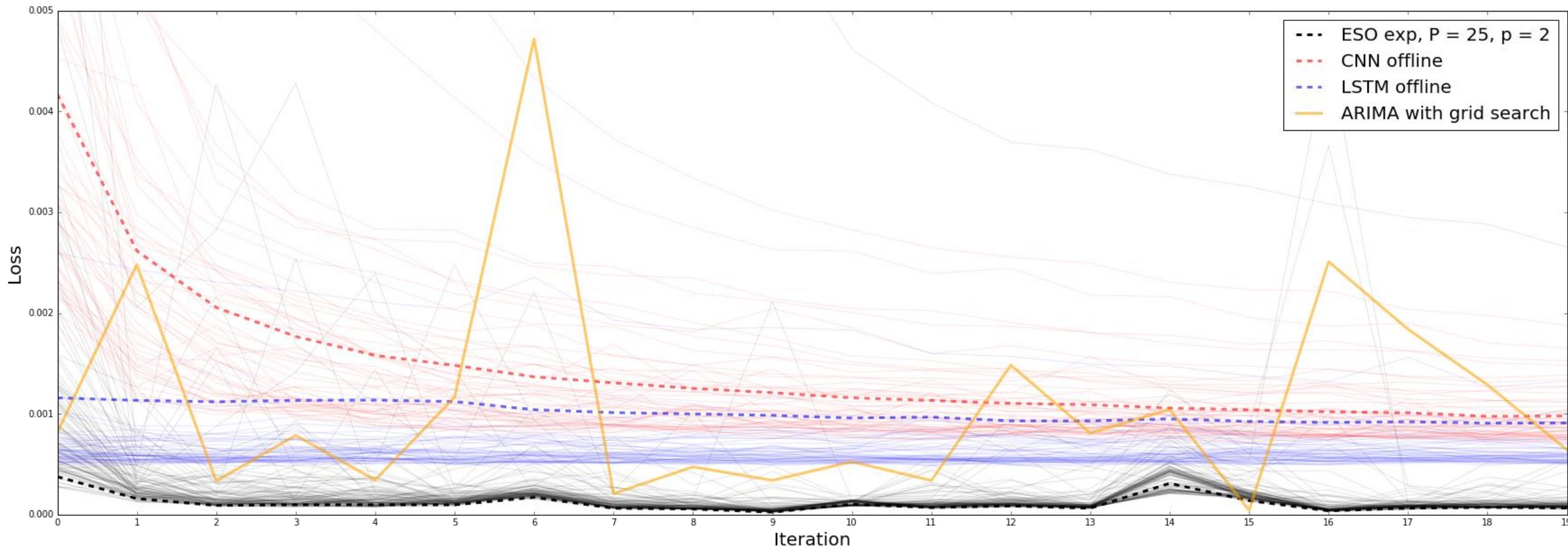


Example: results





Example: comparisons



Evolving stochastic optimisation



- *Online* deep learning for pulsed-signal forecasting
- Combines evolutionary *survival of the fittest* strategy with parallel stochastic average gradient descent
- Outperforms classical auto-regressive methods with optimised parameters *a priori*
- Outperforms other deep learning models trained *offline* over same interval with entire dataset known *a priori*

Application to HEP



- ALICE O² upgrade
- DCS conditions data stream
- Other ideas welcome...

Thank you



Questions...



References

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