Deep Learning with Nontrivial Constraints

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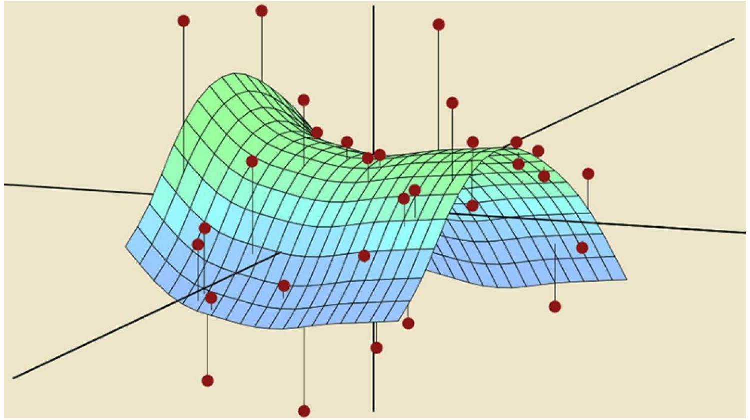
Three fundamental questions in DL



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

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

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

Isn't it solved?

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:

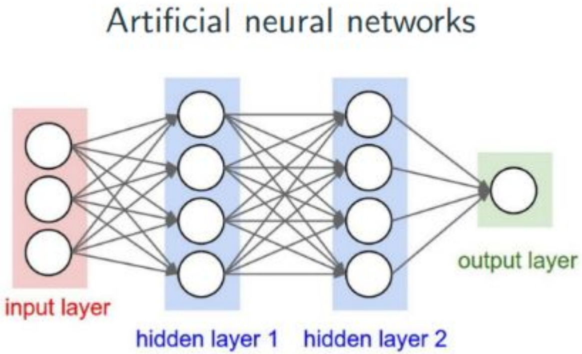
- **params** (*iterable*) – an iterable of to
  Tensors should be optimized.
- **defaults** – (dict): a dict containing d
  when a parameter group doesn't spe

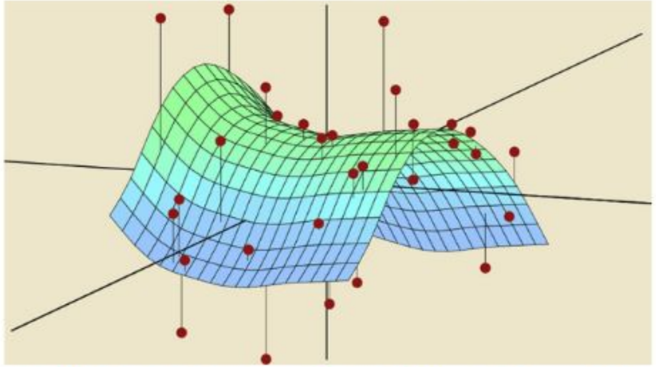
Algorithms

`Adadelta`	Implements Adadelta algorithm.
`Adagrad`	Implements Adagrad algorithm.
	lgorithm

`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.

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

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

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. $g(x) \leq 0$. 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

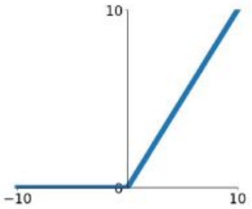
Outline

Constrained deep learning: CDL

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

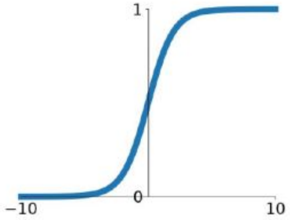
DL with simple constraints

Embedding constraints into DL models



ReLU
(Rectified Linear Unit)

Nonnegativity



Sigmoid

[0, 1]

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

Softmax

Nonnegativity and summed to 1

DL with nontrivial constraints

- Robustness evaluation
- Imbalanced learning
- Topology optimization
- Contrastive learning
- Neuro-symbolic AI

Deep Learning with Nontrivial Constraints: Methods and Applications

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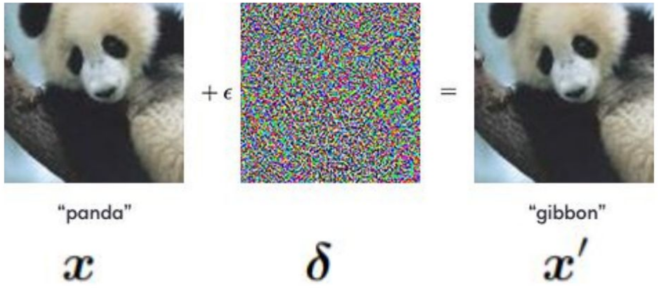
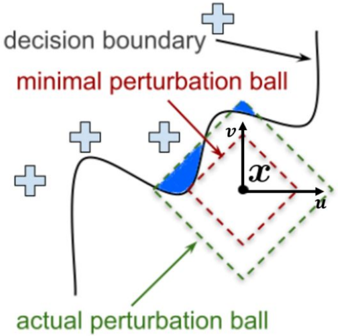
Robustness evaluation (RE)





Maximize loss function

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

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

Allowable perturbation

Valid image

Minimize robustness radius

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

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

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

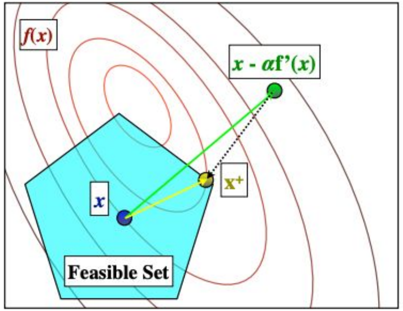
$$\min_{\mathbf{x}\in\mathcal{Q}} f(\mathbf{x})$$

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

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

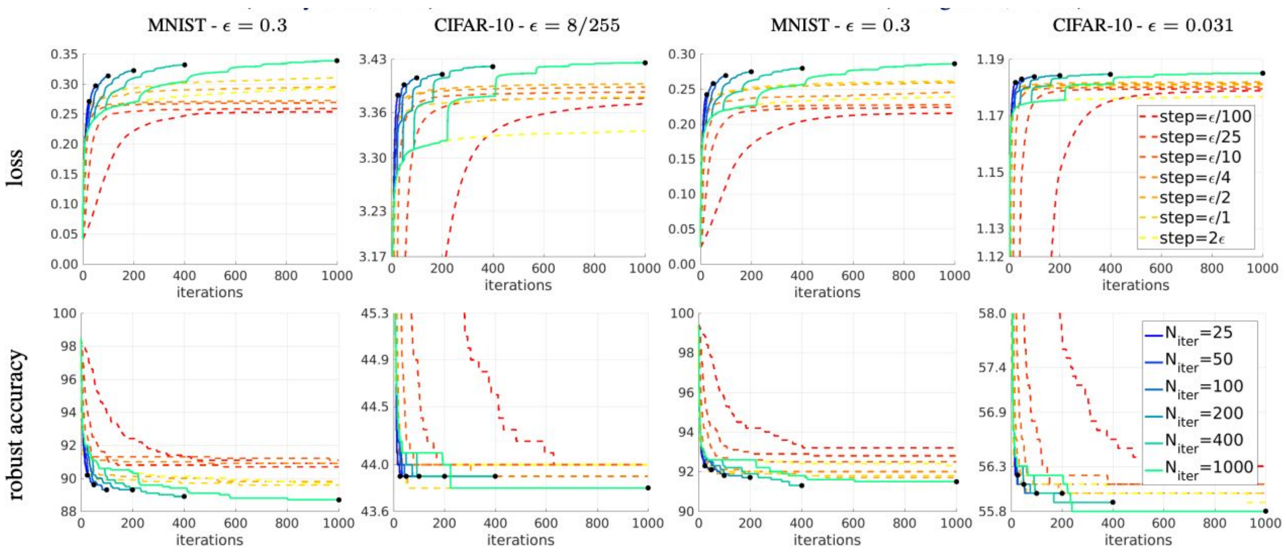
$$\text{s.t.}\; d(\boldsymbol{x}, \boldsymbol{x}') \leq \varepsilon\,, \quad \boldsymbol{x}' \in [0,1]^n$$

Algorithm 1 APGD

Input: f, S, $x^{(0)}$, η, N_{iter}, $W = \{w_0, \ldots, w_n\}$
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)

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

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

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

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

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

	cross-entropy loss		margin loss	
Method	**Viol. (%) ↓**	**Att. Succ. (%) ↑**	**Viol. (%) ↓**	**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

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

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

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

SDPT3 - 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

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

Outline

Constrained deep learning: CDL

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

projected gradient descent

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

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

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

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

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

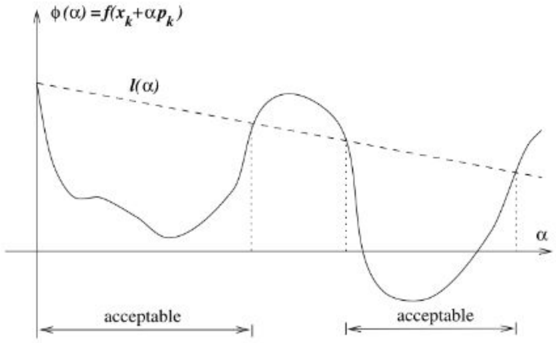
- **Feasible & stationary solution**

  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

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

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

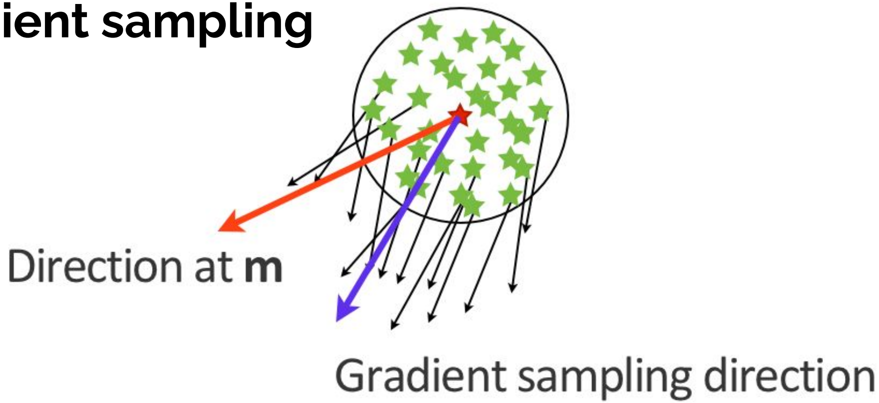
If feasibility improvement is insufficient : $l_\delta(d_k; x_k) < c_v v(x_k)$

Stationarity based on (approximate) gradient sampling

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

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

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



Key take-away

GRANSO

- 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 ...

Introduction

Installation

Settings

Examples

Home

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

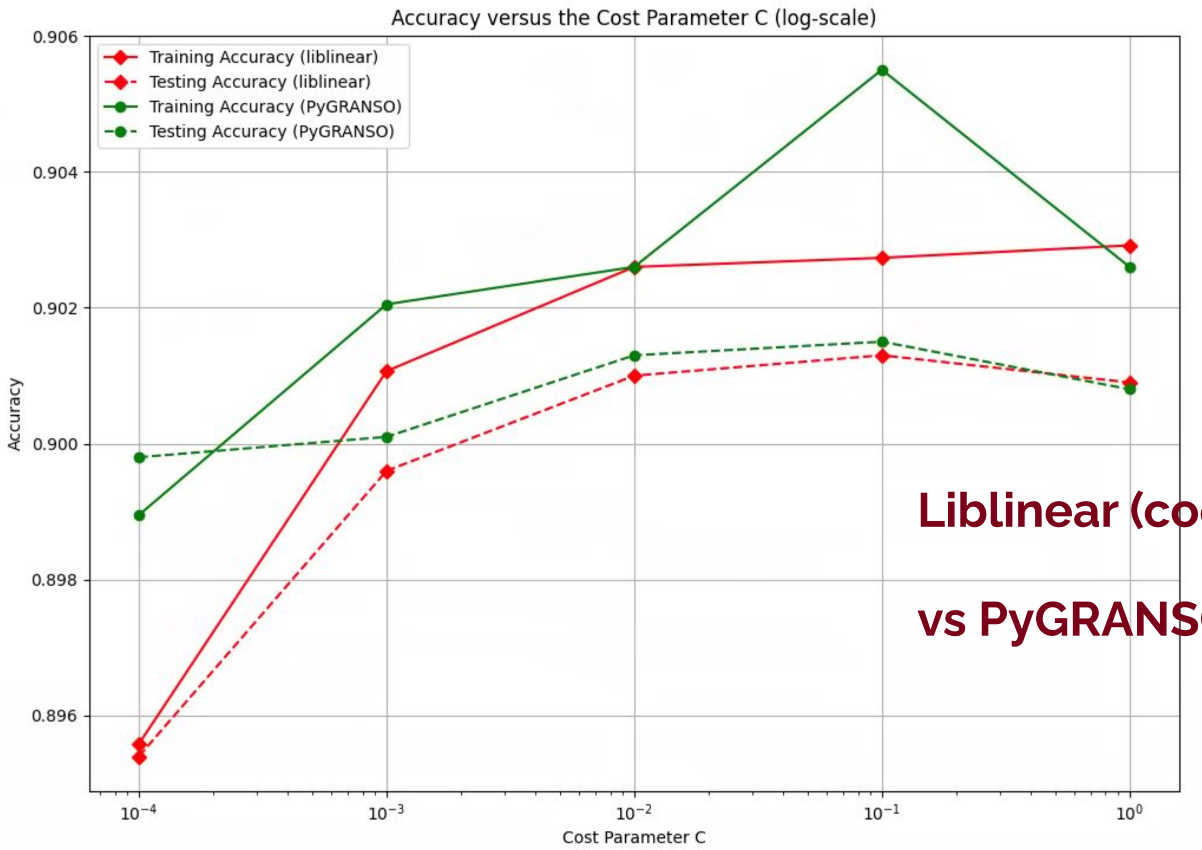
Soft-margin SVM

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

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

```
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

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

```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)
```

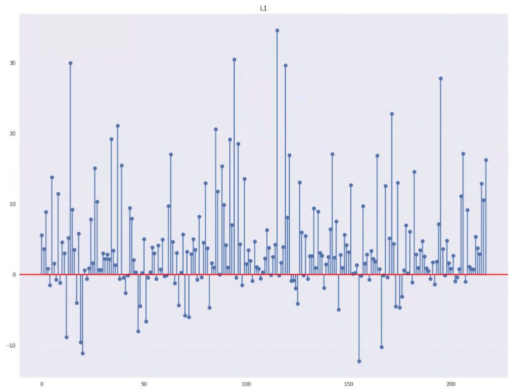
CIFAR10 dataset

Compared with FAB [iterative constraint linearization + projected gradient]

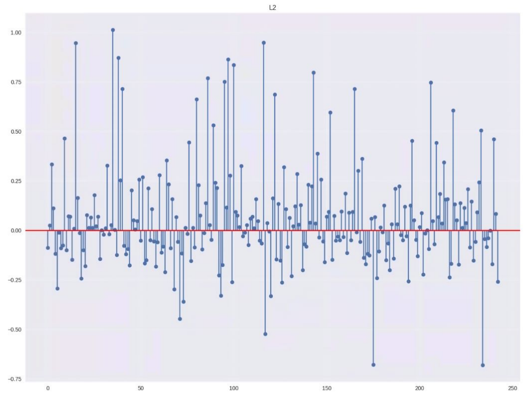
https://github.com/fra31/auto-attack

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

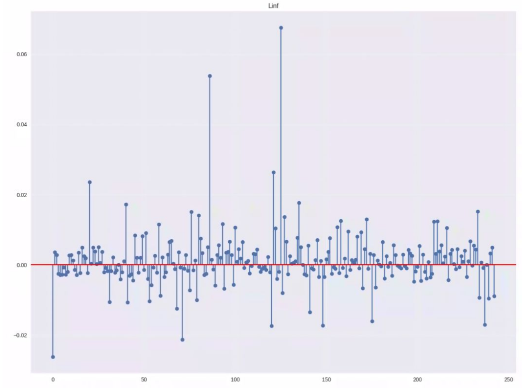
X-axis: image index; Y-axis: PyGRANSO radius - FAB radius



L1 attack



L2 attack



Linf attack

https://ncvx.org/

Many others

NCVX PyGRANSO Documentation

Search the docs ...

- Introduction
- Installation
- Settings
- Examples
  - Rosenbrock
  - Eigenvalue Optimization
  - Dictionary Learning
  - Nonlinear Feasibility Problem
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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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NCVX

NCVX Package

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

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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(CS, Queens Col.)

Prof. Ying Cui
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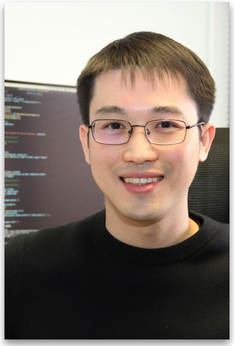

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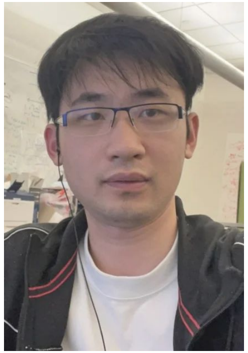

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