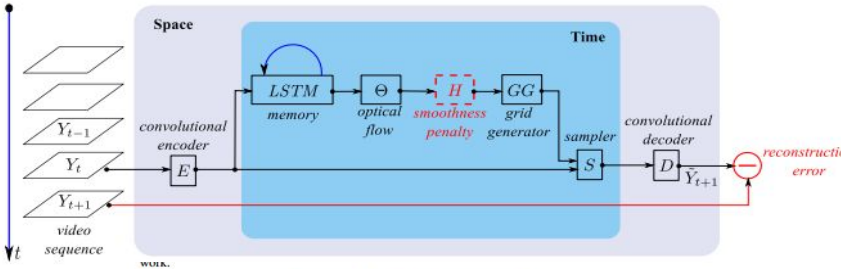
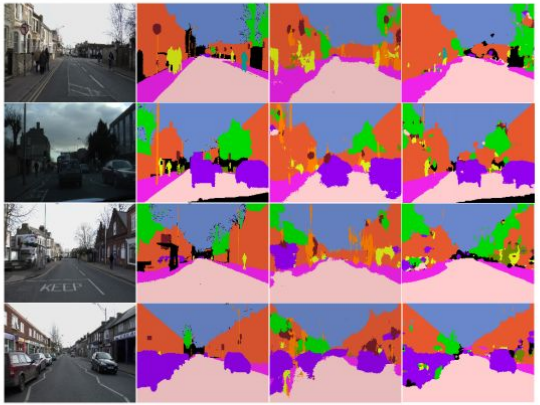
Deep learning on Video Analysis

Deep learning on Videos

Spatio-temporal video autoencoder with differentiable memory

- The autoencoder is based on a classic spatial image autoencoder and a novel nested temporal autoencoder
- The temporal encoder is composed of convolutional long short-term memory (LSTM) cells that integrate changes over time.
- The system predicts the optical flow based on the current observation and the LSTM memory state and applies it to the current frame to generate the next frame.
- By minimising the reconstruction error between the predicted next frame and the corresponding ground truth next frame, the whole system is trained in unsupervised manner.

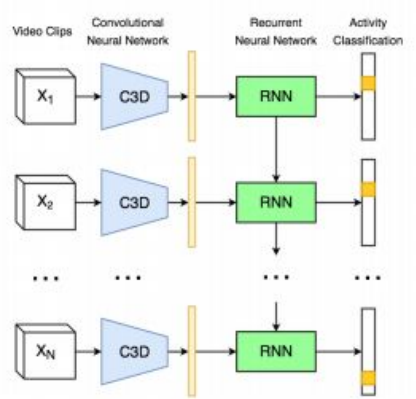




Code: https://github.com/viorik/ConvLSTM

Temporal Activity Detection in Untrimmed Videos with Recurrent Neural Networks

- A simple pipeline to classify and temporally localize activities in untrimmed videos.
- It uses features from a 3D Convolutional Neural Network (C3D) as input to train a recurrent neural network (RNN) that learns to classify video clips of 16 frames.
- After clip prediction, the output of the RNN is post-processed to assign a single activity label to each video, and determine the temporal boundaries of the activity within the video



Video ID: ArzhjEk4j_Y
Ground Truth: Building sandcastles

Prediction:
0.7896 Building sandcastles
0.0073 Doing motocross
0.0049 Beach soccer

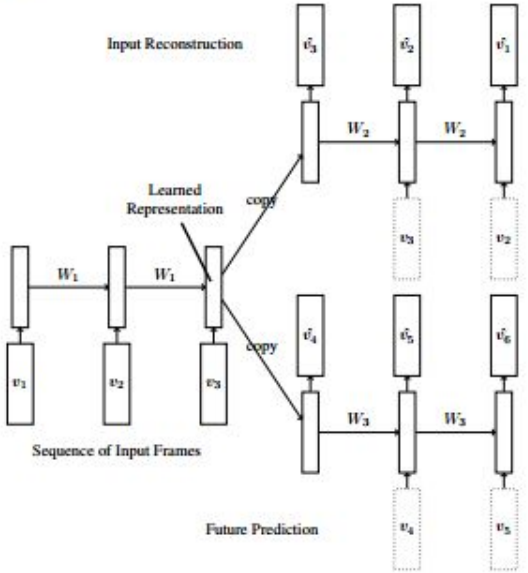
Video ID: AimG8xzchfI
Activity: Curling

Prediction:
0.3843 Shoveling snow
0.1181 Ice fishing
0.0633 Waterskiing

Code:https://github.com/imatge-upc/activitynet-2016-cvprw

Unsupervised Learning of Video Representations using LSTMs

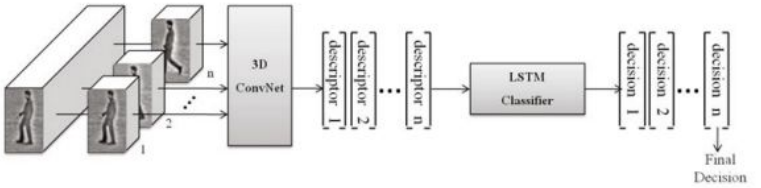
- LSTM network is used to learn representations of video sequences.
- The model uses an encoder LSTM to map an input sequence into a fixed length representation.
- This representation is decoded using single or multiple decoder LSTMs to perform different tasks, such as reconstructing the input sequence, or predicting the future sequence.
- 2 kinds of input sequences – patches of image pixels and high-level representations (“percepts”) of video frames extracted using a pretrained convolutional net.

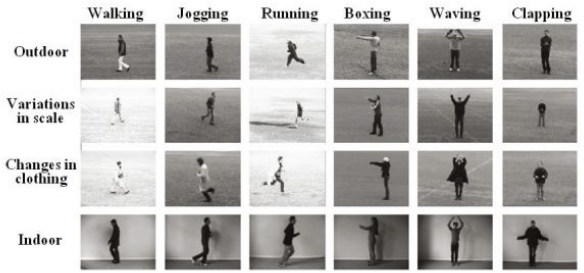


Code: https://github.com/emansim/unsupervised-videos

Sequential Deep Learning for Human Action Recognition

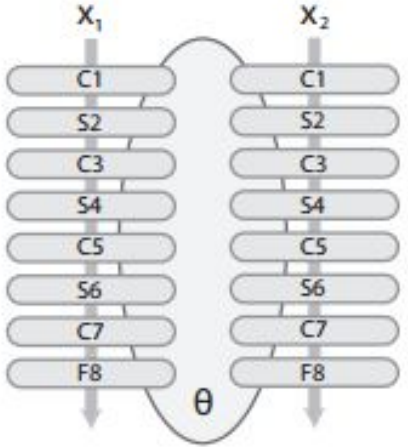
- Convolutional Neural Networks to 3D, automatically learns spatio-temporal features.
- The features are automatically constructed with the 3D-ConvNet and the entire sequence is labeled based on the accumulation of several individual decisions corresponding each to a small temporal neighbourhood,
- An LSTM is then trained to classify each sequence considering the temporal evolution of the learned features for each timestep





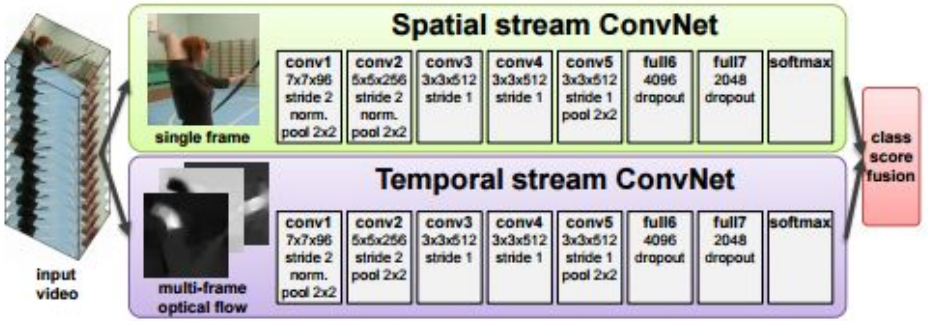
Deep Learning from Temporal Coherence in Video

- The system takes advantage of the fact that two successive frames are likely to contain the same object or objects.
- This coherence is used as a supervisory signal over the unlabeled data, and is used to improve the performance on a supervised task of interest.
- The cost(L1 norm) is minimized for all pairs of images by stochastic gradient descent over a “siamese network” architecture.



Two-Stream Convolutional Networks for Action Recognition in Videos

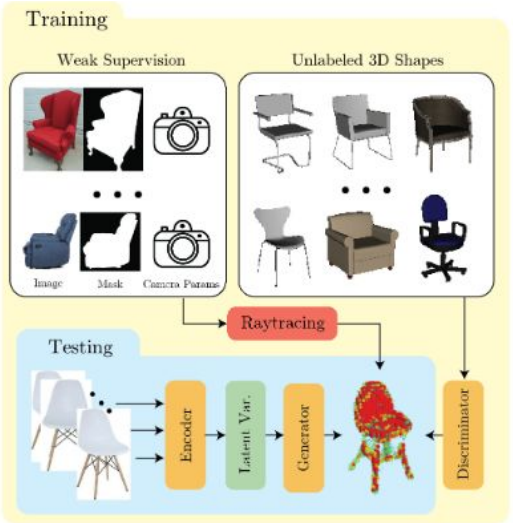
- A two-stream ConvNet architecture which incorporates spatial and temporal networks.
- Bidirectional optical flow based on optical flow stacking and trajectory stacking is used as input.
- SVM-based fusion of softmax scores outperforms fusion by averaging.



Deep learning for 3D Data

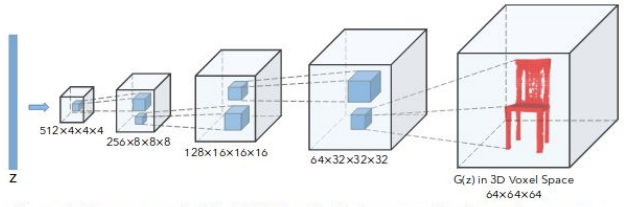
Weakly Supervised Generative Adversarial Networks for 3D Reconstruction

- Reduces reliance on expensive 3D supervision.
- WS-GAN takes an input image, a sparse set of 2D object masks with respective camera parameters, and an unmatched 3D model as inputs during training.
- WS-GAN uses a learned encoding as input to a conditional 3D-model generator trained alongside a discriminator, which is constrained to the manifold of realistic 3D shapes.
- The representation gap between 2D masks and 3D volumes is bridged through a perspective raytrace pooling layer, that enables perspective projection and allows back-propagation.



Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling

- The problem of 3D object generation is addressed by 3D Generative Adversarial Network (3D-GAN), which generates 3D objects from a probabilistic space.
- An adversarial network enables the generator to capture object structure implicitly and to synthesize high-quality 3D objects.
- The generator establishes a mapping from a low-dimensional probabilistic space to the space of 3D objects without a reference image or CAD models.
- The adversarial discriminator provides a powerful 3D shape descriptor which, learned without supervision, has wide applications in 3D object recognition.



Code: https://github.com/zck119/3dgan-release

SfM-Net: Learning of Structure and Motion from Video

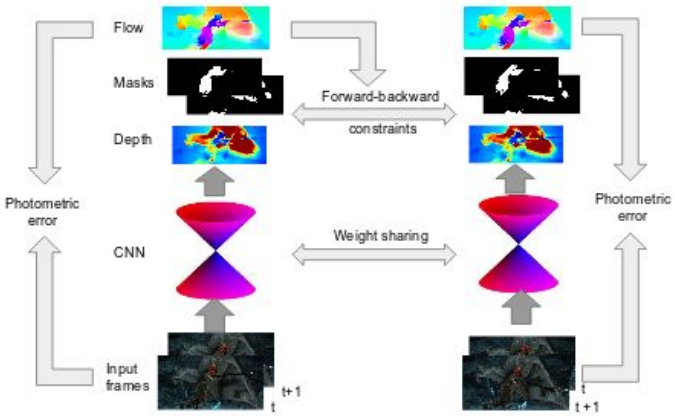
A geometry-aware neural network for motion estimation in videos that decomposes frame-to-frame pixel motion in terms of scene and object depth, camera motion and 3D object rotations and translations.

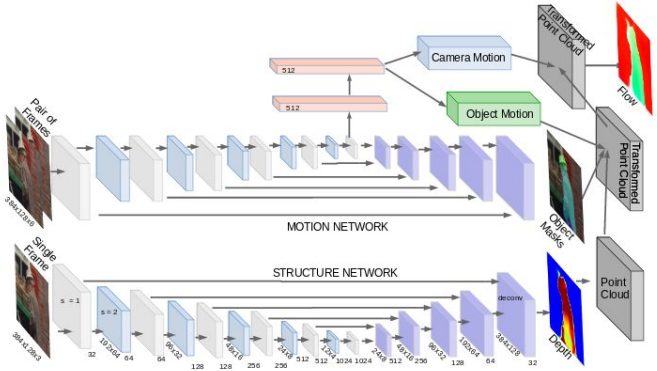
Given a sequence of frames, it predicts depth, segmentation, camera and rigid object motions, converts those into a dense frame-to-frame motion field (optical flow), differentiably warps frames in time to match pixels and back-propagates.

Can be trained with self-supervision by the reprojection photometric error

Can also be trained by supervised by ego-motion (camera motion)

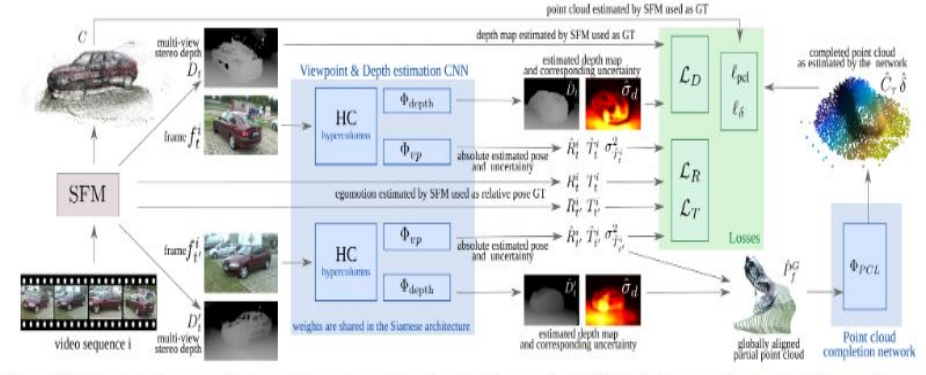
Can be supervised by depth (e.g., as provided by RGBD sensors).





Learning 3D Object Categories by Looking Around Them

- An unsupervised method that observes objects from a moving vantage point.
- A Siamese viewpoint factorization network is used that robustly aligns different videos together without explicitly comparing 3D shapes.
- A 3D shape completion network is used that can extract the full shape of an object from partial observations.
- As a preprocessing, structure from motion (SFM) extracts egomotion and a depth map for every frame.
- For training, our architecture takes pairs of frames f, f_t and produces a viewpoint estimate, a depth estimate, and a 3D geometry estimate.
- At test time, viewpoint, depth, and 3D geometry are predicted from single image.



Thank You