Comparing different state-of-the-art solutions for image prediction using time-series analysis

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- Close with a conclusion

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    - Propagate the error $\rightarrow$ Greater error in later images

Autoencoder

- Two networks chained together

[1] h is the so named **code**. Output layer is named **bottleneck layer**.

- Two networks chained together
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Autoencoder

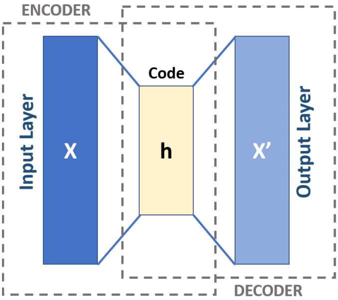

Figure: Autoencoder schema [9]

CNN

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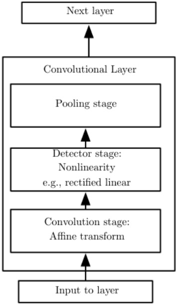

Figure: Stages of a CNN [4]

CNN (First stage)

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- $(I * K)(i, j) = \sum_m \sum_n I(m, n) K(i - m, j - n)$

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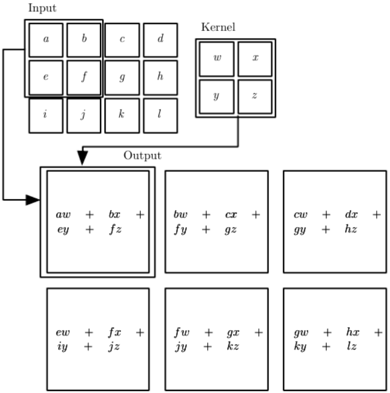

Figure: Two dimensional convolutional operation [4]

CNN (Second stage)

- Non-linearity layer

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- ReLU: $R(x) = max(0, x)$

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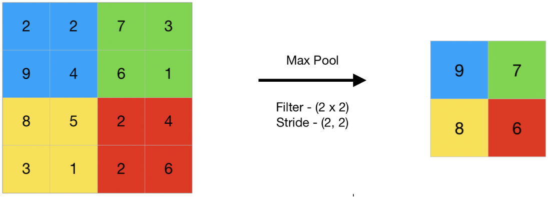

Figure: Max-Pooling (Filter := Kernel)[1]

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- Typically trained using BPTT

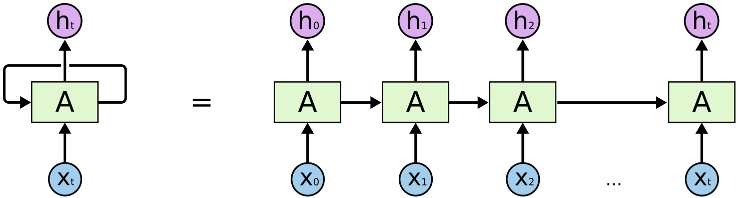

Figure: RNN schema. **Left:** Folded graph, **Right:** Unfolded graph [2]

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$$h_t = o_t tanh(c_t) \tag{5}$$

LSTM

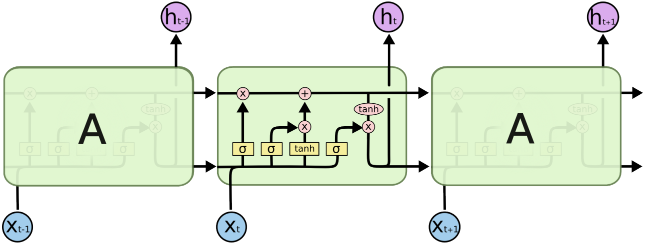

Figure: LSTM Architecture [2]

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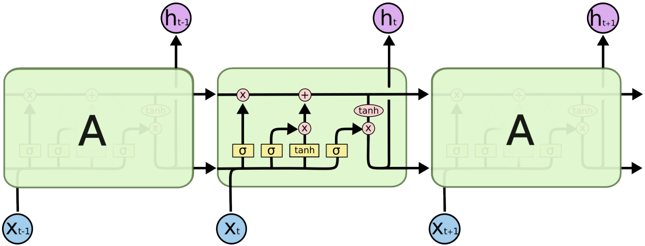

Figure: LSTM Architecture [2]

- Top horizontal line: Cell-state

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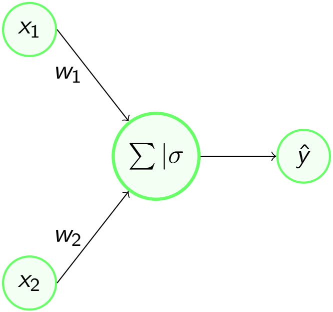

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- Computing the error with e.g. **MSE**
- $$L(y, \hat{y}) = \frac{1}{N} ||y - \hat{y}||_2^2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (14)$$

Backprojection Backward Pass

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- $$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)(1-\sigma(x)) \tag{16}$$

- $$\frac{\partial L}{\partial \sum_{i=1}^{2} x_i w_i} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \sum_{i=1}^{2} x_i w_i} = \frac{2}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)\cdot\sigma(\sum_{i=1}^{2} x_i w_i)(1-\sigma(\sum_{i=1}^{2} x_i w_i)) \tag{17}$$

Backpropagation Backward Pass

Backward Pass:

- $$\frac{\partial L}{\partial \hat{y}} = \frac{2}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i) \tag{15}$$
- $$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)(1 - \sigma(x)) \tag{16}$$
- $$\frac{\partial L}{\partial \sum_{i=1}^{2} x_i w_i} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \sum_{i=1}^{2} x_i w_i} = \frac{2}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i) \cdot \sigma(\sum_{i=1}^{2} x_i w_i)(1 - \sigma(\sum_{i=1}^{2} x_i w_i)) \tag{17}$$
- $$\frac{\partial L}{\partial w_1} = \ldots = \frac{2}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i) \cdot \sigma(\sum_{i=1}^{2} x_i w_i)(1 - \sigma(\sum_{i=1}^{2} x_i w_i)) \cdot x_1 \tag{18}$$

Backpropagation Update

Update weights using Gradient Descent

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  - and because of its parallelism properties [13]

BPTT

- Backpropagation through time

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- Unfolding graph during backpass and propagate through the steps
- Simple example on RNN found in Goodfellow [4]

BPTT Forward Pass

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-
$$h_t = tanh(Wh_{t-1} + Ux_t + b_1) \tag{20}$$
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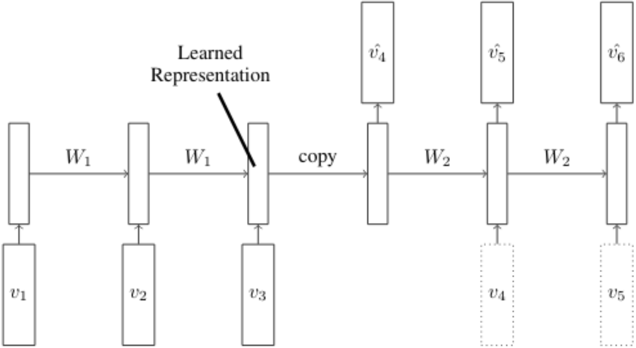

Figure: Future image prediction model [15]

LSTM Autoencoder

- Composed model can do image prediction and reconstruction simultaneously

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    - Consisting of one encoder and two decoder

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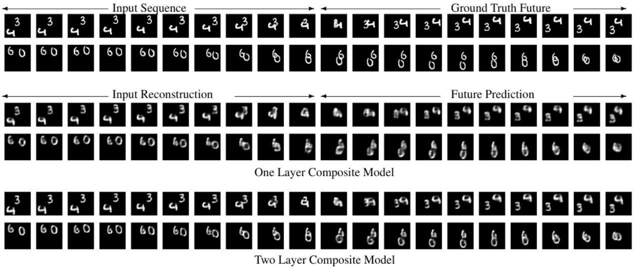

Figure: Results of MovingMNIST experiment [15]

ConvLSTM Autoencoder

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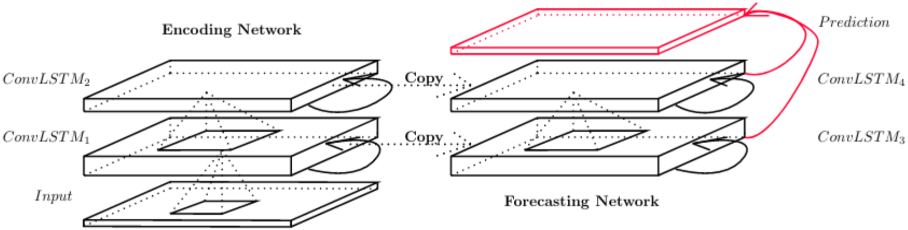

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- Architecture is only used for forecasting, but might be able to have the same composed model as Srivastava et al. solution

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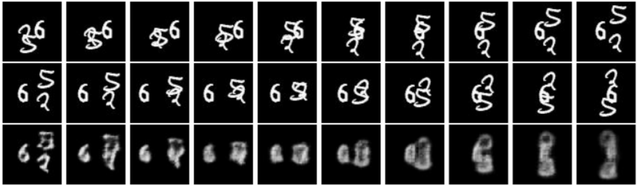

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- Spatial autoencoder is a simple undercomplete autoencoder
- Temporal autoencoder consists of a ConvLSTM as temporal encoder and optical flow as temporal decoder

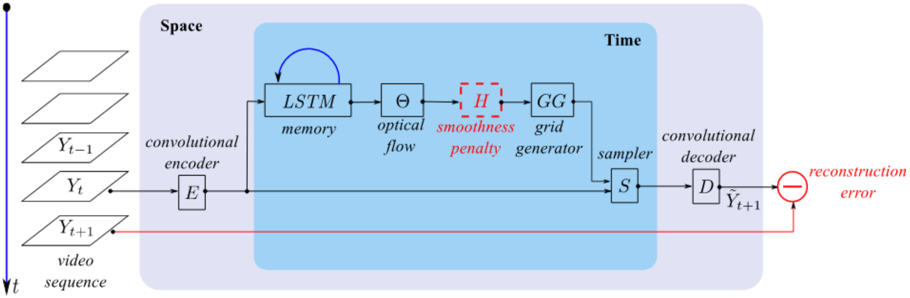

Figure: Spatio-temporal Video Autoencoder Architecture [11]

Spatio-temporal Video Autoencoder

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- Architecture could be used for multi-frame prediction with a feedback loop

Spatio-temporal Video Autoencoder

Figure: Results of MovingMNIST experiment [11]

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PredNet

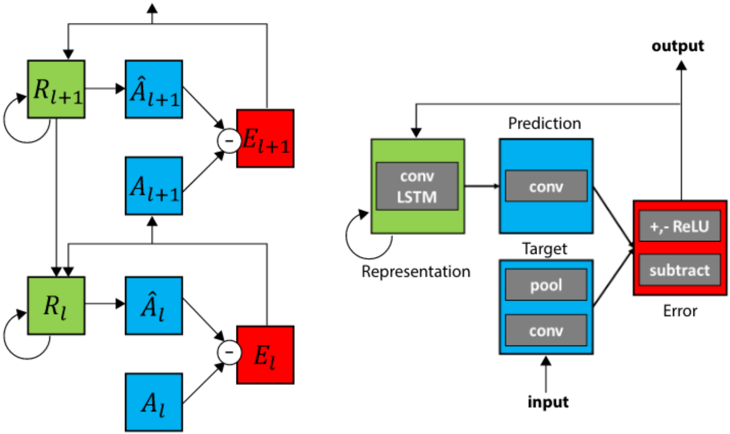

Figure: PredNet Architecture [8]

PredNet

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- $$R^t_l = ConvLSTM(E^{t-1}_l, R^{t-1}_l, Upsample(R^t_{l+1}) \qquad (33)$$

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- If current layer is *neq* lowest layer, compute A_l^t
  - A_0^t is an image of the input sequence

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PredNet

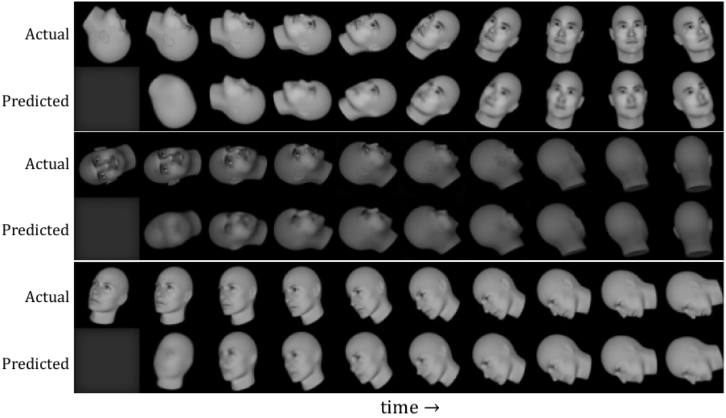
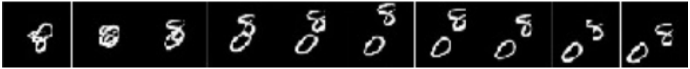


Figure: Results of FaceGen [8]

PredNet



(a) Ground truth

(b) ConvLSTM

Figure: Results for MovingMNIST [3].

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PredRNN

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$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H^l_{t-1} + b_i) \tag{36}$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H^l_{t-1} + b_f) \tag{37}$$

$$C^l_t = f_t \odot C^l_{t-1} + i_t \odot g_t \tag{38}$$

$$g_{t\prime} = tanh(W_{xg\prime} * X_t + W_{mg} * M^{l-1}_t + b_{g\prime}) \tag{39}$$

$$i_{t\prime} = \sigma(W_{xi\prime} * X_t + W_{mi} * M^{l-1}_t + b_{i\prime}) \tag{40}$$

$$f_{t\prime} = \sigma(W_{xf\prime} * X_t + W_{mf} * M^{l-1}_t + b_{f\prime}) \tag{41}$$

$$M^l_t = f_{t\prime} \odot M^{l-1}_t + i_{t\prime} \odot g_{t\prime} \tag{42}$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H^l_{t-1} + W_{co} * C^l_t + W_{mo} * M^l_t + b_o) \tag{43}$$

$$H^l_t = o_t \odot tanh(W_{1\times 1} * [C^l_t, M^l_t]) \tag{44}$$

PredRNN

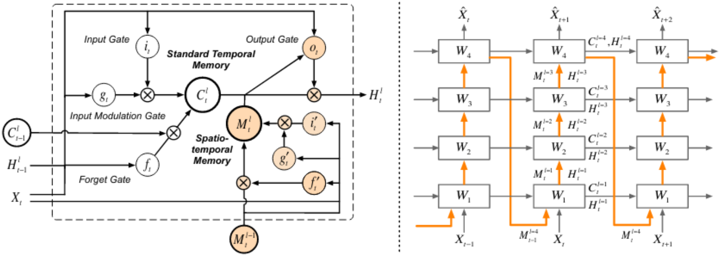

Figure: **Left:** ST-LSTM architecture, **Right:** PredRNN architecture [16]

PredRNN

- End-to-End differentiable

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PredRNN

Figure: Results for MovingMNIST [16].

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- The last architecture introduces a novel ConvLSTM named ST-LSTM and also a novel architecture named PredRNN
- $\Rightarrow$ Even though, the algorithms have different approaches to perform state-of-the-art image-/video-prediction, they all use some kind of LSTM as recurrent module.

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- Other hyperparamter can be found in the yml-folder of the implementation

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- Second experiments are performed using HP optimization, using early-stopping and with „optimal values“
- Only one out of 18 experiments performed, to get the importance of HP optimization and a tendency of how the results should look using optimal conditions

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- Secondly table of mean MSE for testing and some example output

MovingMNIST

Model	ConvLSTM	PredRNN
Autoencoder (Depth 2)	537.411	773.018
PredNet	6.909.818	12.421.090
Spatiotemp	1.001.324	1.415.639

Table: Number of trainable parameter for MovingMNIST.

MovingMNIST

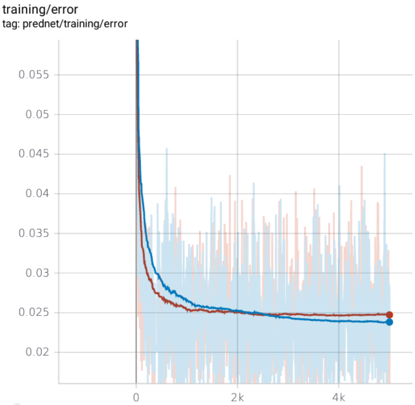
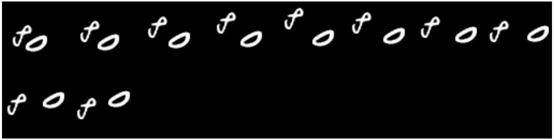


Figure: Training PredNet with ConvLSTM (blue) and PredRNN (red) on MovingMNIST.

MovingMNIST



(a) Ground truth

(b) ConvLSTM

(c) PredRNN (vanished)

Figure: Test results for PredNet on MovingMNIST.

MovingMNIST

Model	ConvLSTM	PredRNN
Autoencoder (Depth 2)	0.027	0.028
PredNet	0.035	0.041
Spatiotemp	0.024	0.022

Table: Mean MSE for MovingMNIST.

KTH

Model	ConvLSTM	PredRNN
Autoencoder (Depth 2)	542.531	781.760
PredNet	850.325	1.285.730
Spatiotemp	1.007.598	1.421.913

Table: Number of trainable parameter for KTH.

KTH

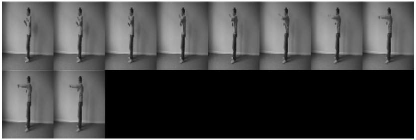


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Figure: Test results for PredNet on KTH.

KTH

Model	**ConvLSTM**	**PredRNN**
Autoencoder (Depth 2)	$1.55e-3$	0.05 (didn't converged)
PredNet	$1.95e-3$	$1.93e-3$
Spatiotemp	$3.1e-3$	0.025 (didn't converged)

Table: Mean MSE for KTH.

Kitti

Model	ConvLSTM	PredRNN
Autoencoder (Depth 2)	542.531	781.760
PredNet	8.222.559	12.430.626
Spatiotemp	1.640.321	2.200.641

Table: Number of trainable parameter for Kitti.

Kitti

(a) Ground truth

(b) ConvLSTM

(c) PredRNN

Figure: Test results for PredNet on Kitti.

Kitti

Model	ConvLSTM	PredRNN
Autoencoder (Depth 2)	0.02	0.013
PredNet	0.019	0.02
Spatiotemp	0.018	0.017

Table: Mean MSE for Kitti.

Experimental Results (Second setup)

- Performed on KTH dataset with optimal values and lr of 0.0001

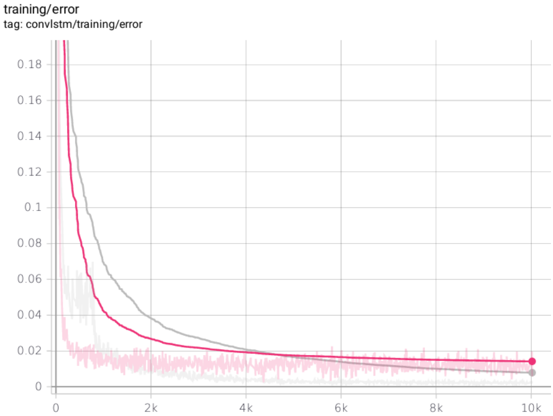

Figure: Training Autoencoder with ConvLSTM (red) and PredRNN (gray) on KTH using hyperparameter optimization and early stopping.

Experimental Results (Second setup)

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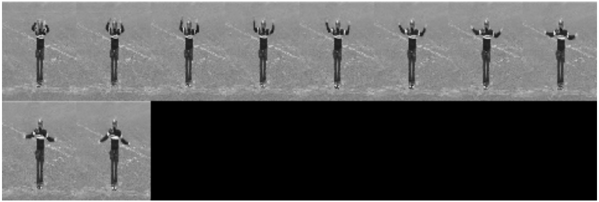

(a) Ground truth

(b) ConvLSTM

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Figure: Test results for Autoencoder on KTH using hyperparameter optimization and early stopping.

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- Using HP optimization, the tables turned and even one example outperformed the ConvLSTM solution with a performance boost of $> 80\%$

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- For future experiments, it would be nice to have all 18 experiments performed with HP optimization to get the overall results

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