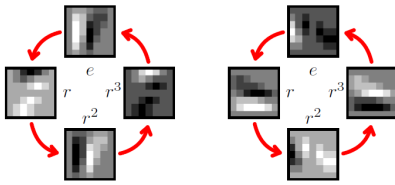


### Project: Group-equivariant neural networks



Group-equivariant networks are a natural generalization of convolutional neural networks, where translation equivariance is replaced by equivariance with respect to the action of other groups. This gives rise to a more general notion of convolution, that in practice can be directly plugged into existing architectures without too much hassle or

fine-tuning. With this project, you will study this family of learning models and: 1) report on their main properties, 2) confirm experimentally their performance, and 3) suggest further generalizations or applications that are not present in the current literature (to the best of your investigation).

**Reference:** <https://arxiv.org/abs/1602.07576>

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### Project: Embedding a data distribution into a decision tree

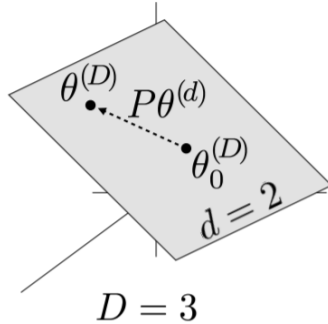


Autoencoders aim to model the data distribution and can be used as generative models or to compress input samples. To accomplish nice generative properties, VAEs introduce a stochastic signal in the training process and make the strong assumption that data is distributed as a multidimensional unimodal gaussian. Yet other assumptions are possible, for instance in VQ-DRAW the data distribution is embedded in the leaves of a decision tree, accomplishing a very effective compression of the input.

With this project, you will study VQ-DRAW and: 1) report on its main properties, 2) test experimentally its performance on data different from images, for instance 3D models and 3) compare the performance to other existing methods using different autoencoder architectures on the same data.

**Reference:** <https://arxiv.org/abs/2003.01599>

## Project: Training on parameters subspaces



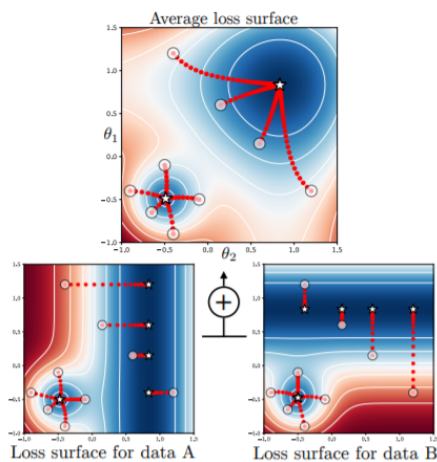
PCA reduces data dimensionality by projecting each sample to a subspace maximizing variance. In a sense, the effect of PCA pre-processing in a learning problem is equivalent to working with a larger dataset, since it augments the density of our data-space. Similarly, a desirable feat for a learning problem is to work with a smaller hypothesis space, i.e. less training parameters. We can apply the same projection idea to the training parameters  $K$  of a neural network, let  $K = PW$ , with  $W$  being lower dimensional than  $K$ , and  $P$  being a projection matrix. What is the performance of

such a neural network when trained on  $W$  with a fixed  $P$ ? In this project, you will discuss this family of learning models and: 1) report on their main properties compared to a standard smaller neural network, 2) test experimentally their performance for different subspace dimensions, and 3) test experimentally their performance for different families of  $P$ .

Reference: <https://arxiv.org/abs/1804.08838>

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## Project: Learning invariances



Searching for invariances among data collected in different environments is at the basis of modern data-based approaches yearning for out-of-distribution (o.o.d.) generalization. In this project you will explore further two ideas in this direction, Invariant Risk Minimization and the AND-mask, comparing their performance on new kinds of data, such as 3D models. With this project, you will study the problem of o.o.d. generalization and: 1) present the two approaches, highlighting their similarities and differences; 2) compare experimentally their performance on a new kind of data; and 3) suggest further generalizations or applications that are not present in the current literature (to the best of your investigation).

References: <https://arxiv.org/abs/2009.00329> <https://arxiv.org/abs/1907.02893>

## Project: Geometric interpretability



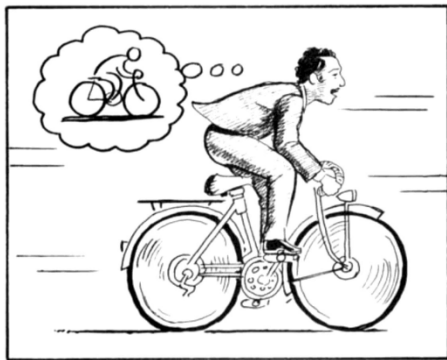
What kind of features are actually learned in a neural network? Recent investigation has shed some light on this notoriously open question, by proposing computational techniques to actually visualize the prototypical features that trigger the responses of specific neurons in a given net. However, to date, very little work has explored these ideas when dealing with structured data (as opposed to images), such as graphs, 3D shapes, or point clouds. With this exploratory project, you will 1) investigate the applicability of existing feature visualization techniques to geometric or graph data, 2) report your findings, and 3) suggest preliminaries lines of attack and elaborate on the main

differences with the classical image-based setting.

**Reference:** <https://distill.pub/2017/feature-visualization/> and references therein.

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## Project: World Models

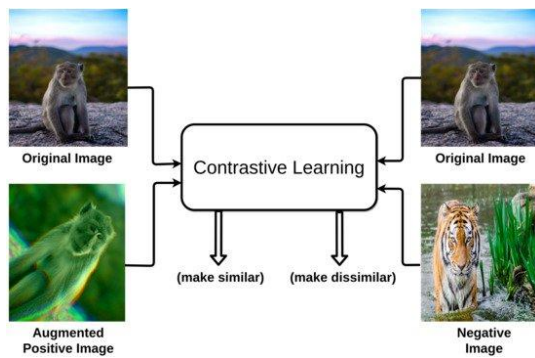


The idea behind model-based reinforcement learning is that modeling the entire environment can be a shortcut to learn faster good policies, where with faster we mean with less actual real world simulations. This idea is extensively and nicely presented in the paper World Models. With this project, you will study World Models and: 1) report on the main ideas behind model based RL with respect to standard RL; 2) test experimentally the performance of model based RL on a new environment, for instance one of the [OpenAI PROCGEN games](#); and 3) discuss the pros and cons of model-based RL and possible evolutions of

this paradigm (to the best of your investigation).

**References:** <https://worldmodels.github.io/>

## Project: Contrastive Learning



Contrastive learning is a machine learning technique used to learn representations without supervision. This technique can be used as a pre-training step to exploit large amounts of unlabeled data. In this project you will study this technique and: 1) report on the main ideas and state of the art of contrastive techniques, 2) implement a contrastive learning regimen for a non-Euclidean data type of your choice (e.g. 3D shapes) and 3) test experimentally the performance on a task of your choice.

**References:** <https://www.mdpi.com/2227-7080/9/1/2>, <https://arxiv.org/abs/2006.10029>

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## Project: Financial Markets



Financial markets offer an interesting environment to perform sequence prediction. They present self-correcting and highly non-stationary behavior that pose many problems to current approaches. In this project you will learn how to perform sequence prediction with deep learning and: 0) Choose a stock dataset available online, e.g. historical data from kaggle or from yahoo finance (example [here](#)), 1) perform the necessary data wrangling, 2) implement your own sequence forecasting system (with

significant differences from existing methods) and 3) compare the performance against the naive LSTM approach.

**References:** <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>, <https://arxiv.org/abs/2009.10819>, [http://cs230.stanford.edu/projects\\_winter\\_2020/reports/32066186.pdf](http://cs230.stanford.edu/projects_winter_2020/reports/32066186.pdf) <https://towardsdatascience.com/lstm-time-series-forecasting-predicting-stock-prices-using-an-lstm-model-6223e9644a2f>

## Project: Birdcall Identification



This is a kaggle competition with the deadline on June 1 2021, and \$5,000 prize money. You are not required to complete the project before the kaggle deadline for the exam, but you will not be allowed to use solutions from other kaggle participants as your exam project.

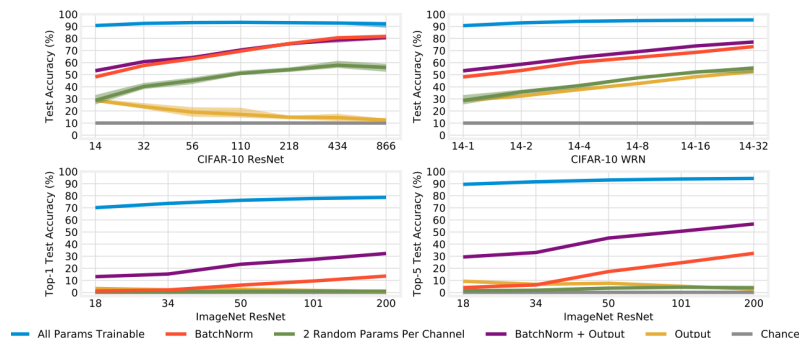
In this competition, you'll automate the acoustic identification of birds in soundscape recordings. You'll examine an acoustic dataset to build detectors

and classifiers to extract the signals of interest (bird calls). Innovative solutions will be able to do so efficiently and reliably.

**References:** <https://www.kaggle.com/c/birdclef-2021/overview>

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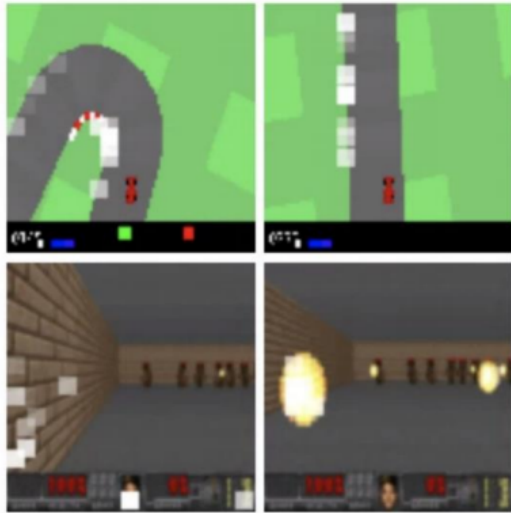
## Project: Training BatchNorm and only BatchNorm



A CNN with weights frozen at their random original value and trained only on the beta and gamma parameters of the batch-normalization can achieve surprisingly good results on image classification problems, much better than training an equivalent number of weights chosen at random. With this project, you will investigate further this idea and: 1) discuss why this happens, 2) test experimentally this result on other architectures and other kinds of data, like MLPs or GNN, and 3) suggest further generalizations or applications that are not present in the current literature (to the best of your investigation).

**Reference:** <https://arxiv.org/abs/2003.00152>

## Project: Neuroevolution of Self-Interpretable Agents



Sometimes less is more, even in Reinforcement Learning. Agents capable of seeing only a portion of the pixel inputs from the environment not only can solve the tasks with simpler models, but also achieve better generalization. In *Neuroevolution of Self-Interpretable Agents* the portion to look is learned through an attention mechanism.

With this project, you will investigate this idea and: 1) discuss the benefits of attention in RL, 2) confirm experimentally this idea on a new environment, for instance one of the [OpenAI PROCGEN games](#); and 3) test further ideas in this direction, for instance what if we choose a feature different from the patch position?

Reference: <https://attentionagent.github.io/>

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## Project: Growing Neural Cellular Automata



Cellular automata are capable of generating very complex patterns and high level behaviours from very simple rules and initializations. Can we use a simple neural network to learn the proper rules to generate *specific* patterns? This is the idea investigated in *Growing Neural Cellular Automata*.

With this project, you will investigate this idea and: 1) explain how we can define a trainable cellular automata, 2) test experimentally this idea on a new environment, for instance a 3D cellular automata to replicate simple 3D patterns, like minecraft animals; and 3) suggest further generalizations or applications that are not present in the current literature (to the best of your investigation).

Reference: <https://distill.pub/2020/growing-ca/>



**Project:** Choose your own



If none of the above whets your appetite, you can propose your own idea for a project. However, your proposal must be approved by us.

In order to propose a new project, you are required to write a well motivated 1-page description (references can be put in a second page). This should include references, describe its feasibility and data availability, describe the expected outcome, the possible risks, what is your intended line of attack, and state in what way it tackles an interesting and new problem in the field of deep learning.

The choose-your-own project must contain aspects of originality. Simply reproducing the results of an existing work is not sufficient and will not be approved. Submitting projects from previous exams is also not allowed.

If you choose this path, please send your proposal to all these addresses:  
[rodola@di.uniroma1.it](mailto:rodola@di.uniroma1.it), [moschella@di.uniroma1.it](mailto:moschella@di.uniroma1.it), [norelli@di.uniroma1.it](mailto:norelli@di.uniroma1.it) .

Please use the subject “[DLAI21 projects] Project name”.