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Predictable Feature Analysis

A variant of PFA allows to optimize predictability regarding to an additional stream of information.





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An abstract, interactive setting

Consider an agent in an environment. It can perform certain actions and receives some perception from the environment.

We consider the actions to be a signal (just like the perception) and assume a sufficiently high temporal resolution, such that an action and its result appear at different signal-timesteps.

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We assume to have a training-phase, in which action is performed by a trainer or randomly, while the agent can observe it together with the resulting perception.



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We analyze the relationship between action and perception during the training-phase with PFA.

Image: A math a math



We formulate a goal in terms of the extracted features by feeding the sensor-value at goal position into the feature extractor.



The arising optimization-problem is an inhomogeneous eigenvalue problem and can be solved efficiently (in case of constant speed).

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Simplified vision model



The simplified vision is like a 360°-camera realizing every wall segment in a separate signal component. Each component expresses the field of view angle it occupies in the camera's vision.

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Random walk



We train in an exhaustive random walk of 150k steps (40k steps sketched here).

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One room PFA navigation



In a plain one-room environment PFA-based navigation performs well.





Obstacle PFA navigation



Also with an obstacle it works more or less.

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Obstacle PFA navigation



With the goal centered behind the obstacle PFA inherently fails.





Back to SFA



Slowness leads to monotony.

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Why is monotony good?



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Why is monotony good?



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Why is monotony good?



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It turns out that PFA is not needed for this scenario.

It is sufficient to fit the prediction model (with control info and quadratic expansion) on the slow features.

However this might be specific for this scenario as SFA might throw away features that are crucial for prediction.

More complex dynamical systems can be examples where PFA is needed as first step.





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More examples



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More examples



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More examples







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