

prediction

targets

Time

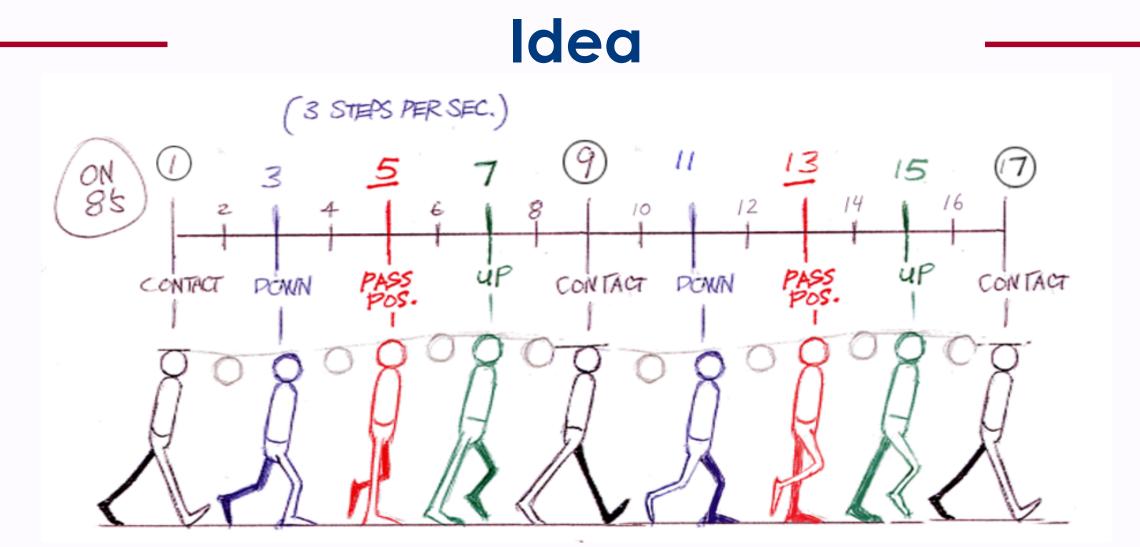
Keyln: Discovering Subgoal Structure with Keyframe-based Video Prediction



Predicted



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Inspiration: Real-world videos can often be summarized with just few key snapshots (keyframes).

Task: We want to discover keyframes in videos by finding the subset of frames that best describes the sequence.

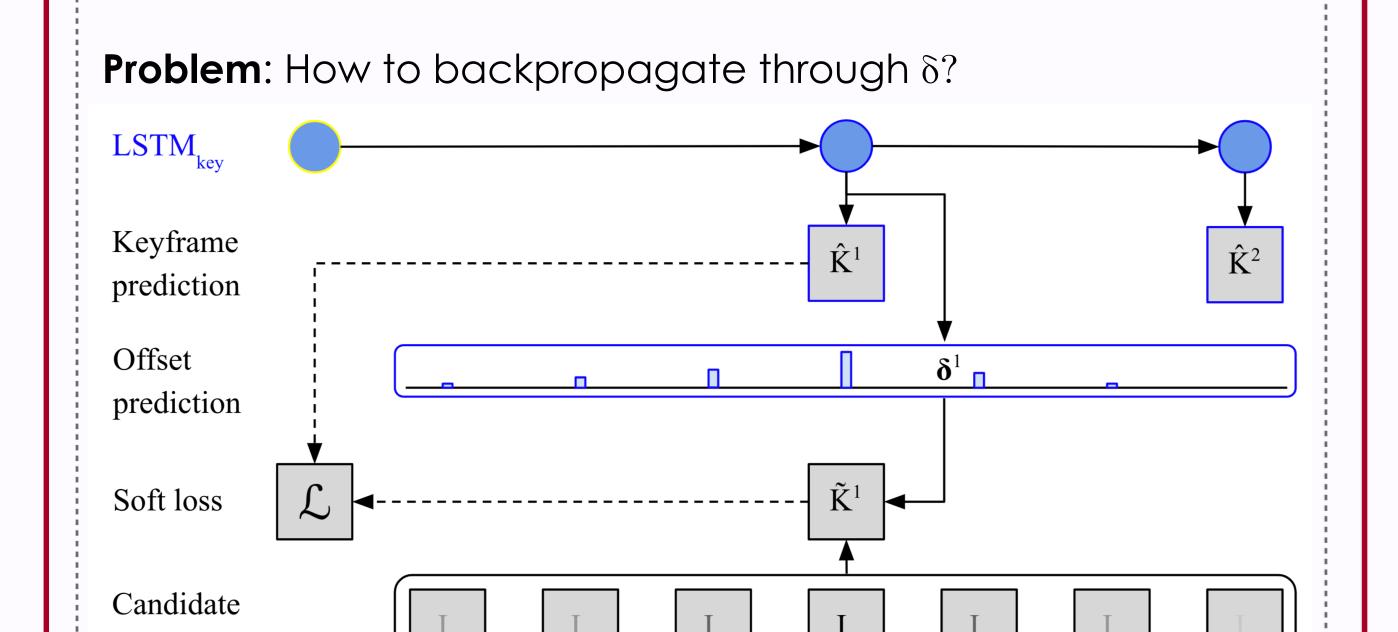
Idea: Train a variational model to select frames from which it can reconstruct the rest of the video.

Application: We focus on hierarchical planning: we first plan the subgoals (keyframes) and then plan how to reach them.

Keyframe-based Prediction LSTM_{key} Keyframe prediction LSTM_{inter} Intermediate

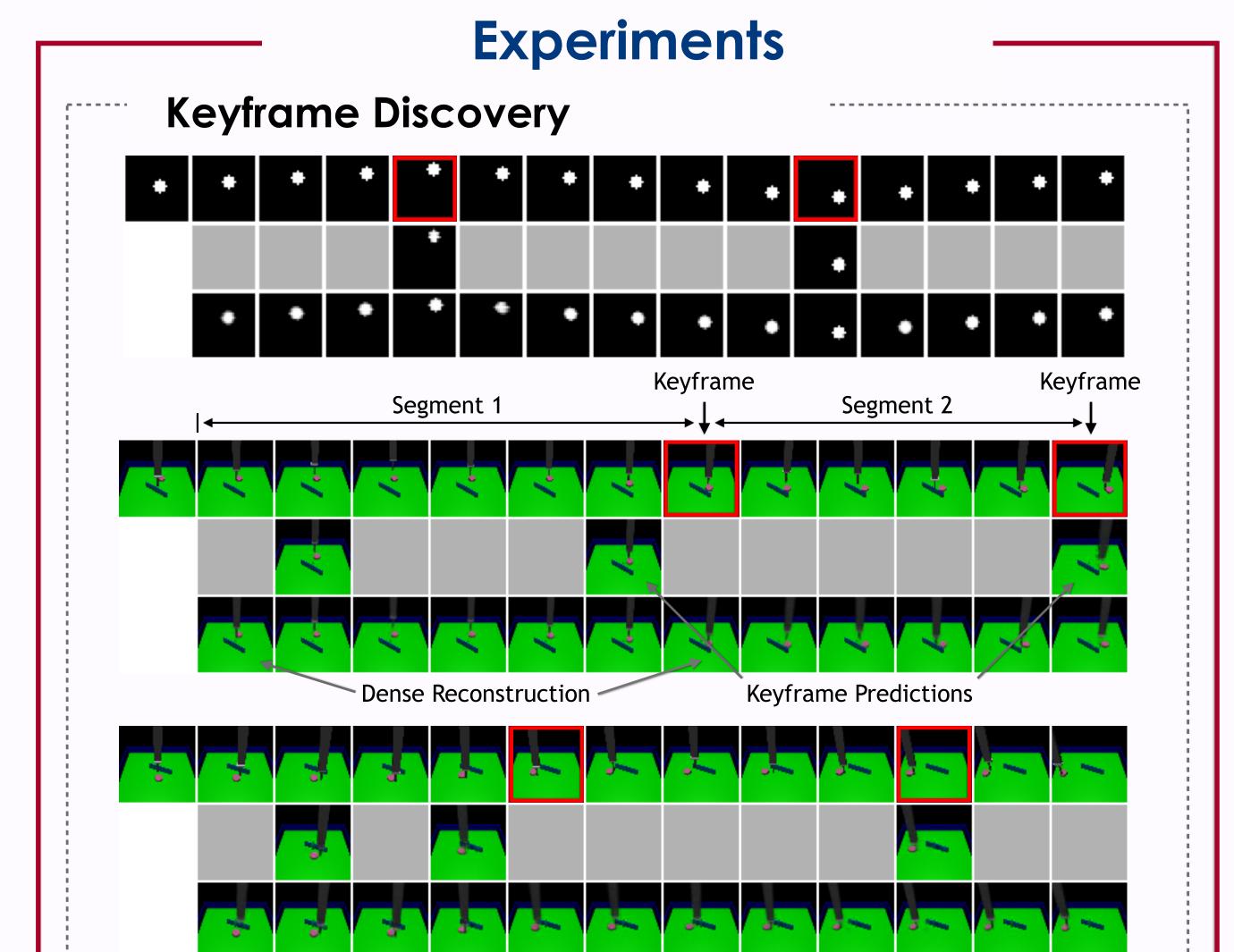
The high-level network predicts a sequence of keyframes K and distributions over time offsets δ , the low level network interpolates between each pair of keyframes.

Soft Reconstruction Loss

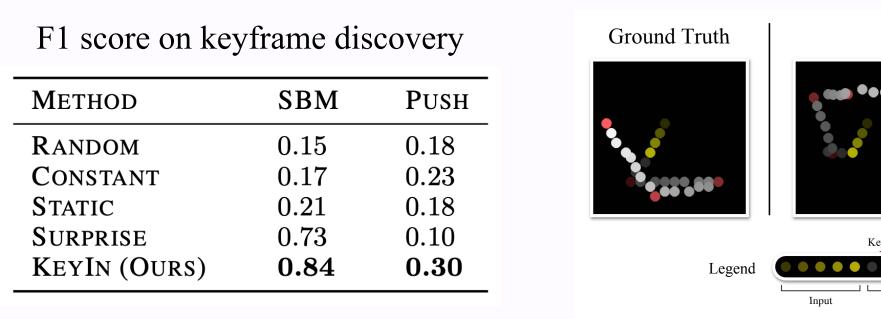


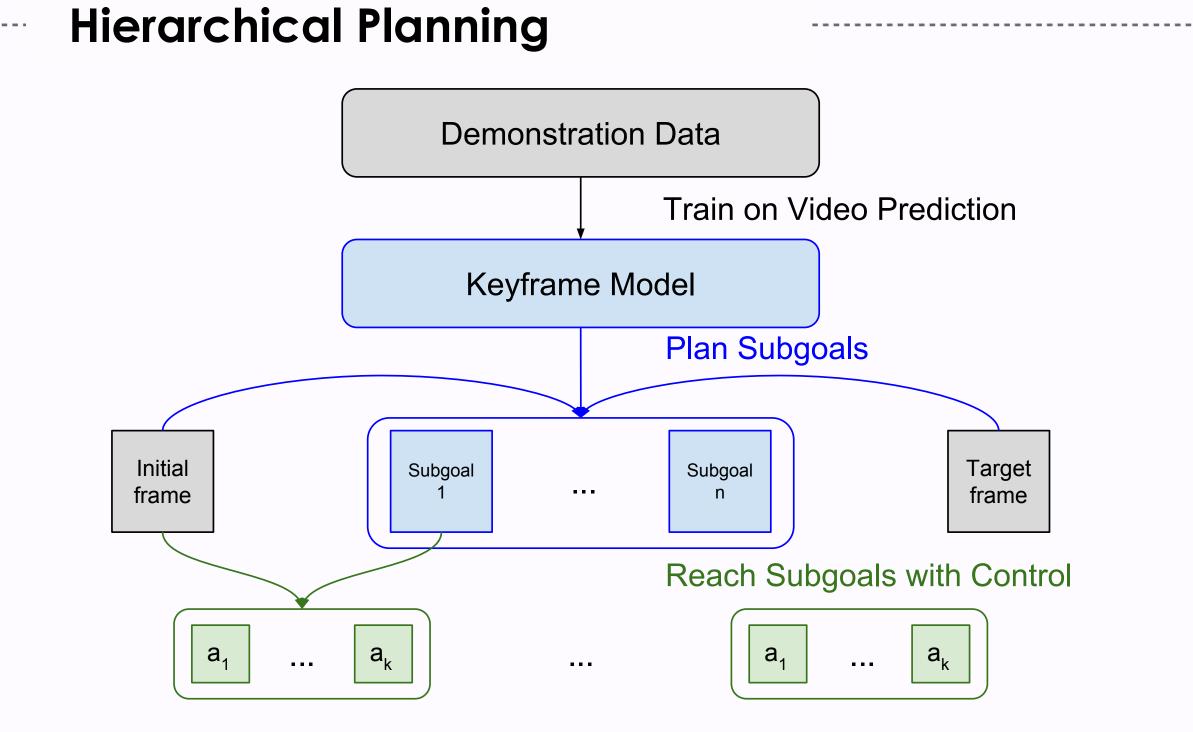
Proposed solution: The reconstruction loss is computed as an expectation over δ . There is no sampling.

$$\mathcal{L}_{rec} = \sum_{t} c^{t} \beta_{ki} ||\hat{K}^{t} - \tilde{K}^{t}||^{2} + \sum_{t,i} ||I_{i}^{t} - \tilde{I}_{i}^{t}||^{2}$$
$$\tilde{K}^{t} = \sum_{i} \tilde{\delta}_{i}^{t} I_{i} \qquad \tilde{I}_{i} = (\sum_{t,i} \tilde{\delta}_{i,i}^{t} \hat{I}_{i}^{t}) / \sum_{t,i} \tilde{\delta}_{i,i}^{t}$$



Our model can correctly select descriptive keyframes from a given sequence (above) and predict a distribution of possible next keyframes (below, right).





We use a model predictive control method (CEM) to (a) generate a plan of high-level subgoals (the keyframes predicted by Keyln), and (b) plan trajectories between these subgoals.

