Source: Pixabay

Pros and cons of various Machine Learning algorithms

Shailaja Gupta Feb 28, 2020 · 8 min read ★

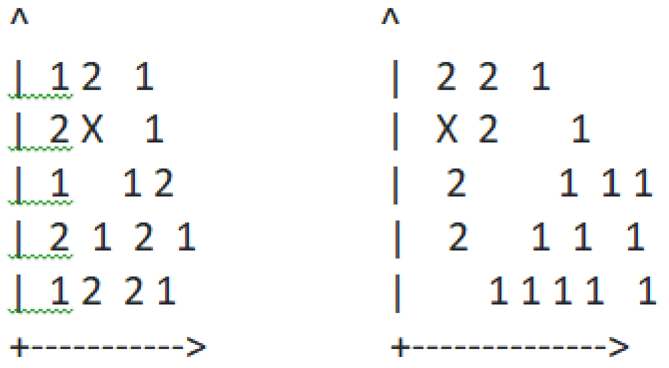
There are many classification algorithms in machine learning. But ever wondered which algorithm should be used for what purpose and what kind of application. If yes, then please read the pros and cons of various machine learning algorithms used in classification. I have also listed down their use cases and applications.

SVM (Support Vector Machine)

Pros

1. **Performs well in Higher dimension.** In real world there are infinite dimensions (and not just 2D and 3D). For instance image data, gene data, medical data etc. has higher dimensions and SVM is useful in that. Basically when the number of features/columns are higher, SVM does well

2. **Best algorithm when classes are separable.** (when instances of both the classes can be easily separated either by a straight line or non-linearly). To depict separable classes, lets take an example(here taking an example of linear separation, classes can also be non-linearly separable, by drawing a parabola for e.g. etc). In first graph you cannot tell easily whether X will be in class 1 or 2, but in case 2 you can easily tell that X is in class 2. Hence in second case classes are linearly separable.



```
^                      ^
| 1 2  1               |  2 2  1
| 2 X   1              |  X 2     1
| 1    1 2             |   2      1 1 1
| 2  1  2  1           |   2    1  1   1
| 1 2  2 1             |      1 1 1 1   1
+----------->          +-------------->
```

First is non-separable class, second is separable class.

3. **Outliers** have less impact.

4. SVM is suited for extreme case binary classification.

Cons:

1. **Slow:** For larger dataset, it requires a large amount of time to process.

2. **Poor performance with Overlapped classes** : Does not perform well in case of overlapped classes.

3. **Selecting appropriate hyperparameters is important:** That will allow for sufficient generalization performance.

4. **Selecting the appropriate kernel** function can be tricky.

Applications:

Bag of words application(many features and columns), speech recognition data, classification of images(non-linear data), medical analytics(non linear data), text classification(many features)

Naive Bayes

Pros

1. **Real time** predictions: It is very fast and can be used in real time.

2. **Scalable** with Large datasets

3. **Insensitive to irrelevant features.**

4. **Multi class prediction** is effectively done in Naive Bayes

5. **Good performance with high dimensional data**(no. of features is large)

Cons

1. **Independence of features does not hold:** The fundamental Naive Bayes assumption is that each feature makes an independent and equal contribution to the outcome. However this condition is not met most of the times.

2. **Bad estimator:** Probability outputs from predict_proba are not to be taken too seriously.

3. **Training data should represent population well:** If you have no occurrences of a class label and a certain attribute value together (e.g. class=”No”, shape=”Overcast “) then the posterior probability will be zero. So if the training data is not representative of the population, Naive bayes does not work well.(This problem is removed by smoothening techniques).

Applications:

Naive Bayes is used in Text classification/ Spam Filtering/ Sentiment Analysis. It is used in text classification (it can predict on multiple classes and doesn’t mind dealing with irrelevant features), Spam filtering (identify spam e-mail) and Sentiment Analysis (in social media analysis, to identify positive and negative sentiments), recommendation systems (what will the user buy next)

Logistic Regression

Pros

1. **Simple** to implement

2. **Effective**

3. **Feature scaling not needed:** Does not require input features to be scaled (can work with scaled features too, but doesn’t require scaling)

3. **Tuning of hyperparameters not needed.**

Cons

1. **Poor performance on non-linear data**(image data for e.g)

2. **Poor performance with irrelevant and highly correlated features** (use Boruta plot for removing similar or correlated features and irrelevant features).

3. **Not very powerful** algorithm and can be easily outperformed by other algorithms.

4. **High reliance on proper presentation of data**. All the important variables / features should be identified for it to work well.

Applications:

Any classification problem that is preferably binary (it can also perform multi class classification, but binary is preferred). For example you can use it if your output class has 2 outcomes; cancer detection problems, whether a student will pass/fail, default/no default in case of customer taking loan, whether a customer will churn or not, email is spam or not etc.

Random Forest

Pros:

1. Random forest can **decorrelate trees**. It picks the training sample and gives each tree a subset of the features(suppose training data was [1,2,3,4,5,6], so one tree will get subset of training data [1,2,3,2,6,6]. Note that size of training data remains same, both datas have length 6 and that feature '2' and feature '6' are repeated in the randomly sampled training data given to one tree. Each tree predicts according to the features it has. In this case tree 1 only has access to features 1,2,3 and 6 so it can predict based on these features. Some other tree will have access to features 1,4,5 say so it will predict according to those features. If features are highly correlated then that problem can be tackled in random forest.

2. **Reduced error:** Random forest is an ensemble of decision trees. For predicting the outcome of a particular row, random forest takes inputs from all the trees and then predicts the outcome. This ensures that the individual errors of trees are minimized and overall variance and error is reduced.

3. **Good Performance on Imbalanced datasets** : It can also handle errors in imbalanced data (one class is majority and other class is minority)

4. **Handling of huge amount of data:** It can handle huge amount of data with higher dimensionality of variables.

5. **Good handling of missing data:** It can handle missing data very well. So if there is large amount of missing data in your model, it will give good results.

6. **Little impact of outliers:** As the final outcome is taken by consulting many decision trees so certain data points which are outliers will not have a very big impact on Random Forest.

7. **No problem of overfitting:** In Random forest considers only a subset of features, and the final outcome depends on all the trees. So there is more generalization and less overfitting.

8. **Useful to extract feature importance** (we can use it for feature selection)

Cons:

1. **Features** need to have **some predictive power** else they won't work.

2. **Predictions of the trees need to be uncorrelated**.

3. **Appears as Black Box:** It is tough to know what is happening. You can at best try different parameters and random seeds to change the outcomes and performance.

Applications:

Credit card default, fraud customer/not, easy to identify patient's disease or not, recommendation system for ecommerce sites.

Decision Trees

Pros

1. **Normalization or scaling of data not needed**.

2. **Handling missing values**: No considerable impact of missing values.

3. **Easy to explain** to non-technical team members.

4. **Easy visualization**

5. **Automatic Feature selection** : Irrelevant features won't affect decision trees.

Cons

1. **Prone to overfitting.**

2. **Sensitive to data.** If data changes slightly, the outcomes can change to a very large extent.

3. **Higher time required to train** decision trees.

Applications:

Identifying buyers for products, prediction of likelihood of default, which strategy can maximize profit, finding strategy for cost minimization, which features are most important to attract and retain customers (is it the frequency of shopping, is it the frequent discounts, is it the product mix etc), fault diagnosis in machines(keep measuring pressure, vibrations and other measures and predict before a fault occurs) etc.

XGBoost

Pros

1. **Less feature engineering required** (No need for scaling, normalizing data, can also handle missing values well)

2. **Feature importance** can be found out(it output importance of each feature, can be used for feature selection)

3. **Fast** to interpret

4. **Outliers** have minimal impact.

5. **Handles large sized datasets** well.

6. **Good Execution** speed

7. **Good model performance** (wins most of the Kaggle competitions)

8. **Less prone to overfitting**

Cons

1. **Difficult interpretation** , visualization tough

2. **Overfitting** possible if parameters not tuned properly.

3. **Harder to tune** as there are too many hyperparameters.

Applications

Any classification problem. Specially useful if you have too many features and too large datasets, outliers are present, there are many missing values and you don't want to do much feature engineering. It wins almost all competitions so this is an algo you must definitely have in mind while solving any classification problem.

k-NN (K Nearest Neighbors)

Pros

1. **Simple** to understand and impelment

2. **No assumption about data** (for e.g. in case of linear regression we assume dependent variable and independent variables are linearly related, in Naïve Bayes we assume features are independent of each other etc., but k-NN makes no assumptions about data)

3. **Constantly evolving** model: When it is exposed to new data, it changes to accommodate the new data points.

4. **Multi-class** problems can also be solved.

5. **One Hyper Parameter:** K-NN might take some time while selecting the first hyper parameter but after that rest of the parameters are aligned to it.

Cons

1. **Slow** for large datasets.

2. **Curse of dimensionality**: Does not work very well on datasets with large number of features.

3. **Scaling** of data absolute must.

4. **Does not work well on Imbalanced data.** So before using k-NN either undersamplemajority class or oversample minority class and have a balanced dataset.

5. Sensitive to **outliers**.

6. Can’t deal well with **missing values**

Applications:

You can use it for any classification problem when dataset is smaller, and has lesser number of features so that computation time taken by k-NN is less. If you do not know the shape of the data and the way output and inputs are related (whether classes can be separated by a line or ellipse or parabola etc.), then you can use k-NN.

Conclusion

As the models came later , they became more and more advanced. So usually if you look at a model strictly from the performance perspective, then neural networks, XGBoost etc. are the best models since they are relatively recent. However , different models work better for different data.

For e.g. if features are highly independent then Naive Bayes will work great. If there are too many features and dataset is medium sized, SVM is good. If there is linear relationship between dependent and independent variables, then linear regression, logistic regression, SVM are good. If dataset is small and you don't know the relationship between the dependent and independent variable, then you can use k-NN. Hence before you decide on which ML algorithm to use, you must know and analyse the data. If you are unable to zero in on one machine learning algorithm, then you can evaluate all the models and check their accuracies on training and test set and then finalize one model.

Ai And Data Science Machine Learning Classification Algorithms Data Science