# Semi-Supervised Chest X-Ray Pneumonia Classification using Auxiliary Deep Generative Models

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## Introduction

Pneumonia accounts for over 15% of all deaths of children under 5 years old internationally. In 2015, 920,000 children under the age of 5 died from the disease. Chest X-Rays (CXRs) are the most commonly performed diagnostic imaging study. The availability of radiologists is however low: as a result radiologists are overburdened, and unqualified generalist practitioners are often left with the task of image analysis. The availability of ground truth data, in some cases, is scarse. With these premises, it is clear that there is a strong need of an automatic classification model that can learn with just few examples. We propose a generative model that can classify CXRs images from few labelled samples while obtaining competitive results.

## Model Specification

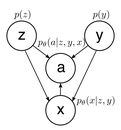
### Deep Generative Model

Generative models are a powerful way of learning the data distribution using unsupervised learning and they achieved great success in the last few years [1, 2, 3]. All types of generative models aim at learning the true data distribution of the training set so as to generate new data points with some variations. Usually, due to intractable integrals, it is not possible to learn the exact distribution of the data, so variational inference (VI) is used [4]. The idea behind VI, is to model a distribution which is as similar as possible to the true data distribution, while having an analytical approximation.

### Auxiliary Deep Generative Model

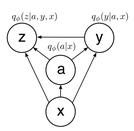
In [5], Kingma et al. revisited the approach to semi-supervised learning with generative models and developed new models that allow for effective generalisation from small labelled data sets to large unlabelled ones. The Auxiliary Deep Generative Model (ADGM) [6] is a generative model that include, from [5], an auxiliary approach [7] in order to learn a classifier from labeled and unlabeled data. The auxiliary variables leave the generative model unchanged while making the variational distribution more expressive. The probabilistic graphical model consists of a generative model $P$ and a inference model $Q$. The generative model $P$ is defined as $p(y)p(z)p_\theta(a|z,y,x)p_\theta(x|y,z)$:

$$p(z) = \mathcal{N}(z|0, I), \tag{1}$$
$$p(y) = \text{Cat}(y|\pi), \tag{2}$$
$$p_\theta(a|z,y,x) = f(a; z, y, x, \theta), \tag{3}$$
$$p_\theta(x|z,y) = f(x; z, y, \theta), \tag{4}$$




where $a$, $y$, $z$ are the auxiliary variables, class labels, and latent features, respectively. $\text{Cat}(\cdot)$ is a multinomial distribution, where $y$ is treated as a latent variable for the unlabeled data points. $f(x; z, y, \theta)$, in these experiments, is a Gaussian distribution for the continuos observation $x$. $p_\theta$ are deep neural networks with parameters $\theta$. The inference model $Q$ is defined as $q_\phi(a|x)q_\phi(z|a,y,x)q_\phi(y|a,x)$:

$$q_\phi(a|x) = \mathcal{N}(a|\mu_\phi(x), \text{diag}(\sigma^2_\phi(x))), \tag{5}$$
$$q_\phi(y|a,x) = \text{Cat}(y|\pi_\phi(a,x)), \tag{6}$$
$$q_\phi(z|a,y,x) = \mathcal{N}(z|\mu_\phi(a,y,x), \text{diag}(\sigma^2_\phi(a,y,x))), \tag{7}$$




where $q_\phi$ are deep neural networks with parameters $\phi$. In order to model Gaussian distributions $p_\theta(a|z,y,x)$, $p_\theta(x|z,y)$, $q_\phi(a|x)$, $q_\phi(z|a,y,x)$ we define two separate outputs from the top deterministic layer in each neural network, $\mu_{\theta\vee\phi}(\cdot)$ and $\log\sigma^2_{\theta\vee\phi}(\cdot)$. From these outputs we are able to approximate the expectations $\mathbb{E}$ by applying the reparametrization trick [1, 2].

### Variational Lower Bound for ADGM

We optimize the model by maximizing the lower bound on the likelihood. The variational lower bound on the marginal likelihood for a single labeled data point is

$$\log p(x,y) = \log \int_a \int_z p(x,y,a,z)dzda \geq \mathbb{E}_{q_\phi(a,z|x,y)}\left[\log \frac{p_\theta(x,y,a,z)}{q_\phi(a,z|x,y)}\right] \equiv -\mathcal{L}(x,y), \tag{8}$$

with $q_\phi(a,z|x,y) = q_\phi(a|x)q_\phi(z|a,y,x)$. For unlabeled data we introduce the variational distribution for $y$, $q_\phi(y|a,x)$:

$$\log p(x) = \log \int_a \int_y \int_z p(x,y,a,z)dzdyda \geq \mathbb{E}_{q_\phi(a,y,z|x)}\left[\log \frac{p_\theta(x,y,a,z)}{q_\phi(a,y,z|x)}\right] \equiv -\mathcal{U}(x), \tag{9}$$

with $q_\phi(a,y,z|x) = q_\phi(z|a,y,x)q_\phi(y|a,x)q_\phi(a|x)$.

The classifier (6) appears in $-\mathcal{U}(x_u)$, but not in $-\mathcal{L}(x_l,y_l)$. The classification accuracy can be improved by introducing an explicit classification loss for labeled data:

$$\mathcal{L}_l(x_l,y_l) = \mathcal{L}(x_l,y_l) + \alpha \cdot \mathbb{E}_{q_\phi(a|x_l}\left[\log q_\phi(y_l|a,x_l)\right], \tag{10}$$

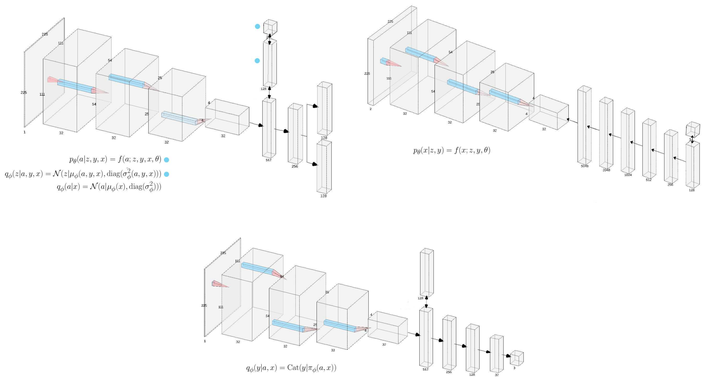
where $\alpha$ is a weight between generative and discriminative learning. The $\alpha$ parameter is set to $\beta \cdot \frac{N_l+N_u}{N_l}$, where $\beta$ is a scaling constant, $N_l$ is the number of labeled data points and $N_u$ is the number of unlabeled data points. The objective function for labeled and unlabeled data is

$$\mathcal{J} = \sum_{(x_l,y_l)} \mathcal{L}_l(x_l,y_l) + \sum_{(x_u)} \mathcal{U}(x_u) \tag{11}$$

## Experiments

### Implementation

The model is parametrized by 5 convolutional neural networks (CNN): (1) auxiliary inference model $q_\phi(a|x)$, (2) latent inference model $q_\phi(z|a,y,x)$, (3) classification model $q_\phi(y|a,x)$, (4) generative model $p_\theta(a,\cdot)$, and (5) the generative model $p_\theta(x,\cdot)$. We apply ReLU, batch normalization and dropout (0.2) between each convolutional/deconvolutional layer. We trained the model for 100-200 epochs using Adam optimizer with learning rate of 1e-4 and first and second momentum at 0.9 and 0.999, respectively. The $\beta$ constant was set to 1 and weight decay to 1e-5. We set the temperature on the KL-divergence going from 0 to 1 within the first 100 epochs of training.

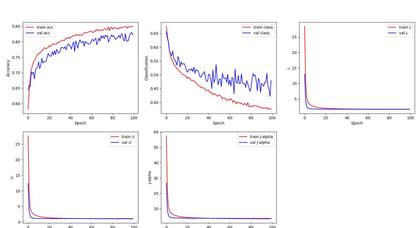



### Dataset

The dataset used is the 2018 RSNA Pneumonia Detection Challenge [8]. It consists of 27000 images with manual annotations from radiologists. There are three classes: Opacity, No-Opacity/Not-Normal and Normal. The classification between No-Opacity/Not-Normal and Opacity is a difficult task since the images labeled with No-Opacity/Not-Normal look like they contain lung opacities but they don't. We split this dataset in training set (90%) e validation set (10%). We first downsampled the images from $1024 \times 1024$ to $225 \times 225$, for computational reasons. We performed online data augmentation during training, using imgaug [9]. Every training batch is augmented with random flips and random affine transformations.

### Normal vs Abnormal

In this case we merged the No-Opacity/Not-Normal and Opacity class into one class. The task then becomes to classify normal chest X-Ray images and abnormal chest X-Ray images. Here an example of training with 4000 labels per class.



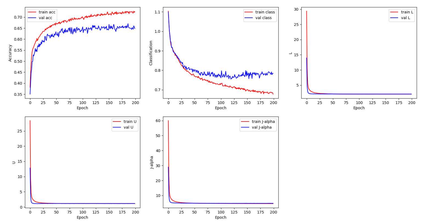

Confusion Matrix

| | A | N |
|---|---|---|
| A | **1384** | 386 |
| N | 89 | **810** |

Abnormal: 78,19%
Normal: 90,10%
Total accuracy: 82,20%

### Normal vs Opacity vs No-Opacity/Not-Normal

Here we use all the classes. As expected the No-Opacity/Not-Normal class has low accuracy. Here an example of training with 4000 labels per class.



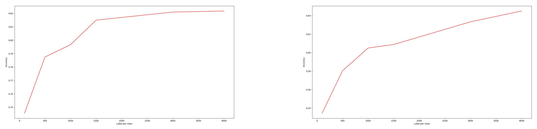

Confusion Matrix

| | O | N-N | N |
|---|---|---|---|
| O | **375** | 73 | 23 |
| N-N | 436 | **599** | 260 |
| N | 20 | 123 | **756** |

Opacity: 78,95%
No-Opacity/Not-Normal: 46,25%
Normal: 84,09%
Total accuracy: 64,82%

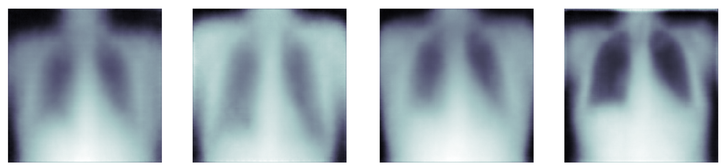
### Accuracy vs number of labels per class

We compare the accuracy of the model for different number of labels per class. On the left we have the two classes classification task and on the right the three classes classification task.



### Conditional generation

From the model we can generate samples conditionally given some normal distributed noise $z$ and a label $y$. Here some examples generated when $y$=Opacity.



## Summary

We implement ADGM models that classify pneumonia on chest X-Ray images. We then show how the models can obtain competitive results with few labeled data. Finally we evaluated the accuracy of the models with different number of labels per class.

## References

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[8] `https://www.kaggle.com/c/rsna-pneumonia-detection-challenge`.

[9] `https://imgaug.readthedocs.io/en/latest/`.