



Partial Boosting of Deep Stacked Networks

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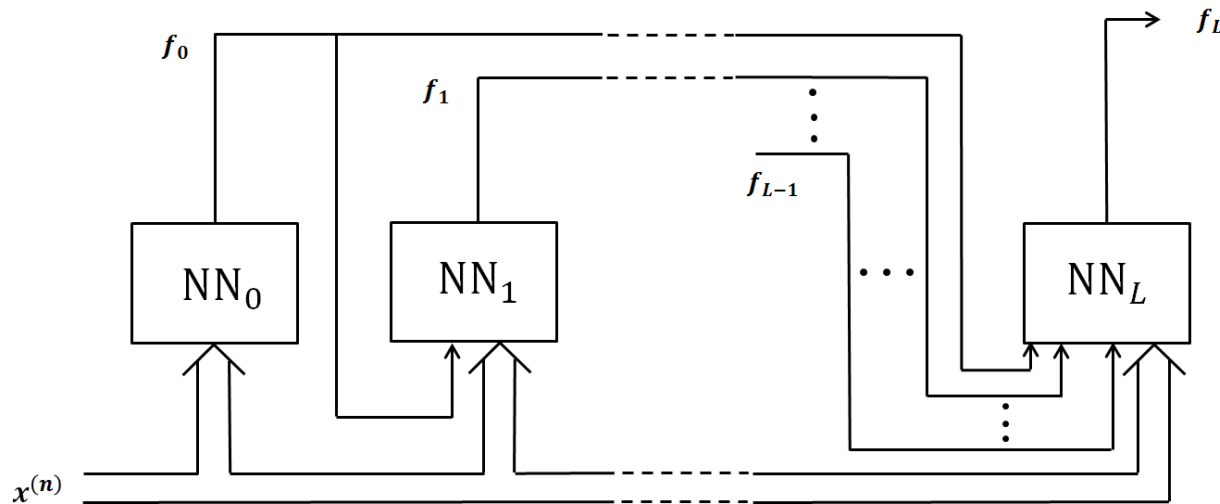
1. Deep Stacked Networks (DSNs)

Deep Learning architecture.

Each unit consists of a MLP whose input is:

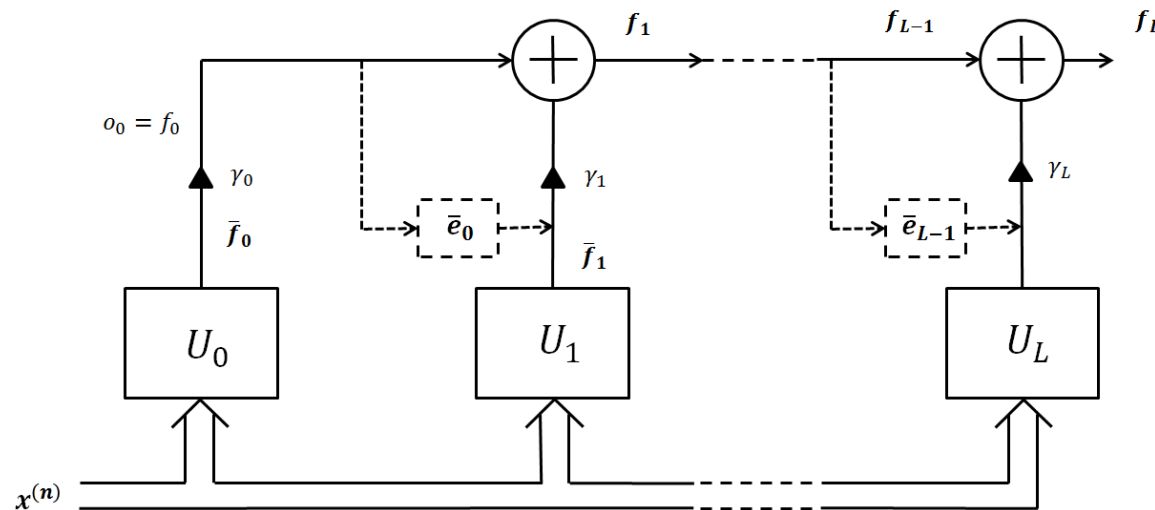
- The observed features and
- the outputs of all previously trained learners.

The output of the DSN is the output of the last unit.



2. Boosting

- Ensemble method in which weak learners are sequentially trained using information from the aggregation of all previously trained units.
 - Samples are weighted using an emphasis function.
- The output of the ensemble is a linear combination of all unit outputs.
- Resistant to overfitting.



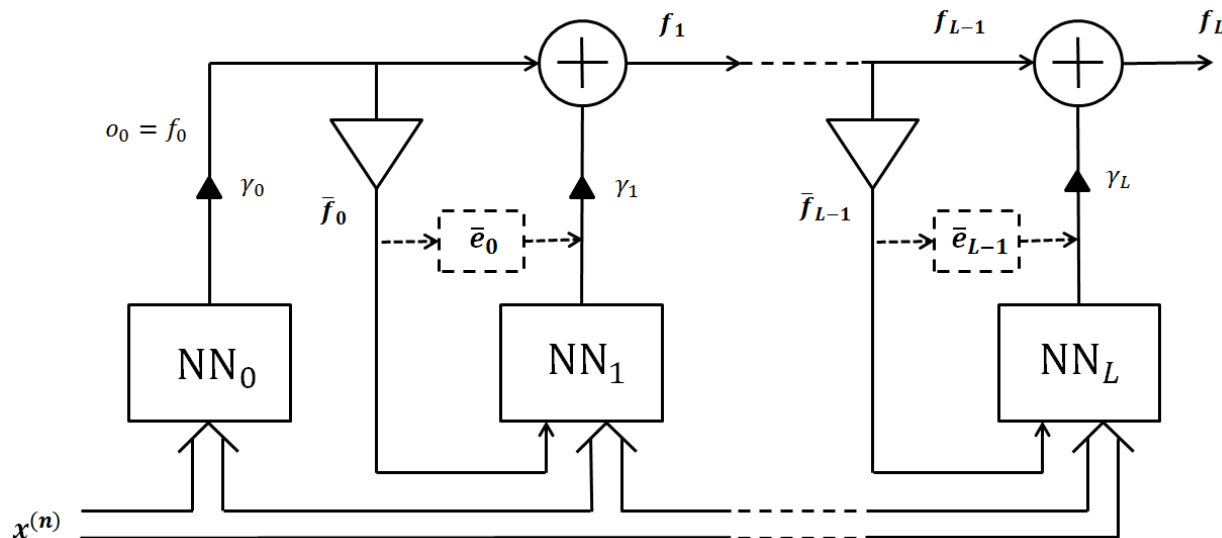
3. Boosted Aggregated Deep Stacked Networks

Combination of DSNs and Boosting by means of an aggregated output injection and a flexible emphasis function. Each unit has 2 additional sources of information:

- Injection of the aggregated output of all previously trained units
- Emphasis function

$\alpha, \beta: CV$

$$p(x^{(n)}) = \frac{\alpha}{N} + \frac{1 - \alpha}{Z_l} \left[\beta (t^{(n)} - \bar{f}_l(x^{(n)}))^2 / 4 + (1 - \beta) (1 - \bar{f}_l(x^{(n)}))^2 \right]$$



4. Experiments

Experiments performed over a set of moderate size binary problems.

Units are MLP sequentially trained using Online Back-Propagation.

Explored values of the non-trainable elements in the CV-search are:

- Number of hidden neurons from 2 to 30.
- Number of epochs from 25 to 200.

	B1-ADSN	B2-ADSN	ADSN	B1	B2
aba	18.4 ± 0.2	18.5 ± 0.2	18.6 ± 0.2	19.1 ± 0.1	19.0 ± 0.1
ima	2.9 ± 0.3	2.9 ± 0.4	3.0 ± 0.3	3.2 ± 0.5	3.2 ± 0.2
hep	6.6 ± 0.0	6.7 ± 0.4	8.0 ± 0.4	6.6 ± 0.5	6.7 ± 0.5

TABLE II

% AVERAGE ERROR RATE \pm STANDARD DEVIATION FOR THE CONSIDERED ARCHITECTURES

5. Properties of the B-ADSNs

- Performance varies smoothly with α, β (some discontinuity for extreme values of alpha).
- Harder problems require extreme values of α .
- Smaller problems (hep) require an intermediate α which seems to fight the initial overfitting.
- The value of β is problem dependent.

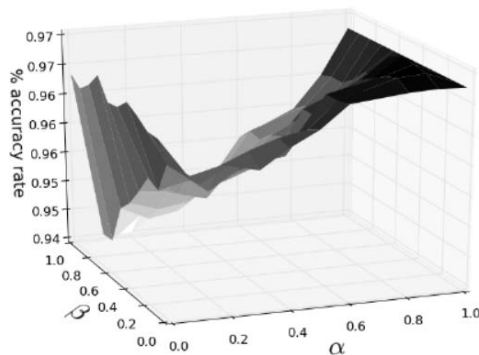


Fig. 2. % average accuracy rate for the Ima dataset with respect to α and β .

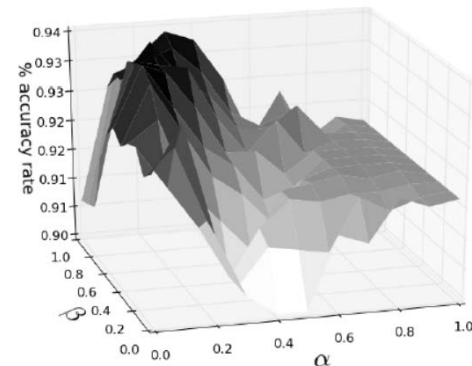


Fig. 3. % average accuracy rate for the Hep dataset with respect to α and β .

6. Conclusions

- The combination of the expressivity of DSNs and the resistance to overfitting of boosting can be successful.
- A flexible emphasis function is required to moderate the boosting contribution.
- There are many other possible combinations of boosting and deep learning.