IMPLEMENTING AN OBJECTIVE FUNCTION AND REPORTING THE EFFECTS OF REGULARISATION ON GENERATIVE MODELS

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ABSTRACT

this paper revises the concept of objective functions as applied in machine learning and identifies the SELECTED OBJECTIVE FUNCTION used by the authors in the implementation of a generative neural network. The generative model maps a gaussian distribution to a uniform distribution, then maps the uniform distribution to a gaussian distribution, for a concatenated gaussian to gaussian network. This paper lists the three main objective functions used in neural networks and **SOMETHING TO SAY GOES THROUGH THE MATH of the selected function: . The results of the implemented neural network show that**

***Index Terms*—** One, two, three, four, five

1. INTRODUCTION

Neural networks have become a mainstay of image processing over the last two decades (compare [1] and [2])

2. OBJECTIVE FUNCTIONS AND REGULARISATION

Training a neural network using stochastic gradient descent is how the network determines the extent to which each neuron and layer needs to adjust wieghts. One of the main decisions for the design of the network is the selection of an objective function to guide the transition from the input dataset toward the desired (target dataset) . Although numerous objective functions are possible, this implementation uses the Maximum Mean Discrepancy which measures the distance between two distributions and for optimisation, the model aims to minimise MMD.

With the distribution p_Y as $\frac{1}{n(n-1)}\sum_{i\neq j} k(y^{(i)}, y^{(j)})$ and p_X as $\frac{1}{m(m-1)}\sum_{i\neq j} k(x^{(i)}, x^{(j)})$, where $k(x, y)$ is a positive definite kernel (in this case, the gau

$$
\begin{aligned}
&MMD(\{x^{(i)}\}_{i=1,\dots,m}, \{y^{(j)}\}_{j=1,\dots,n}) \\
&\quad = \\
&\quad + \\
&\quad - 2\frac{1}{mn}\sum_{i,j} k(x^{(i)}, y^{(j)})
\end{aligned}
$$

2.1. Kernel transformation

The kernel transforms our input vector in a lower dimensional space to the dot product output vector in a higher dimensional space [3] [4].

The theory: Why obective functions? - machine learning applies models to iteratively improve performance at generating a desired output (ref) - improves by 'moving' actual outputs closer to desired outputs, using an objective function tht calculates the difference or similarity between the actual output an the desired output - can be applied at the level of individual instances or across the distribution of input and output sets why regularisation? - list the options and distinguish between the options (method, output, application) - link the selected option with this problem - which will be the best for low/high outliers - which will be the best for which objective function?

- map the math -

3. RESULTS

3.1. Subheadings

3.1.1. Sub-subheadings

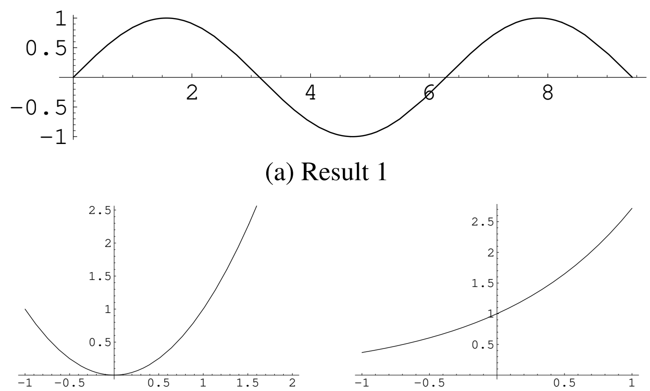
4. ILLUSTRATIONS, GRAPHS, AND PHOTOGRAPHS

Since there are many ways, often incompatible, of including images (e.g., with experimental results) in a LaTeX document, below is an example of how to do this [**?**].

5. CONCLUSION

Here is a citation [**?**].

AIML425



(a) Result 1

(b) Results 3

(c) Result 4

Fig. 1. Example of placing a figure with experimental results.

6. REFERENCES

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