
Learning Exponential Families

Anonymous Author(s)

Affiliation

Address

email

Abstract

[SLOPPY NOTES STAGE JUST TO GET THOUGHTS DOWN]

Recently much attention has been paid to probabilistic models defined by a deep neural network transformation of a simpler random variable; these implicit generative models have been used to great success across variational inference, generative modeling of complex data types, and more. In essentially all of these settings, the model is specified by the network architecture, and a particular member of that model is chosen to minimize some loss (be it adversarial or information divergence)

We treat the problem of learning an exponential family – the model itself, rather than the typical setting of learning a particular member of that model.

Many intractable distributions encountered in machine learning belong to exponential families. In rare cases these distributions are tractable due to either known conjugacy in the problem setup (such as the normal-inverse-Wishart), or due to careful numerical work historically that has made these distributions computationally indistinguishable from tractable (eg the Dirichlet).

1 Introduction

People use lots of implicit generative models:

Across machine learning, including ABC [?] , GANs [1], VAEs [2, 3], and their many follow-ons (too numerous to cite in any detail), models that specify a distribution via the nonlinear transformation of latent random variable. We prefer and use the terminology of [4], calling such a distribution an *implicit generative model*, defined as:

something like eq 1 and 2 in Mohamed:2016aa, defining $q_{\theta}(z)$

Also use the proper notation of the density implied by the pushforward measure of the function $f_{\theta\sharp}$ if useful. Also reference to this being super standard and widespread [5]. The two central uses are at present generative distributions of interesting data types (as in GANs), and for variational inference. Regardless, all of these use cases specify a *model* (or variational family) $\mathcal{Q} = \{q_{\theta} : \theta \in \Theta\}$, and then minimize a suitable loss $\mathcal{L}(q, p)$ over $q \in \mathcal{Q}$. In the case of VI p is the posterior (or the unnormalized log joint) and \mathcal{L} is the *KL* divergence (or so called ELBO), in GAN p is the sample density of a (large) dataset and \mathcal{L} is the adversarial objective whose details do not matter here.

All these learn a single member of a family

Inherent in all the above approaches is an algorithmic procedure to select a *single* distribution $q_{\theta}(z)$ from among the *model* \mathcal{Q} . Implicit in this effort is the belief that \mathcal{Q} is suitably general to contain the true distribution of interest, or at least an adequately close approximation.

Here we learn the family

We leverage the natural parameterization of exponential families to derive a novel objective that is amenable to stochastic optimization.

31 *A note on amortization*

32 Several have pointed out that these IGMs are in fact strictly less expressive than a mean field, at
33 least in the conventional VI setting. See for example [http://dustintran.com/blog/variational-auto-](http://dustintran.com/blog/variational-auto-encoders-do-not-train-complex-generative-models)
34 [encoders-do-not-train-complex-generative-models](http://dustintran.com/blog/variational-auto-encoders-do-not-train-complex-generative-models) (here I like the line “The neural network used in
35 the encoder (variational distribution) does not lead to any richer approximating distribution. It is a
36 way to amortize inference such that the number of parameters does not grow with the size of the data
37 (an incredible feat, but not one for expressivity!) (Stuhlmüller et al., 2013)”). You have to optimize
38 for every data point individually, or instead you get to do so in aggregate once in advance (at a much
39 higher cost) and then recover that cost over future data points within that distribution (and hence the
40 term amortization, though perhaps there is shared statistical power as well) Etc etc what we are doing
41 here is *amortized* amortized inference, in the sense that we are amortizing not the data points, but the
42 distribution itself.

43 REparameterization trick (Kingma and Welling (2013), Rezende et al. (2014) and Titsias and
44 Lazaro-Gredilla 2014).. See also Archer 2015 / Gao 2016 for clean explanation.

45 *Our contributions include:*

46 ...

47 *Our results demonstrate*

48 ...

49 **2 Learning exponential families**

50 *Why this is important*

51 Exp fams are awesome and fundamental []. Also [?] rightly point out that many many inference
52 problems can be cast as exponential families. Can we cast the VAE encoder network as a suitable
53 exp fam... sure I think that’s right; the network parameters of z form the statistics, and then the
54 observations are η ’s.

55 *Why this is coherent*

56 Θ defines quite a big \mathcal{Q} , and indeed the subject of compressibility, generalization, etc is of keen
57 interest to many [?]. So actually the space of distributions is quite large, and in many cases certainly
58 larger than it needs be. Why? Well, we know precisely the parameter space of the exponential family;
59 it is defined by the *natural* parameters $\eta \in \mathbb{R}^p$ (or whatever we choose there).

60 *Figure 1*

61 Figure of model space. Yeah that’s good. Then graphical model. Note that perhaps \mathcal{Q} is too big,
62 and a simpler model space (the $\|\eta\|$ dimensional subspace of Θ) would be better for the usual
63 robustness/generalization reasons.

64 *Aside*

65 A neat idea is to ask if learning the $\theta(\eta)$ network leads to better VI in terms of inference networks,
66 since it is apparently appropriately regularized and can just take suff stats. That’s testable if we have
67 time.

68 *Why Flow Networks*

69 We choose flow networks [] and [] because duh. That makes these comparisons legitimate and apples
70 to apples. Any generalization of this is also dandy though, so could use a mean field approach
71 (standard) or any of the things that go beyond mean field, either classically (Saul and Jordan, 1996;
72 Barber and Wierwille, 1999); this is called *structured variational inference*. Another way to expand
73 the family is to consider mixtures of variational densities, i.e., additional latent variables within the
74 variational family (Bishop et al., 1998). or newer stuff [] [Tran Copula VI, Hoffman and Blei 2015].

75 In many situations, statistical inference attempts to learn, at least approximately, a member of an
76 exponential family. We often consider this exponential family intractable in the sense that we don’t
77 know how to normalize or sample from it. Approximate inference, such as variational

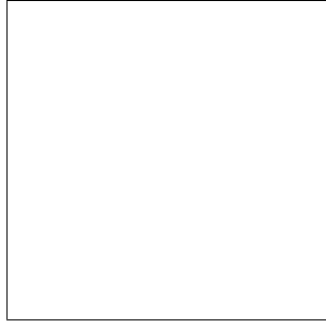


Figure 1: Figure 1: possibly Fig 7.2 bias-variance tradeoff and then benefit of a restricted model from Hastie Book, or similar from W4400 (ask PO for batman permission).

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	~ 100
Axon	Output terminal	~ 10
Soma	Cell body	up to 10^6

78 3 To Do

79 3.1 SRB

- 80 • set up submission at <https://cmt.research.microsoft.com/NIPS2018/>
- 81 • review and conform to style requirements (see website with template); 8 pages not including
- 82 refs and acks and appendices.

83 3.2 JPC

- 84 • Outline
- 85 • Write

```
86 \usepackage[pdftex]{graphicx} ...
87 \includegraphics[width=0.8\linewidth]{myfile.pdf}
```

88 **Acknowledgments**

89 Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end
90 of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper.

91 **References**

92 **References**

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- 103 Stuff on wake sleep and the Helmholtz machine
- 104 Stuff on sampling from Gibbs distributions (max ent models), and sampling from exp fams generally,
105 with MCMC and such.
- 106 Flow networks
- 107 Devroye’s book.
- 108 Hoffman et al 2013 SVI
- 109 From Blei review on VI. The development of variational techniques for Bayesian inference followed
110 two parallel, yet separate, tracks. Peterson and Anderson (1987) is arguably the first variational
111 procedure for a particular model: a neural network. This paper, along with insights from statistical
112 mechanics (Parisi, 1988), led to a flurry of variational inference procedures for a wide class of models
113 (Saul et al., 1996; Jaakkola and Jordan, 1996, 1997; Ghahramani and Jordan, 1997; Jordan et al.,
114 1999). In parallel, Hinton and Van Camp (1993) proposed a variational algorithm for a similar neural
115 network model. Neal and Hinton (1999) (first published in 1993) made important connections to the
116 expectation maximization (EM) algorithm (Dempster et al., 1977), which then led to a variety of
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