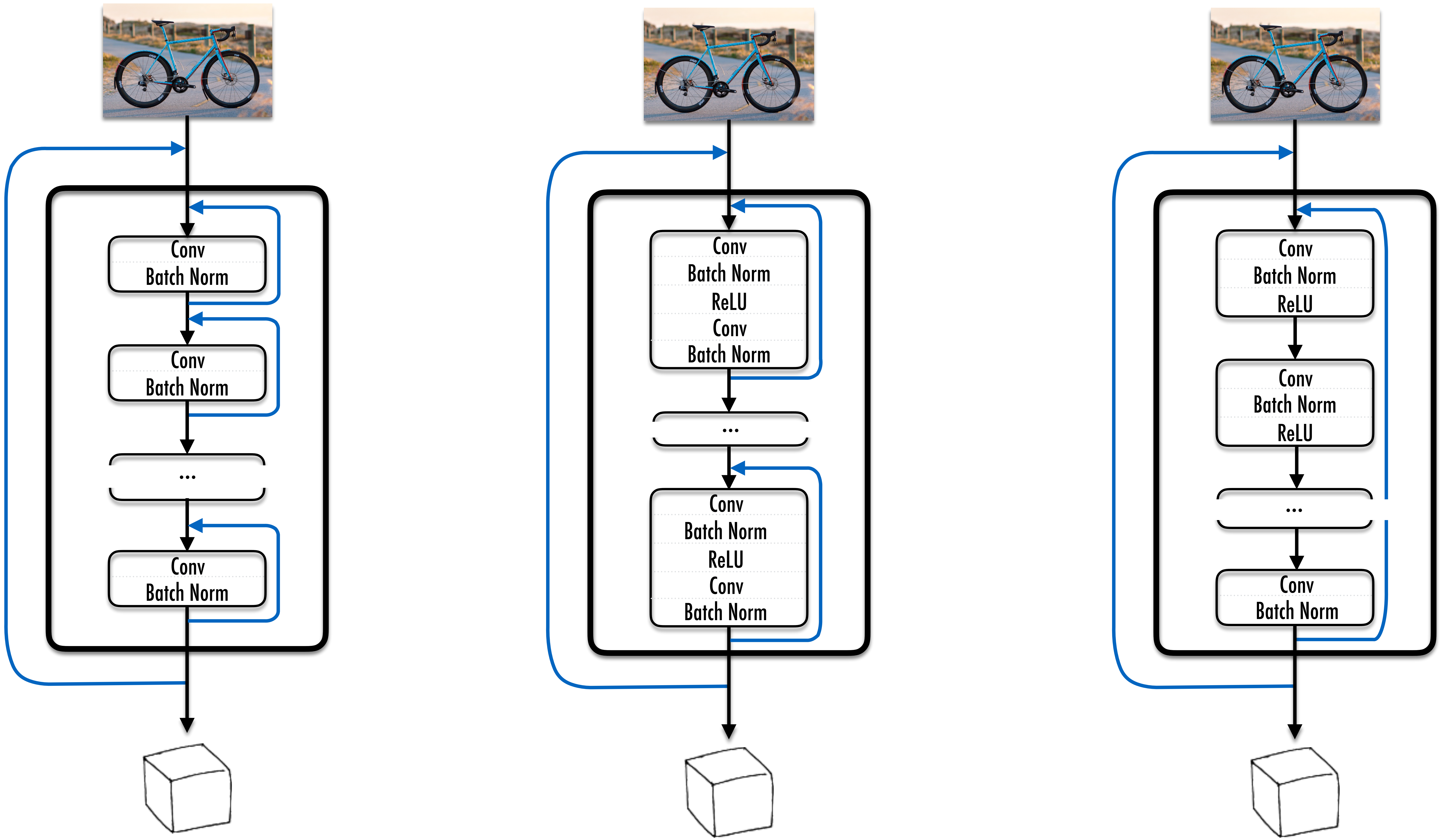

Recurrent module design choices

Input

output

Input

output

Input

output

Gates and Losses

$t=0,1,\ldots,T$ temporal order

$d=0,1,\ldots,D$ spatial order of ConvLSTM module

X = input to ConvLSTM module
C = cell gate
H = hidden state
W = feedforward convolutional neural net

$\mathbf{X}_t^d$, i.e. the output of ConvLSTM module at depth d and time t, depends on:

$\mathbf{X}_t^{d-1}$ input to ConvLSTM module
$\mathbf{H}^d_{t-1}$ temporal hidden state
$\mathbf{C}^d_{t-1}$ temporal cell gate

$$i_t^d = \sigma(W_{d,xi}(\mathbf{X}_t^{d-1}) + W_{d,hi}(\mathbf{H}_{t-1}^d)),$$
$$f_t^d = \sigma(W_{d,xf}(\mathbf{X}_t^{d-1}) + W_{d,hf}(\mathbf{H}_{t-1}^d)),$$

$$\tilde{C}_t^d = tanh(W_{d,xc}(\mathbf{X}_t^{d-1}) + W_{d,hc}(\mathbf{H}_{t-1}^d)),$$
$$\mathbf{C}_t^d = f_t^d \circ \mathbf{C}_{t-1}^d + i_t^d \circ \tilde{C}_t^d.$$

$$o_t^d = \sigma(W_{d,xo}(\mathbf{X}_t^{d-1}) + W_{d,ho}(\mathbf{H}_{t-1}^d)),$$
$$\mathbf{H}_t^d = o_t^d \circ tanh(\mathbf{C}_t^d),$$
$$\mathbf{X}_t^d = \mathbf{H}_t^d,$$

$$\mathbf{L} = \sum_{t=1}^{T} \gamma^t \mathbf{L_t}, \text{ where } \mathbf{L_t} = -log \frac{e^{\mathbf{H_t^D}[C]}}{\sum_j e^{\mathbf{H_t^D}[j]}}.$$