Review and matlab implementation of the paper:

Using neural network ensembles for bankruptcy prediction and credit scoring (Tsai, Wu)

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Summary

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Paper review

Goals

- Observe the performance differences between different ANN ensemble approaches, namely single classifiers, multiple classifiers and diversified multiple classifiers, with regards to based on a set credit scoring and bankruptcy detection. The study is based on three of heterogeneous datasets;
- Evaluate the three classifier architectures performance with regards to Type 1 error and Type 2 error.

Tools

- Multilayer Perceptron feedforward Artificial Neural Network
  - One **hidden** layer
  - Five different values for the **hidden nodes** hyperparameter
  - Four different values for the **training epochs** hyperparameter
- Multiple classifiers with two techniques to compute them:
  1. Best n classifiers for every epoch
  2. Best n classifiers among all the epochs

Note

Technique 1 is only applicable to $n = 3 \land n = 5$, with $n \in [3, 5, 7, 9, 11, 13, 15]$. Multiple classifiers are based on **majority voting**.

Advancements vs previous works

- Employment of **multiple datasets** for system validation;
- Usage of **Type 1 and Type 2 errors** and not only average accuracy measures;
- Testing the classifiers performance on multiple classification tasks rather than a single one, specifically on **credit scoring** and **bankruptcy prediction**.

Brief remark

- **Type 1** error is associated with **false positives**;
- **Type 2** error is associated with **false negatives**.

Examples

- *Type 1*: the model classifies a credit-worthy client as a credit-risky one;
- *Type 2*: the model classifiers a credit-risky client as a credit-worthy one.

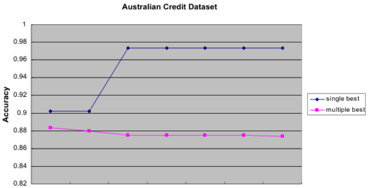
Study 1: single vs multiple classifiers

- Datasets are split into training (70%) and test (10%);
- For single classifiers the number of nodes is $nn \in [8, 12, 16, 24, 32]$ and learning epochs $[50, 100, 200, 300]$.
- Multiple classifers are build with the voting strategy combining the results of the top n classifers, with $n \in [3, 5, 7, 9, 11, 13, 15]$.

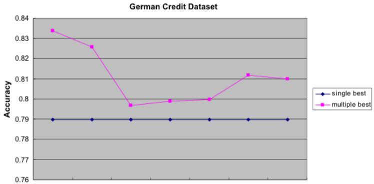
Takeout

On average, the single best classifer outperforms multiple classifers.

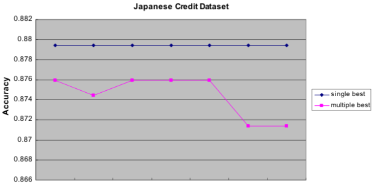
Study 1: single vs multiple classifiers



(a) Australian



(b) German



(c) Japanese

Figure: Comparison between single classifiers and multiple classifiers.

Study 2: single vs multiple vs diversified classifiers

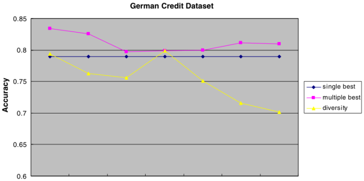
- Train-test dataset generation is different for diversified multiple classifiers. Specifically, every model composing the classifier is trained on a fraction of the observations from the same dataset, then the majority voting is executed using a test dataset;
- The procedure aims at ensuring **diversity** between classifiers.

Takeout

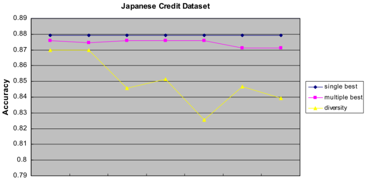
The best single classifier is still, on average, a better classifier than the diversified multiple classifier (and the multiple classifier, as seen before).

Study 2: single vs multiple vs diversified classifiers

(a) Australian



(b) German



(c) Japanese

Figure: Comparison between single, multiple and diversified classifiers.

Study 3: Type 1 and Type 2 errors

- In Study 1 and Study 2 the results of classifiers are compared based on the **accuracy** of the classifiers. Study 3 compares the models performance with regards to Type 1 and Type 2 errors.

Takeout

This study highlights how single classifiers do not totally outperform multiple or diversified classifiers.

Study 3: Type 1 and Type 2 errors

Average error rate of Type I and Type II errors

	Australian credit			German credit			Japanese credit		
	S	M	D	S	M	D	S	M	D
Type I error	*12.16*	12.85	14.28	*44.27*	45.25	59.82	15.02	15.07	*14.42*
Type II error	12.97	12.14	*11.55*	9.48	*8.46*	8.67	10.79	*10.00*	14.06

Figure: Type 1 and Type 2 error across datasets and classifier architectures.

Conclusions

- If the performance is measured with **accuracy**, **single best neural network classifier is more suitable** for bankruptcy prediction and credit scoring tasks, if compared with multiple or diversified multiple neural network classfiers;
- If performance is measured with **type 1 and 2 errors**, there seems to be no **clear winner** among the model architectures analysed.

A couple of remarks. . .

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- The methodology used to build the datasets for diversified multiple classifers could be associated with the poor performance by the classifiers. In fact the higher the n the smaller the train-sets used for each models' training. This could lead to a lot of results variability;
- It's not clear why the authors used two methodologies to build the multiple classifiers even though one of them is applicable only to $n = 3$ and $n = 5$ classifiers.

Matlab implementation

Methodology

- **Pre-processing**. The datasets used for the matlab implementation are (presumably) the same datasets used by the authors of the paper. The datasets pre-processing, specifically:
  - **feature normalization**. In order to apply ANN, all the continuous features need min-max normalization;
  - **one-hot-encoding**. In order to apply ANN, all the categorical features need a different encoding, specifically one-hot-encoding.
- **Datasets**. The three datasets were retrieved from the UC Irvine Machine Learning Repository.
  - Australian (690 x 15);
  - German (1000 x 20);
  - Japanese (690 x 16).

Model

```
epochs = [50 100 200 300];
hidden_nodes = [8 12 16 24 32];

net = fitcnet(X_train, Y_train,...
    'LayerSizes', node,...
    'IterationLimit',epoch,...
testAccuracy = 1 - loss(net,X_test,Y_test,...
"LossFun","classiferror");
```

Single classifier

Methodology

For the single neural network classifier, the dataset is divided into test (70%) and train (30%); then the implementation execute a loop that tests all the possible combinations of hidden nodes and epochs.

Multiple classifiers

Note

Since there seem to not exist a `MATLAB` function for the multiple classifier for `fitcnet`, the implementation has been done by hand.

- For every n and dataset, n models are trained based on the hyperparameters of best n single classifiers;
- Then predictions are formulated by every model with the test dataset;
- The results of the predictions from n models undergo the majority voting process, where the resulting vector is the vector of the n multiple classifier predictions.

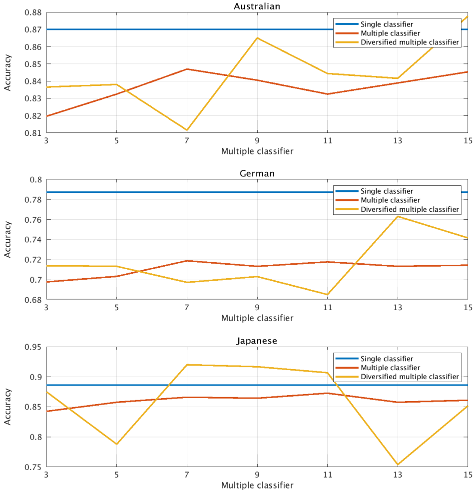
Diversified multiple classifier

- Same structure of multiple classifier, but every model is trained on a different subset of observations from the dataset;
- The algorithm for diversified dataset creation is the following:

Dataset splitting

$split = \frac{nrows(dataset)}{2 \times n + 1}$, then for every classifier the train dataset is $2 \times split$. Test dataset is of size $split$.

Results of Study 1 and 2



Type 1 and 2 error: setup

- **Single classifier**
- **Multiple classifier**

Type 1 and 2 error: results

Citation

An example of the `\cite` command to cite within the presentation:

References

John Smith (2012)
Title of the publication
Journal Name 12(3), 45 – 678.