MADS-ML – Machine Learning

Ensemble Learning

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Moodle ()

Outline

Motivation

Voting

Bagging

Boosting

Why ensembles?

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Idea Combine a set of weak learners into a stronger one.

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- Create a meta classifier.

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- Create a meta classifier.
- Use a strategy to combine the predictions of the base learners into a single (final) classification.

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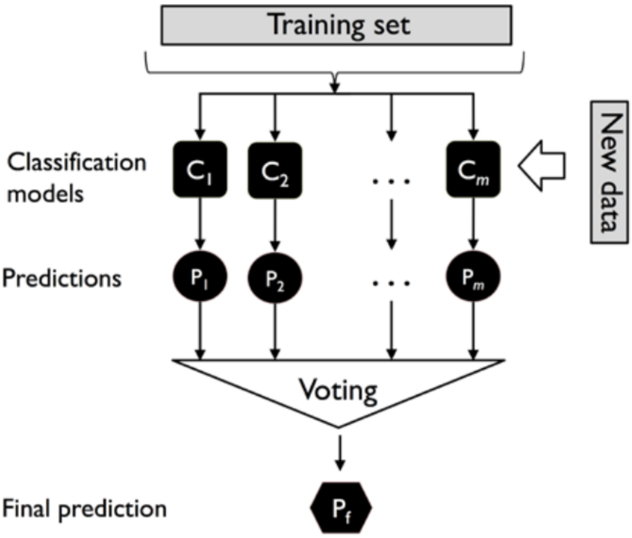
Voting Schemes



Source: [1], p. 220

Voting Schemes

In Python: `sklearn.ensemble.VotingClassifier`

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- Class with the highest sum wins.

The choice of the base predictors (types and number) and the voting scheme are new hyperparameters.

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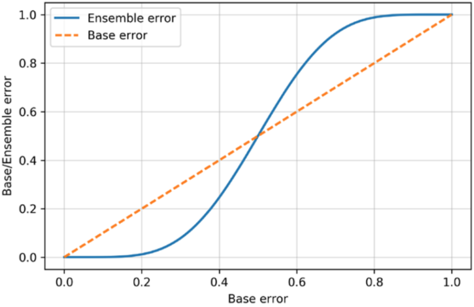

Source: [1], p. 223

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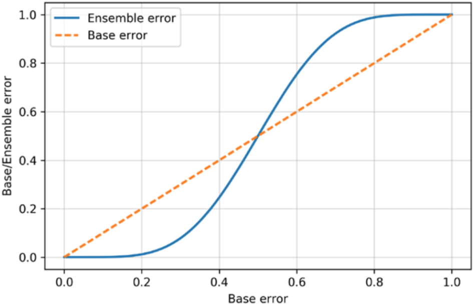

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- idealized binary classification – **independent** error probabilities

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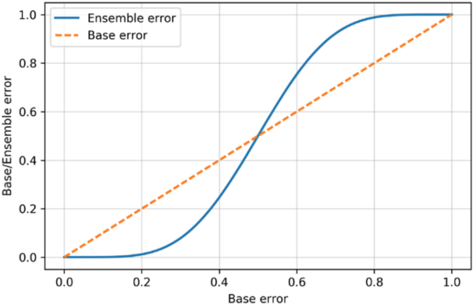

Source: [1], p. 223

- idealized binary classification – **independent** error probabilities
- error probability (missclassification) of the ensemble is lower than that of any base classifier if the base classifiers is better than random guessing

Use Cases

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- combine different data sources (each requiring different algorithms)

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Notebook 07_1_ensembles_wines, Cells 1–7

Algorithm Random Forest

- forest = ensemble of trees
- bagging: each tree learned on a different data subset
- additionally: feature bagging each tree may only choose from a randomly sampled subset of features (random subspace) → more variation among the trees
- main hyperparameters: number of trees + hyperparameters of decision trees
- interpretability of decision trees is lost
- less prone to overfitting
- in sklearn: `sklearn.ensemble.RandomForestClassifier`

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- Compute final prediction using a weighted combination of the m classifiers (weights are combinations of the respective coefficients and a learning rate)

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Note: If $C^{(i)}$ is better than guessing, then $\epsilon^{(i)} < 0.5$. Thus,
$\alpha^{(i)} = .5 \log \frac{1-\epsilon^{(i)}}{\epsilon^{(i)}} > 0$ and $e^{-y_x \hat{y}_x^i \alpha^i} \begin{cases} > 1 \text{ for } y_x \neq \hat{y}_x^i \\ < 1 \text{ for } y_x = \hat{y}_x^i \end{cases}$.

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Notebook 07_1_ensembles_wines, Cells 8–10

References

S. Raschka and V. Mirjalili.
Python Machine Learning.
Packt Publishing Ltd., Livery Place 35 Livery Street Birmingham B3 2PB, UK, second edition, September 2017.