Course Assignment: Project
Skoltech BMML'20, Moscow

Improving Explorability in Variational Inference with Annealed Variational Objectives

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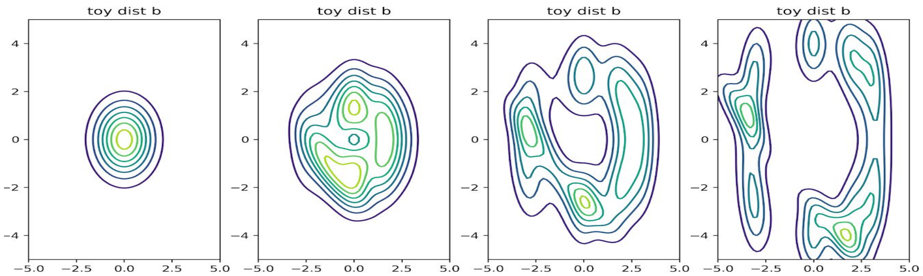
Improving Explorability in Variational Inference with Annealed Variational Objectives. The problem study.



Variational Inference ~ reducing representational bias ~ amortized VI, Variational Auto-Encoders (VAE)

- expressive families of variational distributions >> losing the computational tractability
- reducing the amortization error introduced by the use of a conditional network
- non-parametric methods
  - Importance Weighted Auto-Encoder (IWAE) >> multiple samples >> computationally difficult

Proposed method

- Continuous objective landscape transformation ~ annealed objectives >> Hierarchical VI methods

Project proposal

- demonstrate posterior collapse on toy example
    - show how method from AVO can mitigate this problem
- check if Variational Auto-Encoder (VAE) can be improved by the AVO method on the MNIST dataset.

Find corner cases for the method

Propose any extension

HouseholderAVO [4]

Project outline

The problem of study and motivation:

Analyze behaviour of proposed model, estimate performance , compare with original and similar methods.

1. Implementation of
   a. Variational Auto-Encoder (VAE) [3] with parameters from [4].
   b. Hierarchical Variational Model (HVM) based on [5].
   c. Importance Weighted Auto-Encoder (IWAE) based on [6].
   d. Hierarchical Variational Inference (HVI) method based on [5].
   e. Annealed Variational Objectives (**AVO**) method [1].
2. Analyze a behavior **AVO** method on toy examples.
3. Conduct experiments with VAE and **AVO** on the MNIST and CelebA datasets.

Project experiments

1. Implementation of
   a. Variational-Auto Encoder (VAE) [3] with parameters from [4].
   b. Hierarchical Variational Model (HVM) based on [5].
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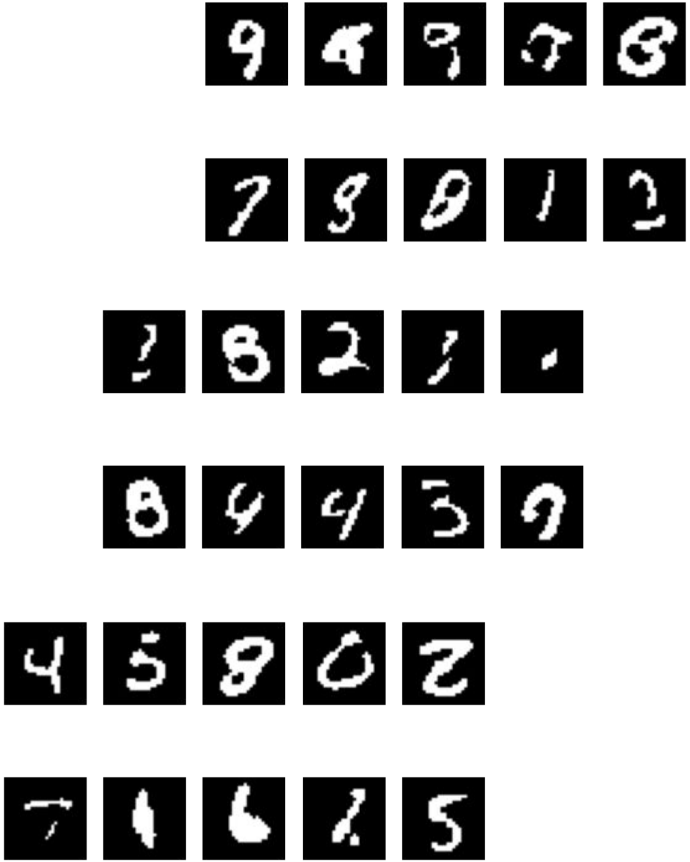
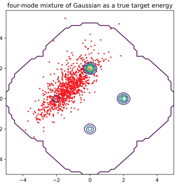
   d. Hierarchical Variational Inference (HVI) method based on [5].
   e. Annealed Variational Objectives (**AVO**) method [1].
2. Analyze a behavior **AVO** method on toy examples.
3. Conduct experiments with VAE and **AVO** on the MNIST and CelebA datasets.

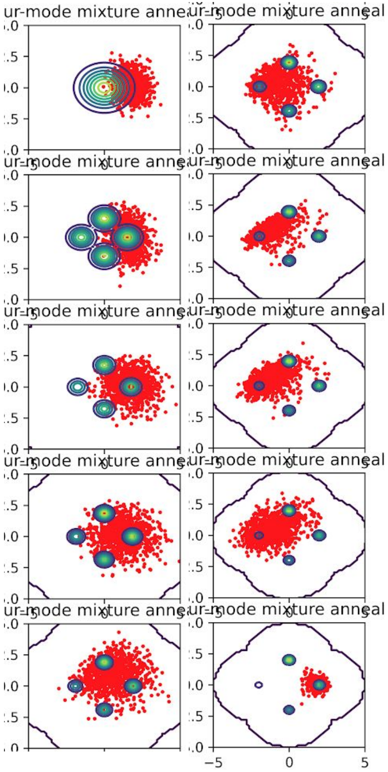
Project experiments
VAE - VAE HVI - VAE HVI AVO

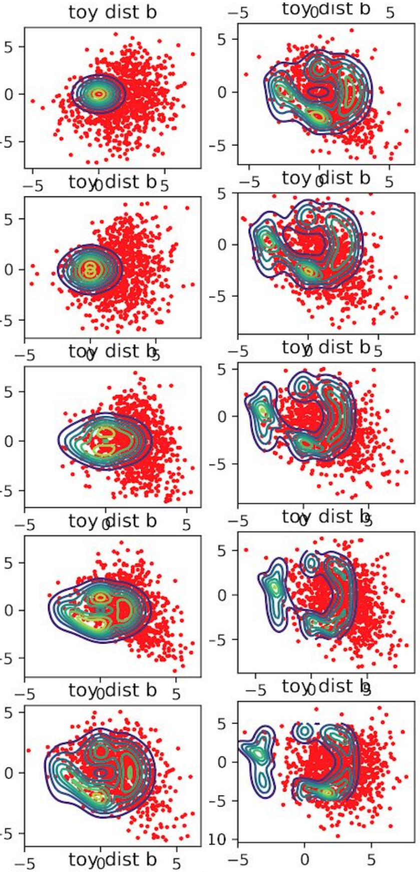
	VAE	VAE HVI AVO	VAE HVI AVO
loss			

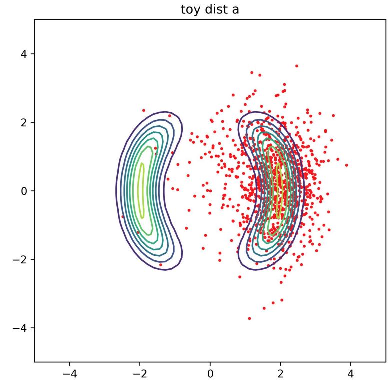


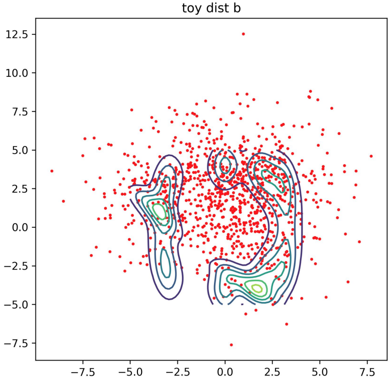
Toy energy fitting
HVI AVO



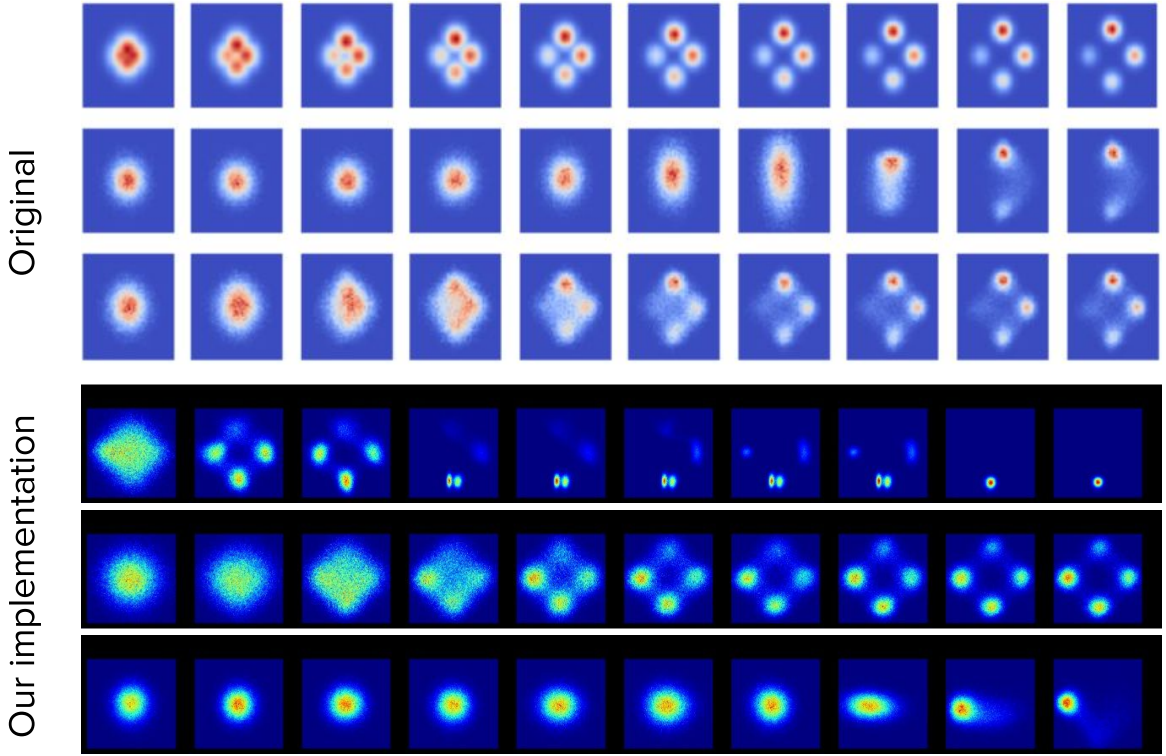








Toy energy fitting: four-mode mixture of Gaussian



Project Code

- https://github.com/alexey-pronkin/annealed
    - AVO.ipynb - Colaboratory
    - HVI.ipynb - Colaboratory
    - VAE_HVI.ipynb - Colaboratory

Models from experiments:

- HVI https://drive.google.com/drive/folders/
-
-

Project Report

Results VAE HVI

Results

Methods	NLL - paper results	Our result
inverse autoregressive flow (IAF)	86.70	
convex combination of IAFs	86.10	
HVI	87.62	
HVI-AVO	86.06	
VAE		93
VAE-HVI		120
VAE HVI AVO		119

Evaluation

The ML reproducibility checklist was first released during NeurIPS 2018 to provide the community with a practical tool for checking that a machine-learning paper contained necessary components and evidence to support its claims

Not following the submission time of report and presenfile:///home/tim/git/annealed/data/transitions_targets_abc.pngtation at the Canvas = 0

points

Structure and clarity of the repo

Quality and relevance the project

Technical quality

Originality of the experiments, ideas

Quality of figures, narrative structure

Check the NIPS Reproducibility Checklist

Project presentation defence

We will write the formal review, as for paper submission, based on the proposal

and presentation

References

joelouismarino/iterative_inference/
jmtomczak/vae_householder_flow
AntixK/PyTorch-VAE
haofuml/cyclical_annealingand
ajayjain/lmconv

[1] C. Huang, Shawn Tan, Alexandre Lacoste, and Aaron C. Courville. Improving explorability invariational inference with annealed variational objectives.ArXiv, abs/1809.01818, 2018.
[2] James Lucas, George Tucker, Roger Grosse, and Mohammad Norouzi. Understanding posterior collapse in generative latent variable models. 2019.
[3] Diederik P Kingma and Max Welling. Auto-encoding variational bayes, 2013.
[4] Jakub M Tomczak and Max Welling. Improving variational auto-encoders using householder flow.arXiv preprint arXiv:1611.09630, 2016.
[5] Rajesh Ranganath, Dustin Tran, and David M. Blei. Hierarchical variational models, 2015.
[6] Yuri Burda, Roger Grosse, and Ruslan Salakhutdinov. Importance weighted autoencoders,2015.
[7] Jeremias Knoblauch, J. Jewson, and T. Damoulas. Generalized variational inference.ArXiv,abs/1904.02063, 2019.