Deep Learning with Nontrivial Constraints

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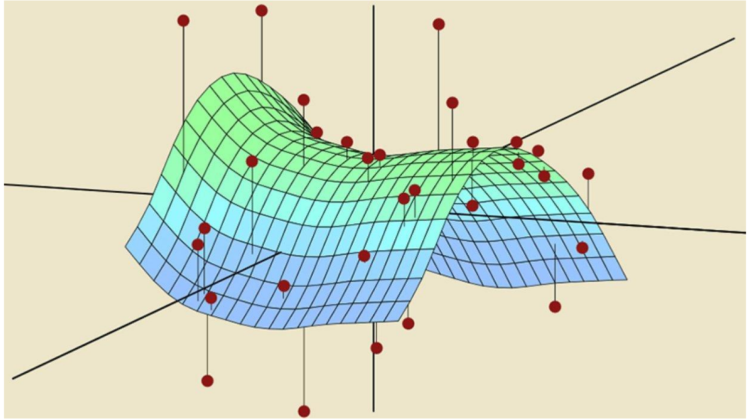
University of Minnesota
Driven to Discover[SM]

Three fundamental questions in DL



- **Approximation**: is it powerful, i.e., the $\mathcal{H}$ large enough for all possible weights?
- **Optimization**: how to solve

$$\min_{\boldsymbol{w}_i' s, \boldsymbol{b}_i' s} \frac{1}{n} \sum_{i=1}^{n} \ell \left[\boldsymbol{y}_i, \left\{ \mathsf{NN} \left(\boldsymbol{w}_1, \ldots, \boldsymbol{w}_k, b_1, \ldots, b_k \right) \right\} \left(\boldsymbol{x}_i \right) \right]$$

- **Generalization**: does the learned NN work well on "similar" data?

Isn't it solved?

Algorithms

Adadelta	Implements Adadelta algorithm.
Adagrad	Implements Adagrad algorithm.
Adamax	Implements Adamax algorithm (a variant of Adam based on infinity norm).
ASGD	Implements Averaged Stochastic Gradient Descent.
LBFGS	Implements L-BFGS algorithm, heavily inspired by minFunc.
NAdam	Implements NAdam algorithm.
RAdam	Implements RAdam algorithm.

lgorithm

Base class

CLASS torch.optim.Optimizer(*params*, *defaults*) [SO

Base class for all optimizers.

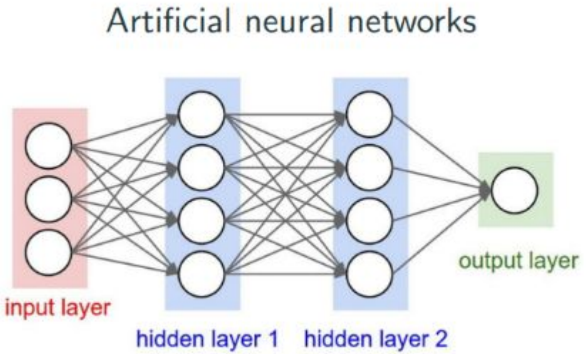
• WARNING

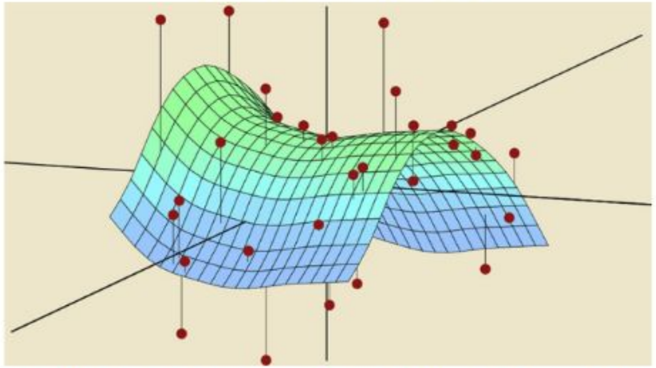
Parameters need to be specified as collections
consistent between runs. Examples of objects t
and iterators over values of dictionaries.

Parameters:

- **params** (*iterable*) – an iterable of to
  Tensors should be optimized.
- **defaults** – (dict): a dict containing d
  when a parameter group doesn't spe

When DL meets constraints





used to approximate nonlinear functions

Unconstrained optimization

$$\min_{\boldsymbol{w}_i's, \boldsymbol{b}_i's} \frac{1}{n} \sum_{i=1}^{n} \ell\left[\boldsymbol{y}_i, \{\mathsf{NN}\left(\boldsymbol{w}_1, \ldots, \boldsymbol{w}_k, b_1, \ldots, b_k\right)\}\left(\boldsymbol{x}_i\right)\right]$$

$$\min_{\boldsymbol{x}} \; f(\boldsymbol{x})$$

"Solved"

Constrained optimization

$$\min_{\boldsymbol{x}} \; f(\boldsymbol{x}) \quad \text{s. t. } \; g(\boldsymbol{x}) \le \mathbf{0}$$

largely "unsolved"

This talk is about GAPS

Constrained optimization

$$\min_{\boldsymbol{x}} \; f(\boldsymbol{x}) \quad \text{s. t.} \;\; g(\boldsymbol{x}) \le \mathbf{0}$$

largely "unsolved"

An imaginary chat between a PhD student working in deep learning (**DLP**) and a PhD student working in optimization (**OP**)

DLP: Man, I've solved a constrained DL problem recently
OP: Oh, that's a hard problem
DLP: Really? I actually did it
OP: How?
DLP: My problem is $\min_x \; f(x)$, s.t. $g(x) \le 0$. I put $g(x)$ as a penalty and then call ADAM
OP: Are you sure it works?
DLP: Yes, the performance is improved and my paper is published at ICML
OP: Why don't you try augmented Lagrangian methods?
DLP: No implementation in Pytorch. Is it possible we work out some theory about my method?
OP: I think it's hard. It's not convex

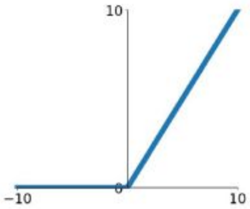
Outline

Constrained deep learning: CDL

- **What, how, and why for CDL**
- No good solvers for CDL yet
- Granso and PyGranso
- PyGranso in action
- Outlook

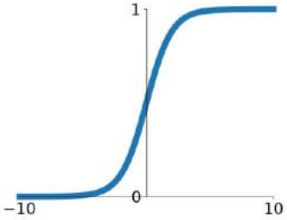
DL with simple constraints

Embedding constraints into DL models



ReLU
(Rectified Linear Unit)

Nonnegativity



Sigmoid

[0, 1]

$$z \mapsto \left[\frac{e^{z_1}}{\sum_j e^{z_j}}, \ldots, \frac{e^{z_p}}{\sum_j e^{z_j}} \right]^{\mathsf{T}}$$

Softmax

Nonnegativity and summed to 1

DL with nontrivial constraints

- **Robustness evaluation**
- Imbalanced learning
- Topology optimization

Deep Learning with Nontrivial Constraints: Methods and Applications

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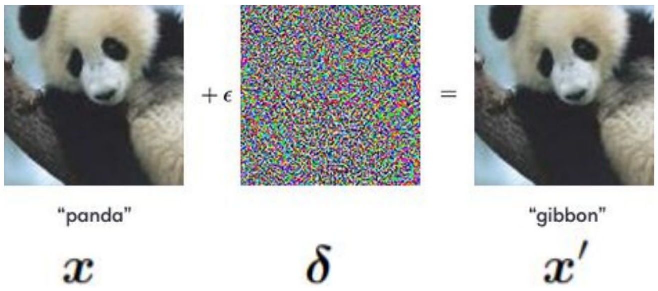
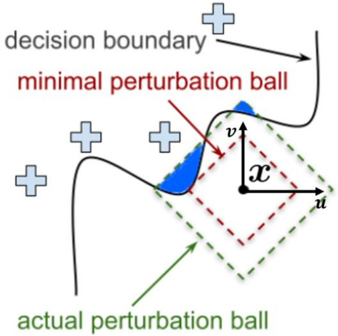
Robustness evaluation (RE)





Maximize loss function

$$\boxed{\max_{\boldsymbol{x}'} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right)}$$

$$\text{s.t.}\ \boxed{d\left(\boldsymbol{x}, \boldsymbol{x}'\right) \leq \varepsilon},\quad \boxed{\boldsymbol{x}' \in [0,1]^n}$$

Allowable perturbation Valid image

Minimize robustness radius

$$\boxed{\min_{\boldsymbol{x}'} d\left(\boldsymbol{x}, \boldsymbol{x}'\right)}$$

$$\text{s.t.}\ \boxed{\max_{i \neq y} f_{\boldsymbol{\theta}}^{i}(\boldsymbol{x}') \geq f_{\boldsymbol{\theta}}^{y}(\boldsymbol{x}')},\ \boxed{\boldsymbol{x}' \in [0,1]^n}$$

Change the predicted class Valid image

Ref Optimization and Optimizers for Adversarial Robustness. Liang, H., Liang, B., Peng, L., Cui, Y., Mitchell, T., & Sun, J. https://arxiv.org/abs/2303.13401

Projected gradient descent (PGD) for RE

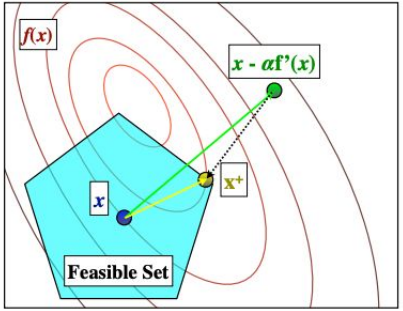
$$\min_{\mathbf{x}\in\mathcal{Q}} f(\mathbf{x})$$

Step size

$$\mathbf{x}_{k+1} = P_{\mathcal{Q}}\Big(\mathbf{x}_k - \alpha_k \nabla f(\mathbf{x}_k)\Big)$$

$$P_{\mathcal{Q}}(\mathbf{x}_0) = \arg\min_{\mathbf{x}\in\mathcal{Q}} \frac{1}{2}\|\mathbf{x}-\mathbf{x}_0\|_2^2$$

Projection operator



Key hyperparameters:
(1) step size
(2) iteration number

$$\max_{\boldsymbol{x}'} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right)$$

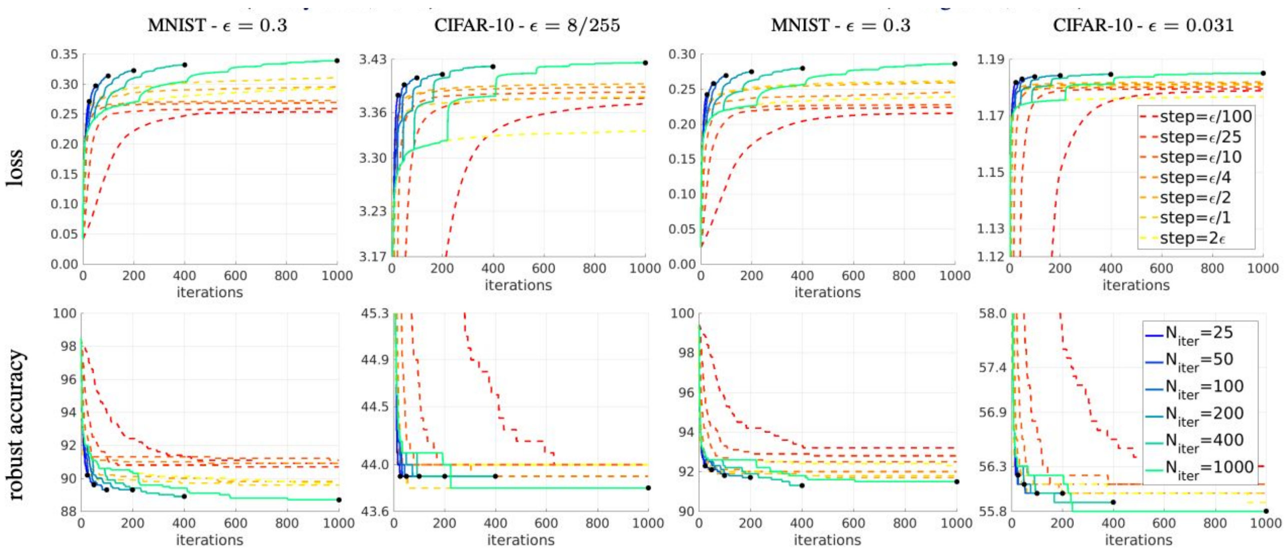
$$\text{s.t. } d(\boldsymbol{x}, \boldsymbol{x}') \le \varepsilon\,, \quad \boldsymbol{x}' \in [0,1]^n$$

Algorithm 1 APGD

Input: f, S, $x^{(0)}$, η, N_{iter}, $W = \{w_0, \dots, w_n\}$
Output: $x_{\max}$, $f_{\max}$
$x^{(1)} \leftarrow P_S\left(x^{(0)} + \eta\nabla f(x^{(0)})\right)$
$f_{\max} \leftarrow \max\{f(x^{(0)}), f(x^{(1)})\}$
$x_{\max} \leftarrow x^{(0)}$ **if** $f_{\max} \equiv f(x^{(0)})$ **else** $x_{\max} \leftarrow x^{(1)}$
for $k = 1$ **to** $N_{\text{iter}}-1$ **do**
  $z^{(k+1)} \leftarrow P_S\left(x^{(k)} + \eta\nabla f(x^{(k)})\right)$
  $x^{(k+1)} \leftarrow P_S\Big(x^{(k)} + \alpha(z^{(k+1)} - x^{(k)})$
    $+(1-\alpha)(x^{(k)} - x^{(k-1)})\Big)$
  if $f(x^{(k+1)}) > f_{\max}$ **then**
    $x_{\max} \leftarrow x^{(k+1)}$ and $f_{\max} \leftarrow f(x^{(k+1)})$
  end if
  if $k \in W$ **then**
    if Condition 1 **or** Condition 2 **then**
      $\eta \leftarrow \eta/2$ and $x^{(k+1)} \leftarrow x_{\max}$
    end if
  end if
end for

Ref https://angms.science/doc/CVX/CVX_PGD.pdf
https://www.cs.ubc.ca/~schmidtm/Courses/5XX-S20/S5.pdf
Reliable evaluation of adversarial robustness with an ensemble of diverse parameter-free attacks. Croce, F., Hein, M., ICML 2020
https://arxiv.org/pdf/2003.01690.pdf

Problem with projected gradient descent



$$\max_{\boldsymbol{x}'} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right)$$
$$\text{s.t. } d\left(\boldsymbol{x}, \boldsymbol{x}'\right) \leq \varepsilon\,, \quad \boldsymbol{x}' \in [0,1]^n$$

Tricky to set:
iteration number & step size
i.e., tricky to decide where to stop

Ref Reliable evaluation of adversarial robustness with an ensemble of diverse parameter-free attacks. Croce, F., Hein, M., ICML 2020
https://arxiv.org/pdf/2003.01690.pdf

Robustness evaluation: penalty methods for complicated d (perceptual attack)

$$\max_{\boldsymbol{x}'} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right)$$

$$\text{s.t. } d\left(\boldsymbol{x}, \boldsymbol{x}'\right) \le \varepsilon\,, \quad \boldsymbol{x}' \in [0,1]^n$$

$$d(\boldsymbol{x}, \boldsymbol{x}') \doteq \|\phi(\boldsymbol{x}) - \phi(\boldsymbol{x}')\|_2$$

$$\text{where} \quad \phi(\boldsymbol{x}) \doteq [\, \widehat{g}_1(\boldsymbol{x}), \ldots, \widehat{g}_L(\boldsymbol{x}) \,]$$

perceptual distance

Projection onto the constraint is complicated

Penalty methods

$$\max_{\widetilde{\mathbf{x}}} \quad \mathcal{L}(f(\widetilde{\mathbf{x}}), y) - \lambda \max\left(0, \|\phi(\widetilde{\mathbf{x}}) - \phi(\mathbf{x})\|_2 - \epsilon\right)$$

Solve it for each fixed λ and then increase λ

Algorithm 2 Lagrangian Perceptual Attack (LPA)

procedure LPA(classifier network $f(\cdot)$, LPIPS distance $d(\cdot,\cdot)$, input $\mathbf{x}$, label y, bound ϵ)
    $\lambda \leftarrow 0.01$
    $\widetilde{\mathbf{x}} \leftarrow \mathbf{x} + 0.01 * \mathcal{N}(0,1)$ ▷ initialize perturbations with random Gaussian noise
    for i in $1, \ldots, S$ **do** ▷ we use $S = 5$ iterations to search for the best value of λ
        for t in $1, \ldots, T$ **do** ▷ T is the number of steps
            $\Delta \leftarrow \nabla_{\widetilde{\mathbf{x}}} \left[\mathcal{L}(f(\widetilde{\mathbf{x}}), y) - \lambda \max\left(0, d(\widetilde{\mathbf{x}}, \mathbf{x}) - \epsilon\right)\right]$ ▷ take the gradient of (5)
            $\hat{\Delta} = \Delta / \|\Delta\|_2$ ▷ normalize the gradient
            $\eta = \epsilon * (0.1)^{t/T}$ ▷ the step size η decays exponentially
            $m \leftarrow d(\widetilde{\mathbf{x}}, \widetilde{\mathbf{x}} + h\hat{\Delta})/h$ ▷ $m \approx$ derivative of $d(\widetilde{\mathbf{x}}, \cdot)$ in the direction of $\hat{\Delta}$; $h = 0.1$
            $\widetilde{\mathbf{x}} \leftarrow \widetilde{\mathbf{x}} + (\eta/m)\hat{\Delta}$ ▷ take a step of size η in LPIPS distance
        end for
        if $d(\widetilde{\mathbf{x}}, \mathbf{x}) > \epsilon$ **then**
            $\lambda \leftarrow 10\lambda$ ▷ increase λ if the attack goes outside the bound
        end if
    end for
    $\widetilde{\mathbf{x}} \leftarrow \text{PROJECT}(d, \widetilde{\mathbf{x}}, \mathbf{x}, \epsilon)$
    return $\widetilde{\mathbf{x}}$
end procedure

Ref Perceptual adversarial robustness: Defense against unseen threat models. Laidlaw, C., Singla, S., & Feizi, S. https://arxiv.org/abs/2006.12655

Problem with penalty methods

Method	cross-entropy loss Viol. (%) ↓	cross-entropy loss Att. Succ. (%) ↑	margin loss Viol. (%) ↓	margin loss Att. Succ. (%) ↑
Fast-LPA	73.8	3.54	41.6	56.8
LPA	**0.00**	80.5	**0.00**	97.0
PPGD	5.44	25.5	**0.00**	38.5
PWCF (ours)	0.62	93.6	**0.00**	100

$$\max_{\boldsymbol{x}'} \ell(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}'))$$
$$\text{s.t. } d(\boldsymbol{x}, \boldsymbol{x}') \le \varepsilon, \quad \boldsymbol{x}' \in [0,1]^n$$

$$d(\boldsymbol{x}, \boldsymbol{x}') \doteq \|\phi(\boldsymbol{x}) - \phi(\boldsymbol{x}')\|_2$$
$$\text{where} \quad \phi(\boldsymbol{x}) \doteq [\, \widehat{g}_1(\boldsymbol{x}), \ldots, \widehat{g}_L(\boldsymbol{x}) \,]$$

LPA, Fast-LPA: penalty methods **PPGD**: Projected gradient descent

Penalty methods tend to encounter **large constraint violation** (i.e., infeasible solution, known in optimization theory) or **suboptimal solution**

PWCF, an optimizer with a principled stopping criterion on **stationarity & feasibility**

Ref Optimization and Optimizers for Adversarial Robustness. Liang, H., Liang, B., Peng, L., Cui, Y., Mitchell, T., & Sun, J. arXiv preprint arXiv:2303.13401.

Outline

Constrained deep learning: CDL

- What, how, and why for CDL
- **No good solvers for CDL yet**
- Granso and PyGranso
- PyGranso in action
- Outlook

DL frameworks

JAX: Autograd and XLA

mxnet

PyTorch

TensorFlow

For unconstrained DL problems

Convex optimization solvers and frameworks

CVX RESEARCH

AMPL

Modeling languages

IBM CPLEX

GUROBI OPTIMIZATION

SDPT^3 - a MATLAB software package for semidefinite-quadratic-linear programming

K. C. Toh, R. H. Tütüncü, and M. J. Todd.

TFOCS: Templates for First-Order Conic Solvers

Solvers

Not for DL, which involves NCVX optimization

Note: Gurobi can handle certain NCVX problems

Manifold optimization

Manopt.jl

Geomstats

$\mathcal{T}_p\mathcal{G}$

geoopt

McTorch Lib, a manifold optimization library for deep learning

Only for **differentiable manifolds constraints**

General constrained optimization

KNITRO

COMPUTATIONAL INFRASTRUCTURE FOR OPERATIONS RESEARCH
COIN|OR

IPOPT

Interior-point methods

ensmallen
flexible C++ library for efficient numerical optimization

GENO

Augmented Lagrangian methods

Cooper

TensorFlow Constrained Optimization (TFCO)

Lagrangian-method-based constrained optimization

Specialized ML packages

scikit learn

Spark MLlib
The Machine Learning Library

WEKA
The University of Waikato

Problem-specific solvers that **cannot be easily extended** to new formulations

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Constrained deep learning: CDL

- What, how, and why for CDL
- No good solvers for CDL yet
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Issues with typical CDL methods

projected gradient descent

$$\min_{\mathbf{x}\in\mathcal{Q}} f(\mathbf{x})$$

$$\mathbf{x}_{k+1} = P_{\mathcal{Q}}\Big(\mathbf{x}_k - \alpha_k \nabla f(\mathbf{x}_k)\Big)$$

Issue: no principled stopping criterion/step size rules

penalty methods

$$\min_{\boldsymbol{x}} \ f(\boldsymbol{x}) \quad \text{s.t.} \ \ g(\boldsymbol{x}) \leq \mathbf{0}$$

$$\min_{\boldsymbol{x}} \ f(\boldsymbol{x}) + \lambda \max(0, g(\boldsymbol{x}))$$

Solved with increasing λ sequence

Issue: infeasible solution

Lagrangian method

$$\min_{\boldsymbol{x}} \max_{\boldsymbol{\lambda}\geq\mathbf{0}} \ f(\boldsymbol{x}) + \boldsymbol{\lambda}^{\mathsf{T}} g(\boldsymbol{x})$$

Idea: alternating minimize $\boldsymbol{x}$ and maximize λ via gradient descent

Issues

- Infeasible solution
- Slow convergence

Want

- **Feasible & stationary solution**
- **Reasonable speed**

Principled answers to these questions

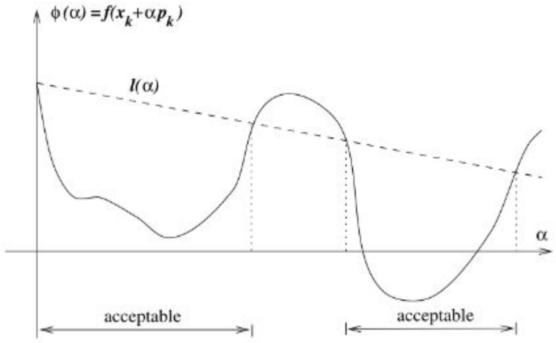
- **Feasible & stationary solution**

  Stationarity and feasibility check: KKT condition

- **Reasonable speed**

  Line search

- **A hidden problem: nonsmoothness**



Armijo (Sufficient Decrease) Condition

Key algorithm

GRANSO

http://www.timmitchell.com/software/GRANSO/

Nonconvex, nonsmooth, constrained

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} f(\boldsymbol{x}), \quad \text{s.t.} \;\; c_i(\boldsymbol{x}) \le 0, \; \forall\, i \in \mathcal{I}; \;\; c_i(\boldsymbol{x}) = 0, \; \forall\, i \in \mathcal{E}.$$

Penalty sequential quadratic programming (P-SQP)

$$\begin{aligned} \min_{d\in\mathbb{R}^n,\; s\in\mathbb{R}^p} \quad & \mu(f(x_k) + \nabla f(x_k)^\mathsf{T} d) + e^\mathsf{T} s + \frac{1}{2} d^\mathsf{T} H_k d \\ \text{s.t.} \quad & c(x_k) + \nabla c(x_k)^\mathsf{T} d \le s, \quad s \ge 0, \end{aligned}$$

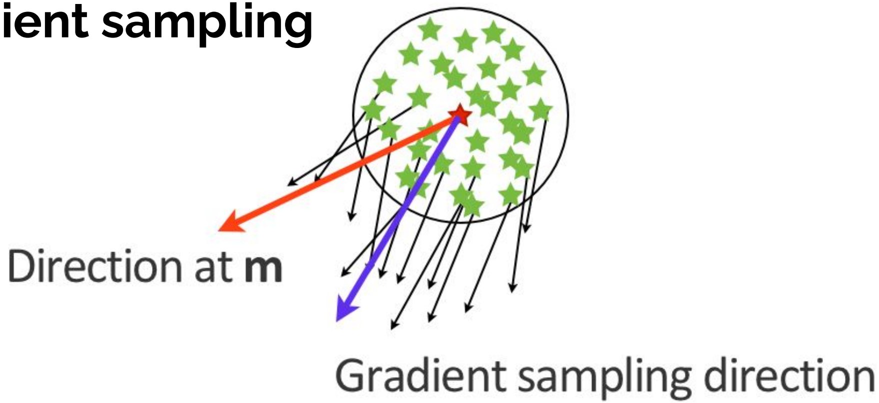
Ref: ***Curtis, Frank E., Tim Mitchell, and Michael L. Overton****. "A BFGS-SQP method for nonsmooth, nonconvex, constrained optimization and its evaluation using relative minimization profiles." Optimization Methods and Software 32.1 (2017): 148-181.*

Algorithm highlights

Steering strategy for the penalty parameter

If feasibility improvement is insufficient : $l_\delta(d_k; x_k) < c_v v(x_k)$

Stationarity based on (approximate) gradient sampling



$$G_k := [\nabla f(x^k) \quad \nabla f(x^{k,1}) \quad \cdots \quad \nabla f(x^{k,m})]$$

$$\min_{\lambda \in \mathbb{R}^{m+1}} \ \frac{1}{2}\|G_k \lambda\|_2^2$$

$$\text{s.t. } \mathbb{1}^T \lambda = 1, \ \lambda \geq 0$$

Key take-away

- Principled stopping criterion and line search, to obtain a **solution with certificate** (stationarity & feasibility check)

- Quasi-newton style method for fast convergence, i.e., **reasonable speed and high-precision solution**

Ref Curtis, Frank E., Tim Mitchell, and Michael L. Overton. "A BFGS-SQP method for nonsmooth, nonconvex, constrained optimization and its evaluation using relative minimization profiles." Optimization Methods and Software 32.1 (2017): 148-181.

Limitations of GRANSO

GRANSO

```
% Gradient of inner product with respect to A
f_grad        = imag((conj(Bty)*Cx.')/(y'*x));
f_grad        = f_grad(:);

% Gradient of inner product with respect to A
ci_grad       = real((conj(Bty)*Cx.')/(y'*x));
ci_grad       = ci_grad(:);
```

analytical gradients required

```
p             = size(B,2);
m             = size(C,1);
X             = reshape(x,p,m);
```

vector variables only

Lack of Auto-Differentiation

Lack of GPU Support

No native support of tensor variables

⇒ impossible to do deep learning with GRANSO

GRANSO meets PyTorch

GRANSO + PyTorch

PyGRANSO

NCVX PyGRANSO Documentation

Search the docs ...

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NCVX

NCVX Package

$$\min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}), \text{ s.t. } c_i(\mathbf{x}) \leq 0, \forall i \in \mathcal{I};\; c_i(\mathbf{x}) = 0, \forall i \in \mathcal{E}$$

First general-purpose solver for constrained DL problems

NCVX: A General-Purpose Optimization Solver for Constrained Machine and Deep Learning

Buyun Liang, Tim Mitchell, Ju Sun

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- **PyGranso in action**
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Example 1: Support Vector Machine (SVM)

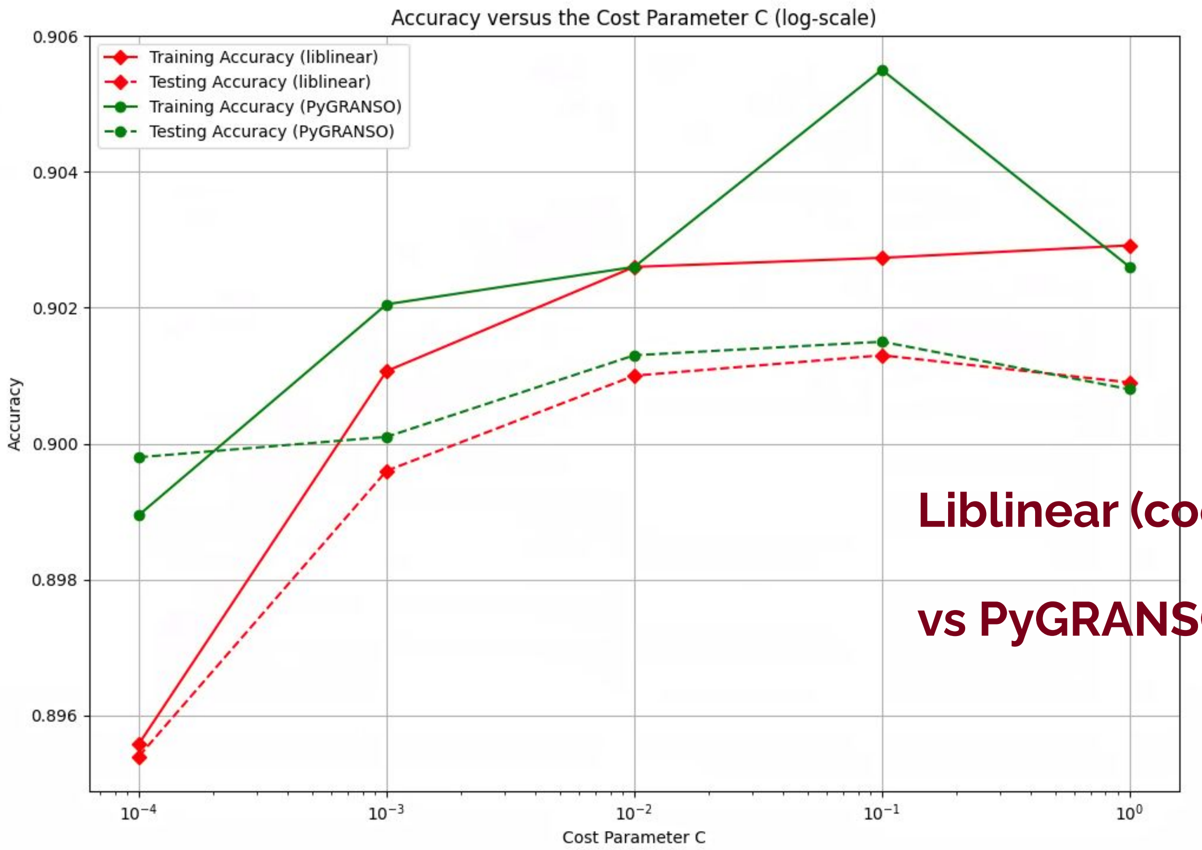
Soft-margin SVM

$$\min_{\boldsymbol{w},b,\zeta} \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{n}\zeta_i$$

$$\text{s.t.} \quad y_i\left(\boldsymbol{w}^\intercal \boldsymbol{x}_i + b\right) \geq 1 - \zeta_i,\ \zeta_i \geq 0 \ \ \forall i = 1, \ldots, n$$

```python
def comb_fn(X_struct):
    # obtain optimization variables
    w = X_struct.w
    b = X_struct.b
    zeta = X_struct.zeta
    # objective function
    f = 0.5*w.T@w + C*torch.sum(zeta)
    # inequality constraints
    ci = pygransoStruct()
    ci.c1 = 1 - zeta - y*(x@w+b)
    ci.c2 = -zeta
    # equality constraint
    ce = None
    return [f,ci,ce]
# specify optimization variables
var_in = {"w": [d,1], "b": [1,1], "zeta": [n,1]}
# pygranso main algorithm
soln = pygranso(var_in,comb_fn)
```

Binary classification (odd vs even digits) on MNIST dataset



Liblinear (coordinate descent)

vs PyGRANSO

Example 2: Robustness—min formulation

$$\begin{aligned} \min_{\boldsymbol{x}'} \quad & d(\boldsymbol{x}, \boldsymbol{x}') \\ \mathrm{s.\,t.} \quad & \max_{\ell \neq c} f_{\boldsymbol{\theta}}^{\ell}(\boldsymbol{x}') \geq f_{\boldsymbol{\theta}}^{c}(\boldsymbol{x}') \\ & \boldsymbol{x}' \in [0,1]^n \end{aligned}$$

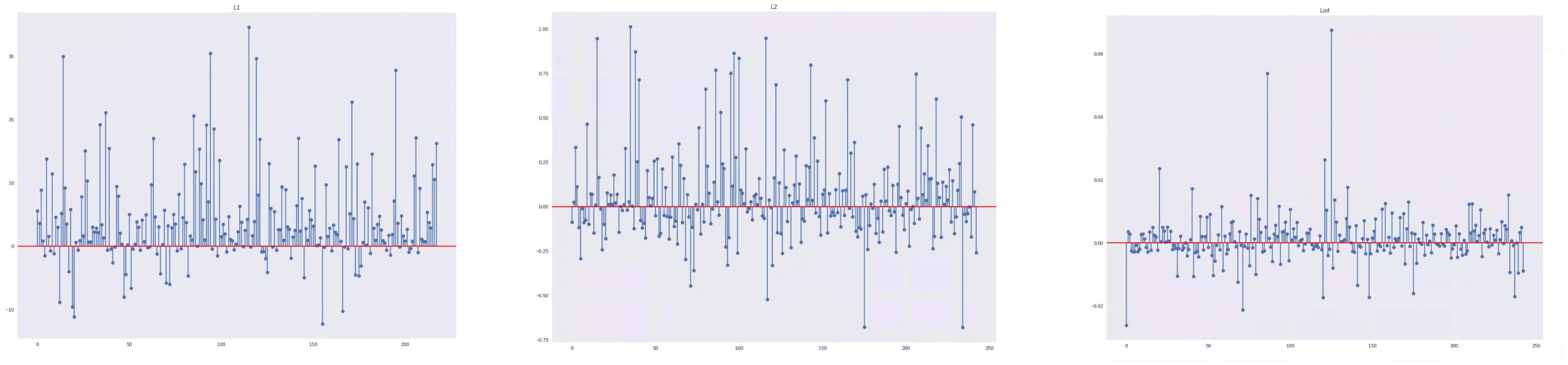
```python
def comb_fn(X_struct):
    # obtain optimization variables
    x_prime = X_struct.x_prime
    # objective function
    f = d(x,x_prime)
    # inequality constraints
    ci = pygransoStruct()
    f_theta_all = f_theta(x_prime)
    fy = f_theta_all[:,y] # true class output
    # output execpt true class
    fi = torch.hstack((f_theta_all[:,:y],f_theta_all[:,y+1:]))
    ci.c1 = fy - torch.max(fi)
    ci.c2 = -x_prime
    ci.c3 = x_prime-1
    # equality constraint
    ce = None
    return [f,ci,ce]
# specify optimization variable (tensor)
var_in = {"x_prime": list(x.shape)}
# pygranso main algorithm
soln = pygranso(var_in,comb_fn)
```

CIFAR10 dataset

Compared with FAB [iterative constraint linearization + projected gradient]
https://github.com/fra31/auto-attack

$$\min_{\boldsymbol{x}'} \quad d(\boldsymbol{x}, \boldsymbol{x}')$$
$$\text{s.t.} \quad \max_{\ell \neq c} f^{\ell}_{\boldsymbol{\theta}}(\boldsymbol{x}') \geq f^{c}_{\boldsymbol{\theta}}(\boldsymbol{x}')$$
$$\boldsymbol{x}' \in [0,1]^n$$

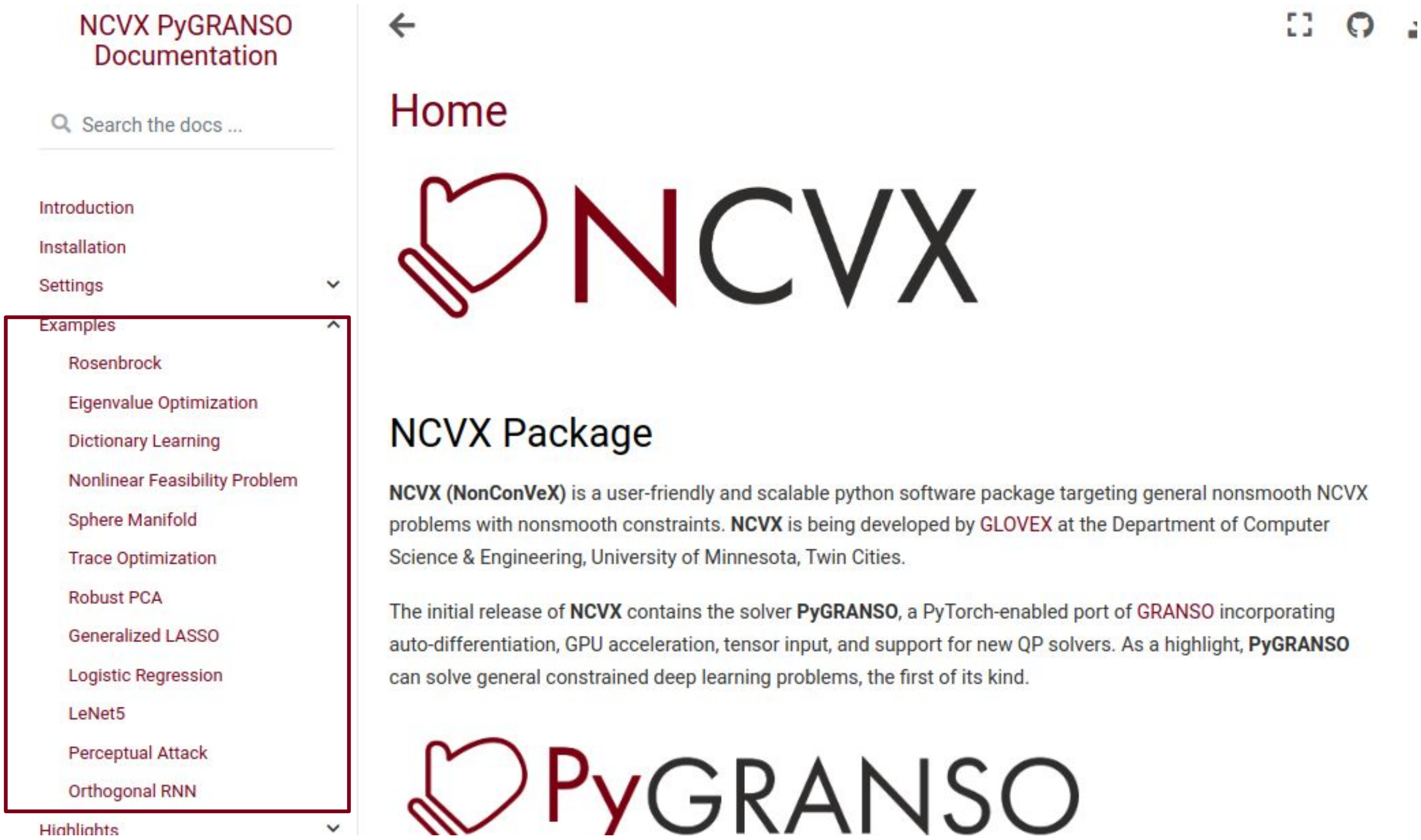
X-axis: image index; Y-axis: PyGRANSO radius - FAB radius



L1 attack **L2 attack** **Linf attack**

https://ncvx.org/

Many others



NCVX PyGRANSO Documentation

Search the docs ...

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Eigenvalue Optimization
Dictionary Learning
Nonlinear Feasibility Problem
Sphere Manifold
Trace Optimization
Robust PCA
Generalized LASSO
Logistic Regression
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Highlights

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NCVX

NCVX Package

NCVX (NonConVeX) is a user-friendly and scalable python software package targeting general nonsmooth NCVX problems with nonsmooth constraints. **NCVX** is being developed by GLOVEX at the Department of Computer Science & Engineering, University of Minnesota, Twin Cities.

The initial release of **NCVX** contains the solver **PyGRANSO**, a PyTorch-enabled port of GRANSO incorporating auto-differentiation, GPU acceleration, tensor input, and support for new QP solvers. As a highlight, **PyGRANSO** can solve general constrained deep learning problems, the first of its kind.

PyGRANSO

Closing

NCVX

Deep Learning with Nontrivial Constraints: Methods and Applications

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PyGRANSO

NCVX PyGRANSO Documentation

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$$\min_{\mathbf{x}\in\mathbb{R}^n} f(\mathbf{x}),\ \text{s.t.}\ c_i(\mathbf{x}) \le 0, \forall i \in \mathcal{I};\ c_i(\mathbf{x}) = 0, \forall i \in \mathcal{E}$$

First general-purpose solver for constrained DL problems

NCVX: A General-Purpose Optimization Solver for Constrained Machine and Deep Learning

Buyun Liang, Tim Mitchell, Ju Sun

Thanks to all contributors

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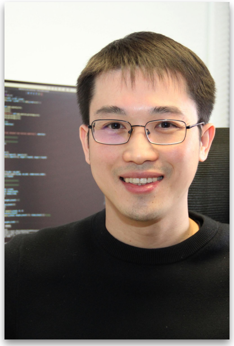

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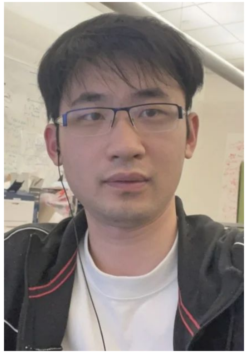

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