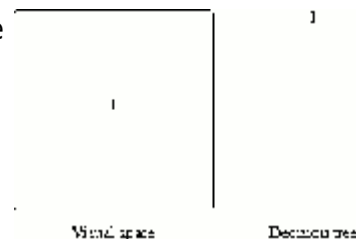


Visual Learning

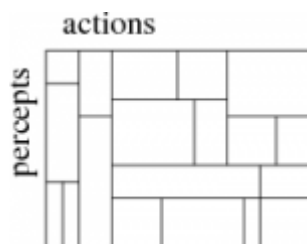
A core interest lies in visual perception as part of closed-loop interactive tasks, and in particular, on systems that improve their performance with experience. Examples of our work include reinforcement learning within perception-action loops, image classification that drives machine learning to the extreme, and [visuomotor learning](#) for various purposes including object detection, recognition and manipulation.

Reinforcement Learning on Visual Perception

Using learning approaches on visual input is a challenge because of the high dimensionality of the raw pixel data. In this work, we bring introduce concepts from appearance-based computer vision to reinforcement learning. Our RLVC algorithm ([Jodogne & Piater, 2007](#)) initially treats the visual input space as a single, perceptually aliased state, which is then iteratively split on local visual features, forming a



decision tree. In this way, perceptual learning and policy learning are interleaved, and the system learns to focus its attention on relevant visual features.



Our RLJC algorithm ([Jodogne & Piater, 2006](#)), extends this idea to the combined perception-action space. This constitutes a promising new approach to the age-old problem of applying reinforcement learning to high-dimensional and/or continuous action spaces.

Image Classification using Extra-Trees and Random Patches

Image classification remains a difficult problem in general, and the best results on specific problems are usually obtained using specifically tailored methods.

We came up with a generic method that turns this principle upside-down and nevertheless achieves highly competitive results on several, very different data sets ([Marée, et.al. 2005](#)). It is based on three straightforward insights:

- **Randomness** to keep classifier bias down,
- **Local patches** to increase robustness to partial occlusions and global phenomena such as viewpoint changes,
- **Normalization** to achieve invariance to various transformations.

The key contribution was probably the demonstration of how far randomization can take us: Local patches are extracted at random, rotational invariance is obtained by randomly rotating the training patches, and classification is done using Extremely Randomized Trees.

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