

# IDENTIFYING DRIVING FACTORS BEHIND INDIAN MONSOON PRECIPITATION USING MODEL SELECTION BASED ON DATA DEPTH

Subhabrata Majumdar, Lindsey Dietz and Snigdhasu Chatterjee

## INTRODUCTION

**Objective:** Selection of important predictors behind Indian Monsoon rainfall, and using them to build a predictive model.

**Challenges for covariate selection:**

- Several sources of variability, e.g. variation across years and weather station;
- Potentially heteroskedastic error structure;
- Linearity or other regression assumptions are not guaranteed to hold and are hard to verify;
- Large number of predictors, hence huge number of possible models:  $2^p$  models when number of predictors is  $p$ .

**Our solution:** Use a novel model selection criterion based on data depth that works on a wide range of models, and **selects important predictors by comparing only  $p + 1$  models**.

## CONTRIBUTIONS

We formulated tracking as path search in a large graph, and solve it efficiently with a modification of Dijkstra's algorithm.

The method is based on [2]. Our main contributions are

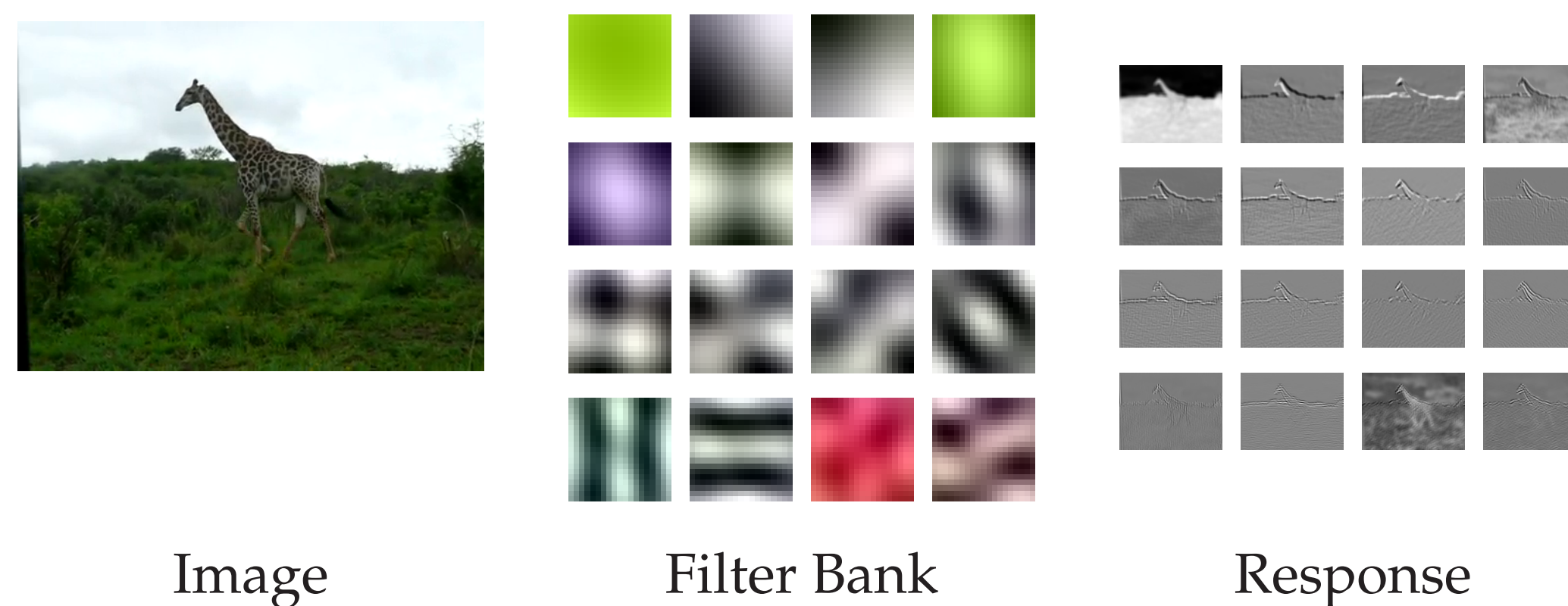
1. Efficient incorporation of a background appearance model
2. Formulation as a shortest path problem
3. (Correct) handling of occlusions
4. High-Efficiency implementation with up to 150 fps for a high resolution video

## RESULTS

Between one and three user clicks were needed to achieve accurate tracking for the head sequence. Note the correct handling of the occluded ear, which required only a single click.

The eye of the running giraffe required three user interactions, of which three marked the correct path.

## SPEED

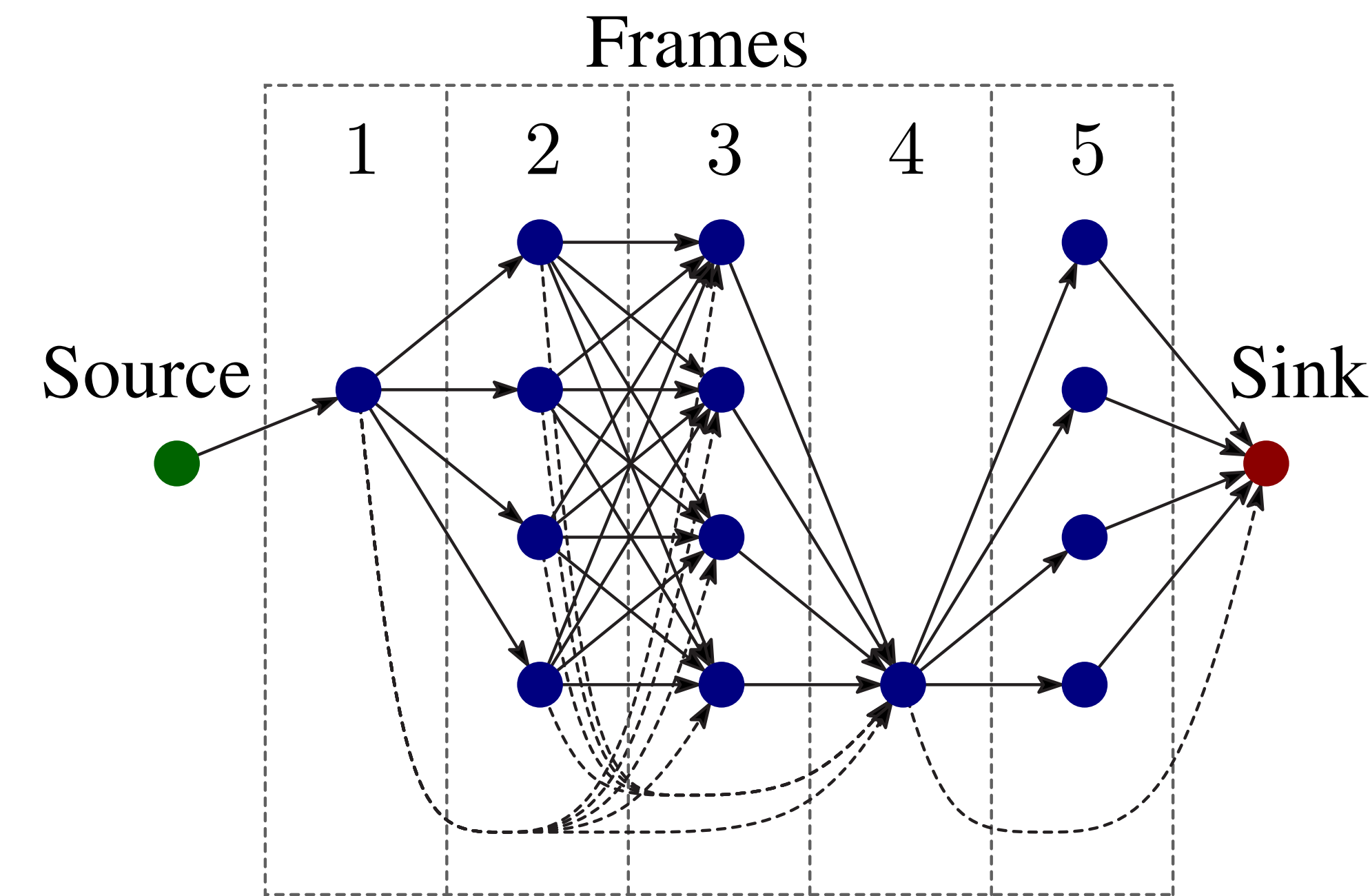


Speed is achieved by preprocessing the video with an adaptive filter bank as in [2]. Preprocessing was sped up significantly, but is still slower than realtime.

This encodes the video into 16 byte feature vectors. We implemented a search for similar patches using the SIFT feature of modern processors, and only evaluated a small number of candidate patches. (Typically 16 patches per frame). Candidate search and matching are highly efficient resulting in an overall fast system.

Note that the preprocessing is not done on the interestpoints tracked later. A single preprocessed video can therefore be used in multiple tracking sessions.

## METHOD



The cost is interpreted as a directed acyclic graph with weights on the nodes and edges. The nodes encode candidate positions, and the edges the transition costs between candidates. Additional edges (dashed) allow occlusion transitions which skip frames.

The optimal track is found with a modification of Dijkstra's shortest path search. The search was sped up by lower bounding the cost, and lazily evaluating the accurate cost only where necessary to find the global optimum.

## BACKGROUND MODEL



We incorporate a background model, such that a click tells us not only 'this is how the landmark looks like', but also 'this is how the landmark does *not* look like' for all other patches in that frame.

The figure contrasts the per frame evidence for each candidate patch with and without a background model. Using the background model

## A FUTURE DIRECTION

Can we also *efficiently* use a background tracks model, allowing us to reason, 'this would be a good track, but part of it can be better explained by tracking another point'.

## SOURCE CODE

The source code and compiled executables with an interactive interface are available at [http://www.cs.unibas.ch/persons/brian\\_amberg/graphtrack](http://www.cs.unibas.ch/persons/brian_amberg/graphtrack)