Neural Decision Forests for Semantic Image Labelling

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1. The problem

Random Forest (RF) + Multi-Layer Perceptron (MLP) = A Neural Decision Forest is an ensemble of decision trees having a multi-layer perceptron per tree-node to drive the routing decision

Inference in NDF and RF is similar. A sample is routed along each tree to a leaf, where a prediction is stored. However, routing decisions are taken through MLPs

At each node a neural network determines the routing decision

The sample is routed along each tree

The leaf provides a class posterior

Predictions from each tree are averaged to deliver the final class posterior

3. Inference

We performed experiments on three datasets: Etrims8, CamVid and Labelled Faces in the Wild (LFW)

We recursively build each tree of a NDF by splitting the actual terminal nodes. To split a terminal node we train a MLP in a way to maximize a novel split quality measure

Optimization of $\theta$

We adopt a $\ell_1$-regularized version of Resilient Back-Propagation (RProp) to learn the MLP parameters

MLP topology

The topology is random with a complexity being proportional to the support size of the training sample's class distribution

Avoid overfitting

We prevent overfitting issues by bagging, by randomizing the MLP input features and topology, and by regularizing the MLP parameters

4. Learning

State-of-the-art

We achieve state-of-the-art results compared to previous forest-based methods

Feature learning

Using RGB only, NDF performs like a RF trained using high-level features

Output layer

The input is the response of a set of random box-average features extracted relative to the sample position

Compactness

We obtain compact trees exhibiting large leaves with low entropy

NDF settings

NDF$_F$: only 1-layer perceptron  
NDF$_{F+}$: up to 2 layers  
NDF$_{F+}$: up to 4 layers  
NDF$_{F+}$: with $\ell_1$ regularization

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5. Experiments