Semi-supervised Learning with Deep Generative Models
Kingma et. al. (2014)

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CS 7180

Motivating Question

How can we model data of increasing size when obtaining label information is difficult?

High-level Answer

We can estimate missing label information by using a probabilistic model.

Most Relevant Previous Work

Pitelis, N., Russell, C., and Agapito, L. (2014). Semi-supervised learning using an unsupervised atlas. *In Proceddings of the European Conference on Machine Learning (ECML)*, volume LNCS 8725, pages 565 – 580.

- ▶ Observing that high-dimensional datasets often lie on or near *manifolds* of locally low rank can help avoid the *curse of dimensionality*
- ▶ Experiments show how using unlabelled data to learn the underlying manifold improves classifier accuracy when trained on limited labelled data
    1. **Unsupervised learning of the underlying manifold:** Approximate the manifold of data on the original space by fitting an atlas of low-dimensional overlapping affine charts.
    2. **Supervised training of an SVM:** Proposed a new family of Mercer Kernels for SVM-based supervised learning which uses soft-assignment of datapoints to the underlying low-dimensional affine charts to generate the kernels

Specifying the Probabilistic Model for Missing Labels

Kingma et. al. (2014)

- ▶ Data appears as pairs $(\mathbf{X}, \mathbf{Y}) = \{(\mathbf{x}_1, y_1), ..., (\mathbf{x}_N, y_N)\}$ with the i-th observation $x_i \in \mathbb{R}^D$ and a corresponding class label $y_i \in \{1, ..., L\}$
    - ▶ Each pair of observations (x_i, y_i) has a corresponding latent variable z_i
    - ▶ Empirical distribution over the labelled and unabelled subsets is referred to as $\tilde{p}_l(\mathbf{x}, y)$ and $\tilde{p}_u(\mathbf{x})$
- ▶ We can estimate y_i for x_i in distribution $\tilde{p}_u(\mathbf{x})$ by finding the maximum probability of $p(y_i)$ by using a set of features related to z_i and a predictive model
    1. **Latent-feature discriminative model (M1)**
    2. **Generative semi-supervised model (M2)**
    3. **Stacked generative semi-supervised model (M1+M2)**

Bayes Rule is used when specifying M1 & M2

$$p(x, y) = p(x)p(y|x)$$
$$= p(y)p(x|y)$$
$$p(x|y) = \frac{p(x)p(y|x)}{p(y)}$$

for models M1 [1], $p(z|x)$, and M2 [2]; $p(y|x)$

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[1]Kingma et. al. (2014) equation (1)
[2]Kingma et. al. (2014) equation (2)

(M1) Latent-feature discriminative model

$$y \Leftarrow p(z|x) = \frac{p(z)p(x|z)}{p(x)}$$

where

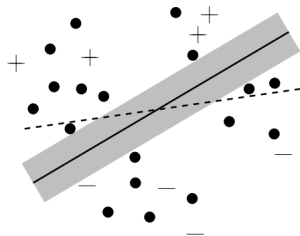$p(z) = \mathcal{N}(z|0, I)$ Gaussian distribution of z given a missing label y

$p(x|z) = f(x; z, \theta)$ likelihood function, parameters θ of a set of z

$p(x) = \tilde{p}_u(x)$ unlabelled subset of $x_i \in \mathbb{R}^D$

Kingma et. al. (2014) eq. (1)

(M1) Predicting Class Labels y

Approximate samples from the posterior distribution over the latent variables $p(z|x)$ are used as features to train a classifier that predicts class labels y

(transductive) SVM[3] finds the largest margin w.r.t. the training **and** the test vectors

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[3] See Figure 6.2 from Chapelle, O., B. Schölkopf, and A. Zien. "Semi-Supervised Learning." (2006).

(M2) Generative semi-supervised model

$$p(y|\mathbf{x}) = \frac{p(\mathbf{x}|y)p(y)}{p(\mathbf{x})} \approx \frac{p_\theta(\mathbf{x}|y, \mathbf{z})p(y)}{p(\mathbf{x})}$$

where

$$
\begin{aligned}
p(y) &= Cat(y|\pi) && \text{multinomial distribution, } y \text{ can be latent} \\
p(\mathbf{z}) &= \mathcal{N}(\mathbf{z}|\mathbf{0}, \mathbf{I}) && \text{Gaussian distribution of } z \text{ when missing } y \\
p_\theta(\mathbf{x}|y, z) &= f(\mathbf{x}; y, \mathbf{z}, \theta) && \text{likelihood function, nonlinear parameters} \\
p(x) && & \text{all } x \text{ in dist. of real numbers; } x \in \mathbb{R}^D
\end{aligned}
$$

Stacked generative semi-supervised model (M1 + M2)

Combine M1 and M2

1. Learn a new latent representation z_1 from M1
2. Use embeddings from z_1 instead of raw data x, to create a generative semi-supervised model M2

TODO: Add a picture or something here

Scaling Up: Lower Bound Objective

Lower Bound Objective[4]: computation of the exact posterior distribution is intractable for models M1 and M2

$$M1: \ q_\phi(z|x) = \mathcal{N}(z|u_\phi(x), \text{diag}(\sigma_\phi^2(\mathbf{x}))) \tag{3}$$

$$M2: \ q_\phi(\mathbf{z}|y, \mathbf{x}) = \mathcal{N}(\mathbf{z}|\mu_\phi(y, \mathbf{x}), \text{diag}(\sigma_\phi^2(\mathbf{x})));$$

$$q_\phi(y|\mathbf{z}) = \text{Cat}(y|\pi_\phi(x)), \tag{4}$$

where

$$\sigma_\phi(x) \qquad \text{vector of standard deviations}$$
$$\pi_\phi(x) \qquad \text{probability vector}$$
$$\mu_\phi(x), \sigma_\phi(x), \pi_\sigma(x) \qquad \text{Maximum likelihood Priors (MLPs)}$$

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[4]Kingma et. al. (2014) equations (3), (4)

Scaling Up: M1 Model Objective

$$\log p_\theta(x) \geq \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - KL[q_\phi(z|x)||p_\theta(z)] = -\mathcal{J}(x)$$

Equation 5

Scaling Up: M2 Model Objective

When y_i is observed for the (x_i, y_i) data pair, extend from M1

$$\log p_\theta(x) \geq \mathbb{E}_{q_\phi(z|x,y)}[\log p_\theta(x|y,z) + \log p_\theta(y) + \log p(z) - q_\theta(z|x,y)]$$
$$= -\mathcal{L}(x,y)$$

In the case where y_i is missing,

$$\log p_\theta(x) \geq \mathbb{E}_{q_\phi(y,z|x)}[\log p_\theta(x|y,z) + \log p_\theta(y)$$
$$+ \log p(z) - \log q_\phi(y,z|x)]$$
$$= \sum_y q_\phi(y|x)(-\mathcal{L}(x,y)) + \mathcal{H}(q_\phi(y|x))$$
$$= -\mathcal{U}(x)$$

The bound on the marginal likelihood for the entire dataset is now[5]

$$\mathcal{J} = \sum_{(x,y)\sim\tilde{p}_l} \mathcal{L}(x,y) + \sum_{x\sim\tilde{p}_u} \mathcal{U}(x)$$

[5]See Kingma et. al. (2014) equations 6-9

Optimization Techniques

- Not using the EM algorithm, that's interesting, why
  - perform efficient joint inference that's easy to scale (pg. 7)
- Using AdaGrad

$$\nabla_{\{\theta,\phi\}}\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] = \mathbb{E}_{\mathcal{N}(\epsilon|0,I)}[\nabla_{\{\theta,\phi\}} \log p_\theta(x|\mu_\theta(x)+\sigma_\phi(x)\odot\epsilon)].$$

Kingma et. al. (2014) equation 11

Optimization Algorithms

Algorithm 1 Learning in model M1

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   while generativeTraining() **do**
      $\mathcal{D} \leftarrow$ getRandomMiniBatch()
      $\mathbf{z}_i \sim q_\phi(\mathbf{z}_i | \mathbf{x}_i) \quad \forall \mathbf{x}_i \in \mathcal{D}$
      $\mathcal{J} \leftarrow \sum_n \mathcal{J}(\mathbf{x}_i)$
      $(\mathbf{g}_\theta, \mathbf{g}_\phi) \leftarrow (\frac{\partial \mathcal{J}}{\partial \theta}, \frac{\partial \mathcal{J}}{\partial \phi})$
      $(\boldsymbol{\theta}, \boldsymbol{\phi}) \leftarrow (\boldsymbol{\theta}, \boldsymbol{\phi}) + \boldsymbol{\Gamma}(\mathbf{g}_\theta, \mathbf{g}_\phi)$
   end while
   while discriminativeTraining() **do**
      $\mathcal{D} \leftarrow$ getLabeledRandomMiniBatch()
      $\mathbf{z}_i \sim q_\phi(\mathbf{z}_i | \mathbf{x}_i) \quad \forall \{\mathbf{x}_i, y_i\} \in \mathcal{D}$
      trainClassifier($\{\mathbf{z}_i, y_i\}$)
   end while

Algorithm 2 Learning in model M2

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   while training() **do**
      $\mathcal{D} \leftarrow$ getRandomMiniBatch()
      $y_i \sim q_\phi(y_i | \mathbf{x}_i) \quad \forall \{\mathbf{x}_i, y_i\} \notin \mathcal{O}$
      $\mathbf{z}_i \sim q_\phi(\mathbf{z}_i | y_i, \mathbf{x}_i)$
      $\mathcal{J}^\alpha \leftarrow$ eq. (9)
      $(\mathbf{g}_\theta, \mathbf{g}_\phi) \leftarrow (\frac{\partial \mathcal{L}^\alpha}{\partial \theta}, \frac{\partial \mathcal{L}^\alpha}{\partial \phi})$
      $(\boldsymbol{\theta}, \boldsymbol{\phi}) \leftarrow (\boldsymbol{\theta}, \boldsymbol{\phi}) + \boldsymbol{\Gamma}(\mathbf{g}_\theta, \mathbf{g}_\phi)$
   end while

Results: Benchmark Classification

Table 1: Benchmark results of semi-supervised classification on MNIST with few labels.

N	NN	CNN	TSVM	CAE	MTC	AtlasRBF	M1+TSVM	M2	M1+M2
100	25.81	22.98	16.81	13.47	12.03	8.10 ($\pm$ 0.95)	11.82 ($\pm$ 0.25)	11.97 ($\pm$ 1.71)	**3.33** ($\pm$ 0.14)
600	11.44	7.68	6.16	6.3	5.13	–	5.72 ($\pm$ 0.049)	4.94 ($\pm$ 0.13)	**2.59** ($\pm$ 0.05)
1000	10.7	6.45	5.38	4.77	3.64	3.68 ($\pm$ 0.12)	4.24 ($\pm$ 0.07)	3.60 ($\pm$ 0.56)	**2.40** ($\pm$ 0.02)
3000	6.04	3.35	3.45	3.22	2.57	–	3.49 ($\pm$ 0.04)	3.92 ($\pm$ 0.63)	**2.18** ($\pm$ 0.04)

Results: Image Classification

Table 2: Semi-supervised classification on the SVHN dataset with 1000 labels.

KNN	TSVM	M1+KNN	M1+TSVM	M1+M2
77.93	66.55	65.63	54.33	**36.02**
($\pm$ 0.08)	($\pm$ 0.10)	($\pm$ 0.15)	($\pm$ 0.11)	($\pm$ 0.10)

Table 3: Semi-supervised classification on the NORB dataset with 1000 labels.

KNN	TSVM	M1+KNN	M1+TSVM
78.71	26.00	65.39	**18.79**
($\pm$ 0.02)	($\pm$ 0.06)	($\pm$ 0.09)	($\pm$ 0.05)

Discussion

You can use this model for a few things
TODO: just summarize their discussion

Any questions? Thanks!