

ELV832: Assignment, Part 1 Report

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Data Generation:

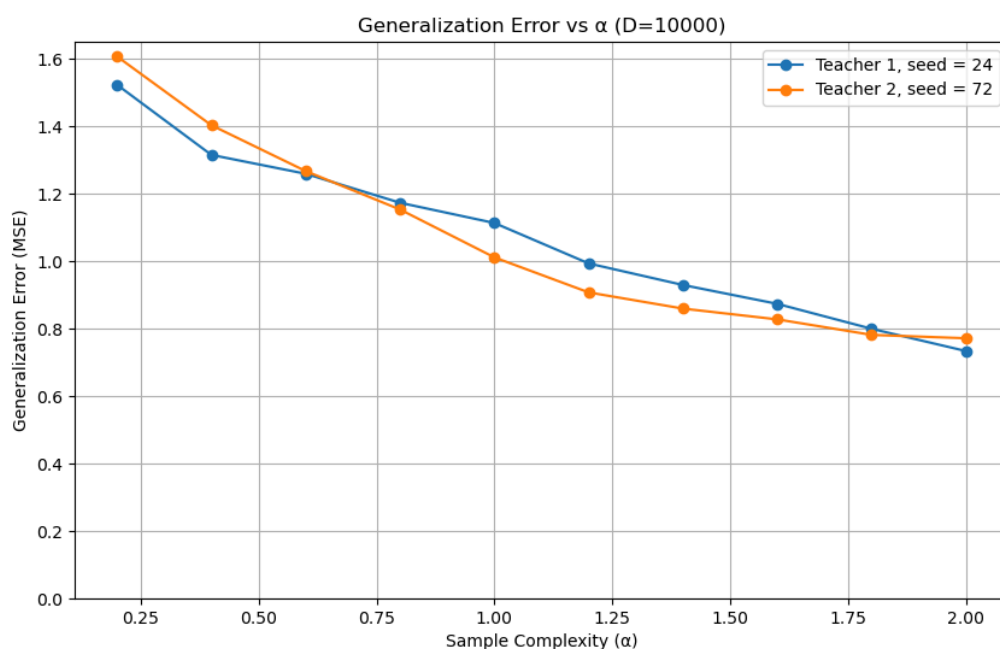
- We generate a random vector of binary weights, i.e., $+1/-1$ with dimensionality D , This constitutes our *teacher* model (binary perceptron) .
- We generate a training set of size $2D$ plus some test data of size $0.2D$. Hence, generate an overall data set of size $2.2D$.
- All feature values should be sampled IID from a standard normal distribution
- Each feature vector is passed through the teacher model (with $\text{sign}()$ activation for the binary perceptron) to obtain its corresponding class label.

Code:

- Attached are two python files, Assignment1.py and Assignment1_opt.py.
- Assignment1.py is a naive implementation and Assignment1_opt.py is an optimised implementation. The attached plots are from Assignment1_opt.py.

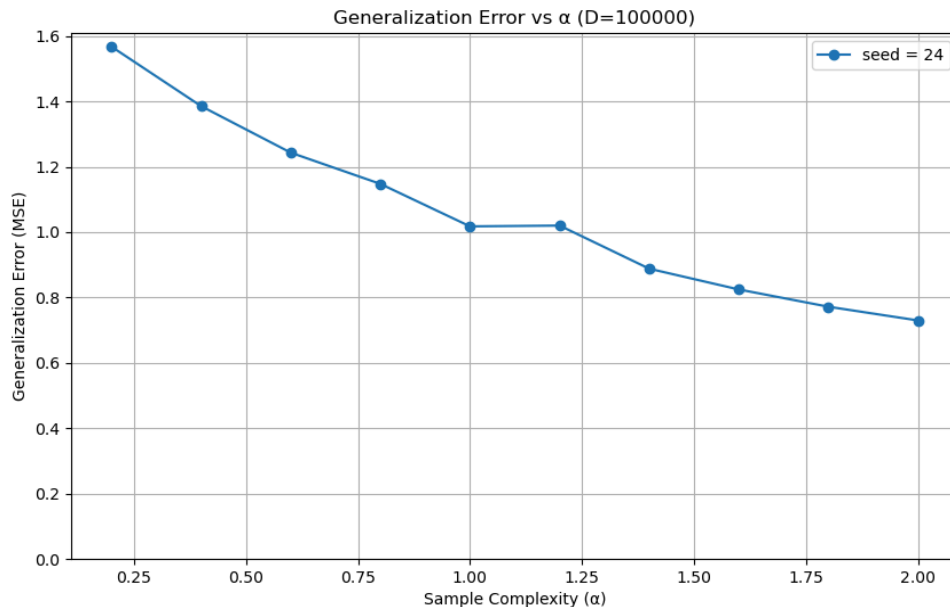
$D = 1e4$ for two different teacher models:

- Below is a plot of generalization error(MSE) vs sample complexity for $D = 1e4$.
- The trend followed is the same for both teacher models (with different random seeds)
- The trend followed is similar to that of fig.2 of [Barbier et al](#) where we observe a decrease in Generalization error with increasing sample complexity. However, we do not observe a phase transition for $D = 1e4$ when using logistic regression.



D = 1e5 for data generated from a teacher model:

- The trend is similar to that of $D=1e4$, we do not observe a phase transition here.
- Scaling to even larger D is challenging due to computational constraints, particularly memory limitations.



Why do we not observe a phase transition:

- For the above setting, we theoretically expect a phase transition ([Barbier et al](#)) at some α . However, we do not observe one for both $D = 1e4$ and $D = 1e5$.
- Using the Bayes optimal algorithm, we observe a phase transition at $\alpha = 1.249$ which is the smallest possible α to observe a phase transition information theoretically.
- Using GAMP, we also observe a phase transition at a slightly higher $\alpha = 1.493$, ie we observe perfect generalisation only above $\alpha = 1.493$ using GAMP.
- Logistic regression does not exhibit a phase transition in this setting, possibly due to differences in weight constraints between the teacher model and logistic regression.
- In the teacher model, the weight vector W is binary (+1/-1), and the class label is given by $y = \text{sign}(W \cdot X)$, where X is a $(2.2D, D)$ matrix with i.i.d. Gaussian entries.
- Logistic regression learns a weight vector W_{LR} and bias b , predicting $y_{prob} = \text{sigmoid}(W_{LR} \cdot X + b)$ and classifying based on $y_{pred} = \text{sign}(W_{LR} \cdot X + b)$. Since W_{LR} and b take real values, the model may fail to perfectly recover the binary W , leading to limited generalization.
- This issue is better handled in GAMP, where W is explicitly constrained to be binary.
- The paper assumes $D \rightarrow \infty$ limit for all its theoretical findings. Trying a larger value of D might help observe a phase transition even using logistic regression, but this is doubtful as even for $D = 1e5$ no such transition was observed.

Ideas to change the settings of the experiment to observe a phase transition:

- Incorporate knowledge of the teacher model when designing the student model, ensuring a well-chosen prior.
- Try training for even larger D if computationally feasible.