Lecture 17: Ensemble Learning

COMP90049

Semester 2, 2021

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Classification

So far:

- Classification algorithms in isolation
- Training and testing one classifier
- Remedies for Overfitting and underfitting

Today:

- Introduction of Ensemble learning
- Stacking
- Bagging
- Boosting

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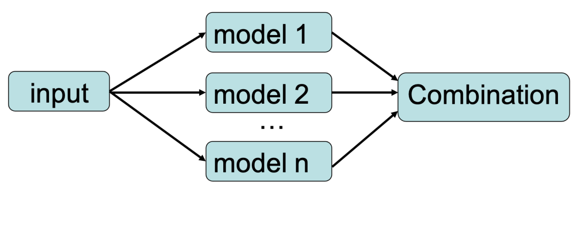
Introduction of Ensemble learning

What is Ensemble Learning

Ensemble learning (aka. Classifier combination): constructs a set of base classifiers from a given set of training data and aggregates the outputs (e.g., using majority voting) into a single meta-classifier.



Approaches for Ensemble Learning

- **Instance manipulation**: generate multiple training datasets through sampling, and train a base classifier over each dataset
- **Feature manipulation**: generate multiple training datasets through different feature subsets, and train a base classifier over each dataset
- **Class label manipulation**: generate multiple training datasets by manipulating the class labels in a reversible manner
- **Algorithm manipulation**: semi-randomly “tweak” internal parameters within a given algorithm to generate multiple base classifiers over a given dataset

Why Ensemble Learning

- **Intuition 1**: the combination of lots of weak classifiers can be at least as good as one strong classifier
- **Intuition 2**: the combination of a selection of strong classifiers is (usually) at least as good as the best of the base classifiers

When does ensemble learning work? I

- The base classifiers should not make the same mistakes
- The base classifiers are reasonably accurate

	t_1	t_2	t_3
C_1	√	√	x
C_2	x	√	√
C_3	√	x	√
C^*	√	√	√

	t_1	t_2	t_3
C_1	√	√	x
C_2	√	√	x
C_3	√	√	x
C^*	√	√	x

	t_1	t_2	t_3
C_1	√	x	x
C_2	x	√	x
C_3	x	x	√
C^*	x	x	x

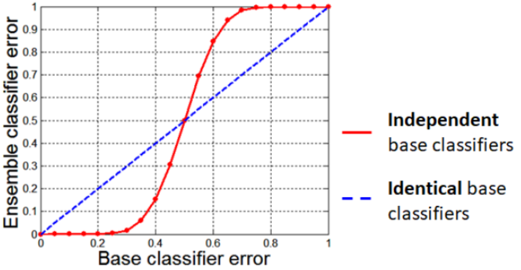
When does ensemble learning work? II

- Given 25 binary base classifiers, each with an error rate of $\epsilon = 0.35$.
- Ensemble by majority voting
  - if the base classifiers are identical, after ensemble, $\epsilon = 0.35$.
  - If the base classifiers are independent, after ensemble,

$$\sum_{i=13}^{25} \binom{25}{i} \epsilon^i (1-\epsilon)^{25-i} \approx 0.06$$

When does ensemble learning work? II

- When does ensemble learning work?



Quiz

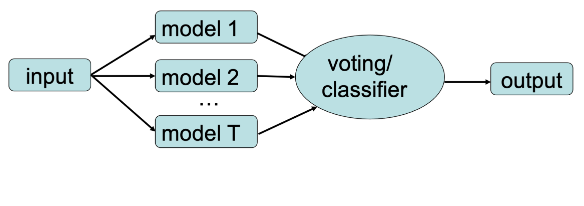
Which of the following statement(s) are TRUE about ensemble learning?

- (a) An ensemble of classifiers may not be able to outperform any of its individual base learners.
- (b) Combining significantly diverse base learners (suppose each produces meaningful predictions) typically yields bad results.

Stacking

Stacking

- **Intuition**: “smooth” errors over a range of algorithms with different biases
- **Method**: use different algorithms to train multiple base classifiers on the dataset.



- **Inputs for second-level classifier (meta-learner):** use base classifiers to generate predictions on unseen samples (using cross-validation).

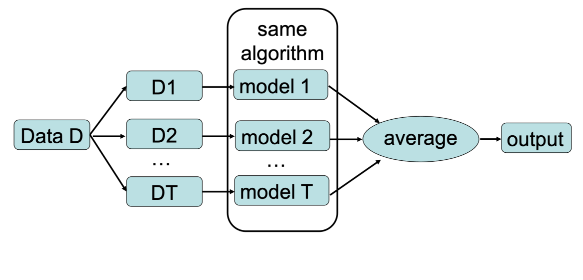
Stacking II

- Mathematically simple but computationally expensive method
- Able to combine heterogeneous classifiers with varying performance
- Generally, stacking results in as good or better results than the best of the base classifiers

Bagging

Bagging I

- **Intuition**: Average multiple models can lower the model variance.
- **Method**: Create multiple new training sets for training multiple classifiers base on the same algorithm and average the predictions.



Bagging II

Dataset generation: randomly sample the original dataset (N instances) N times, with replacement. Any individual instance is absent with probability $(1 - \frac{1}{N})^N$

Example:

- Original dataset:

1	2	3	4	5	6	7	8	9	10

- Bootstrap Samples

7	2	6	7	5	4	8	8	1	10

1	3	8	10	3	5	8	10	1	9

2	9	4	2	7	9	3	10	1	10

$\vdots$

Bagging III

- Possibility to parallelise computation of individual base classifiers
- Highly effective over noisy datasets (outliers may vanish)
- Generally produces the best results on unstable models that have high variance and low bias

Random Forest I

- A “Random Forest” is an ensemble of Random Trees (many trees = forest)
- A “Random Tree” is a Decision Tree where at each node, only some of the possible attributes are considered
- Use random trees instead of decision trees to increase diversity of base classifier

Random Forest II

Practical Properties of Random Forests:

- Embarrassingly parallelisable
- Robust to overfitting
- Interpretability sacrificed

Quiz

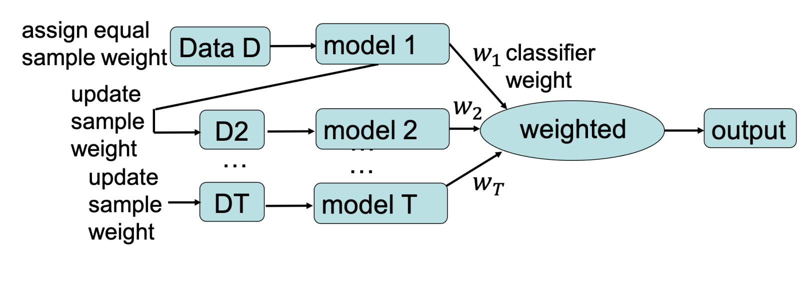
Which of the following statement(s) are TRUE about Random Forest?

- (a) Random Forest provides higher interpretability over the logic behind the predictions than a single random tree.
- (b) Random Forest adopts both feature manipulation and instance manipulation approaches.
- (c) Random Forest minimizes the bias by having multiple random trees trained on different versions of the dataset.

Boosting

Boosting I

- **Intuition**: Build a strong model from several weak models to reduce model bias.
- **Method**: Iteratively change the weights of training instances to train next base classifier and combine the base classifiers via weighted voting



Boosting II

- Original dataset:

1	2	3	4	5	6	7	8	9	10

- Boosting samples:

Iteration 1:	7	2	6	7	5	4	8	8	1	10
Iteration 2:	1	3	8	4	3	5	4	10	1	4
Iteration 3:	4	9	4	2	4	4	3	10	1	4

$\vdots$

AdaBoost I

- Input: Training instances $(x_j, y_j) | j = 1, 2, \ldots, N$
- Initial equal sample weights $w_j^{(0)} = \frac{1}{N} | j = 1, 2, \ldots, N$
- For $i = 1 \cdots T$
    - Construct classifier C_i in iteration i:
        - apply sample weights to the loss or
        - use the weights to re-sample data to train model
    - Calculate weight of the classifier α_i
    - Update the sample weights
- Final classification via weighted voting: multiply vote of each classifier with its weight.

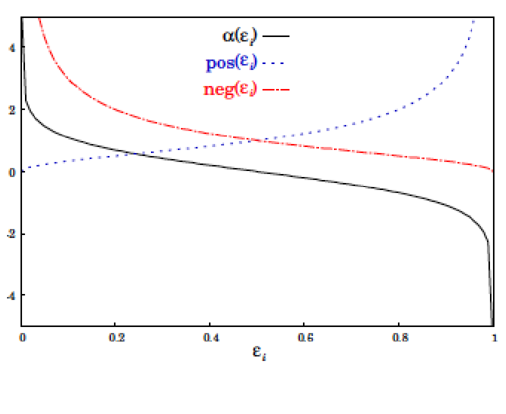
AdaBoost II

- Error rate for C_i:

$$\epsilon_i = \sum_{j=1}^{N} w_j^{(i)} \delta(C_i(x_j) \neq y_j)$$

- "Importance" of C_i (i.e. the weight associated with the classifiers' votes):

$$\alpha_i = \frac{1}{2} \log_e \frac{1 - \epsilon_i}{\epsilon_i}$$



AdaBoost III

- If $\alpha_i > 0$, adjust weights for instance j ($i > 0$):

$$w_j^{(i+1)} = w_j^{(i)} \times \begin{cases} e^{-\alpha_i} & \text{if} \quad C_i(x_j) = y_j \\ e^{\alpha_i} & \text{if} \quad C_i(x_j) \neq y_j \end{cases}$$

$$Z_i = \sum_{j=1}^{N} w_j^{(i+1)}$$

$$w_j^{(i+1)} = w_j^{(i+1)} / Z_i$$

AdaBoost IV

- Classification:

$$C^*(x) = \underset{y}{argmax} \sum_{i=1}^{T} \alpha_i \delta(C_i(x) = y)$$

- Base classification algorithm: decision stumps (OneR) or decision trees

Quiz

Which of the following statement(s) are TRUE about Boosting?

- (a) Boosting adopts feature manipulation approach to train multiple base learners
- (b) Boosting assigns higher weights to better-performing base learners
- (c) Boosting iteratively learns base learners while emphasizing the samples that can be easily classified

Bagging vs. Boosting

Bagging/Random Forests	Boosting/AdaBoost
Builds base models in parallel	Builds base models sequentially
Parallel sampling: Resamples data points with replacement	Iterative sampling: Reweights data points (modifies their distribution)
Base classifiers have the same weight	Base classifiers have the different weight
Reduce variance	Reduce bias
Not prone to overfitting	Prone to overfitting

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Summary

Summary

- What is classifier combination?
- What is bagging and what is the basic thinking behind it?
- What is boosting and what is the basic thinking behind it?
- What is stacking and what is the basic thinking behind it?
- How do bagging and boosting compare?

Quiz

What are the techniques that use instance manipulation approach to combine classifiers?

- (a) Bagging
- (b) Boosting
- (c) Random Forest
- (d) Stacking

References

- Leo Breiman. Random forests. Machine Learning, 45(1):5–32, 2001.
- Pang-Ning Tan, Michael Steinbach, and Vipin Kumar. Introduction to Data Mining. Addison Wesley, 2006.
- Ian H. Witten and Eibe Frank. Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations. Morgan Kaufmann, San Francisco, USA, second edition, 2005.