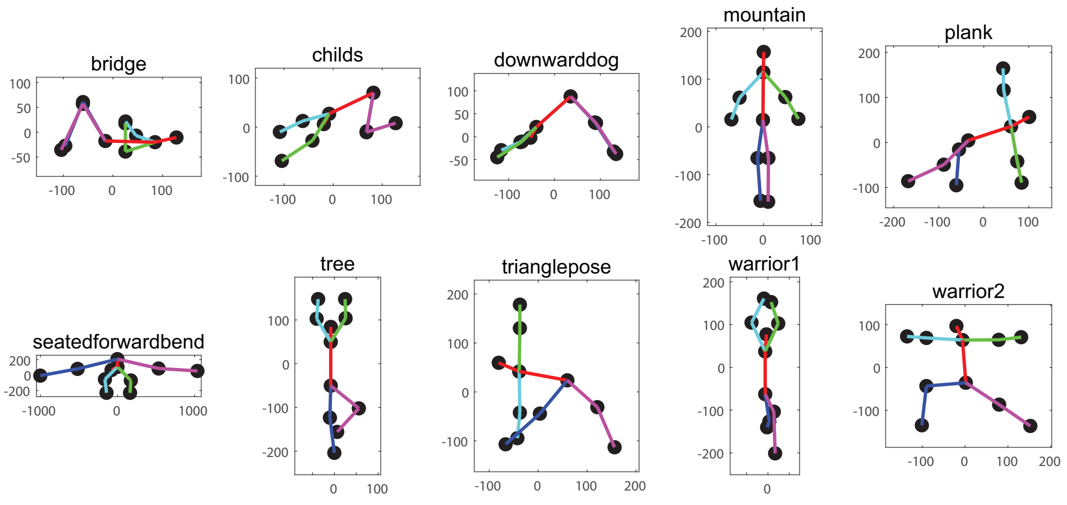
The University of Melbourne
School of Computing and Information Systems
COMP30027 Machine Learning, 2021 Semester 1

Project 1: Pose classification with naïve Bayes

Due:	7 pm, 12 April 2021
Submission:	Source code (in Python) and written responses
Groups:	You may choose to form a group of 1 or 2. Groups of 2 will respond to more questions, and commensurately produce more implementation.
Marks:	The project will be marked out of 16 points (individual project) or 24 points (group project). In either case, this project will contribute 20% of your total mark.



Example instances from the yoga pose classification dataset

Overview

Human pose recognition, and related tasks like gesture recognition and action recognition, are important tasks for AI systems that interact with people. There are many algorithms for classifying pose; for example, deep convolutional neural networks can be trained to classify pose directly from images. However, these methods tend to be "black boxes" and it's difficult to understand what features they are using. Another approach, which we will use in this Project, uses neural networks to first identify keypoints corresponding to the main parts of the body (as shown above), and then learns to recognize pose based on the positions of these body parts.

In this project, you will implement a supervised naïve Bayes learner to classify pose from keypoints provided by a deep convolutional neural network. You will train, test, and evaluate your classifier on a provided dataset, and then you will have a choice of either extending this basic model in various ways, or using it to answer some conceptual questions about naïve Bayes.

Naive Bayes classifier

There are some suggestions for implementing your learner in the "Naïve Bayes" and "Discrete & Continuous Data" lectures, but ultimately, the specifics of your implementation are up to you. Your implementation must be able to perform the following functions:

- `preprocess()` the data by reading it from a file and converting it into a useful format for training and testing
- `train()` by calculating prior probabilities and likelihoods from the training data and using these to build a naive Bayes model
- `predict()` classes for new items in a test dataset
- `evaluate()` the prediction performance by comparing your model's class outputs to ground truth labels

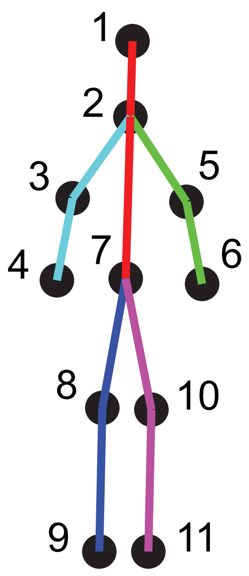
Your implementation should be able to handle numeric attributes and it should assume that numeric attributes are Gaussian-distributed. Your model will not be expected to handle nominal attributes. Your implementation should actually compute the priors, likelihoods, and posterior probabilities for the naïve Bayes model and not simply call an existing implementation such as `GaussianNB` from `scikit-learn`.

Data

The data for this assignment is drawn from a yoga pose classification dataset created by Anastasia Marchenkova and released online here. Separate training and test datasets are provided; please report your results on the provided test set.

The pose keypoints were produced by a computer vision algorithm based on OpenPose. The algorithm identifies 11 keypoints on the body and returns their x and y values. The data is provided as a csv file; the first column is the name of the yoga pose and the remaining columns are the keypoints (11 x values followed by 11 y values). The body parts represented by each of the 11 keypoints are shown to the right.

Since the keypoint data was generated by a computer vision algorithm, it may contain some errors. Some instances have missing keypoints because a part of the body was not visible in the original image or the algorithm failed to detect it. Missing keypoints have x and y values of 9999.



Keypoint diagram

Implementation tips

In the training phase of your algorithm, you will need to set up data structures to hold the prior probabilities for each class, and the likelihoods $P(x_i|c_j)$ for each attribute x_i in each class c_j. Recall that you will need two parameters (mean and standard deviation) to define the Gaussian distribution for each attribute $\times$ class. A 2D array may be a convenient data structure to store these parameters.

Multiplying many probabilities in the range $(0, 1]$ can result in very low values and lead to *underflow* (numbers smaller than the computer can represent). When implementing a naïve Bayes model, it is strongly recommended to take the $log()$ of each probability and sum them instead of multiplying. E.g., instead of computing:

$$P(c_j) \prod_i P(x_i|c_j) \tag{1}$$

compute:

$$log(P(c_j)) + \sum_i log(P(x_i|c_j)) \tag{2}$$

Questions

The following problems are designed to pique your curiosity when running your classifier(s) over the given dataset and suggest methods for improving or extending the basic model.

1. Since this is a multiclass classification problem, there are multiple ways to compute precision, recall, and F-score for this classifier. Implement at least two of the methods for computing multiclass precision and recall from the "Model Evaluation" lecture slide 37 (e.g., macro-averaging) and discuss any differences between them. (The implementation should be your own and should not just call a pre-existing function.)

2. The Gaussian naïve Bayes classifier assumes that numeric attributes come from a Gaussian distribution. Is this assumption always true for the numeric attributes in this dataset? Identify some cases where the Gaussian assumption is violated and describe any evidence (or lack thereof) that this has some effect on the NB classifier's predictions.

3. Implement a kernel density estimate (KDE) naïve Bayes classifier and compare its performance to the Gaussian naïve Bayes classifier. Recall that KDE has kernel bandwidth as a free parameter – you can choose an arbitrary value for this, but a value in the range 5-25 is recommended. Discuss any differences you observe between the Gaussian and KDE naïve Bayes classifiers. (As with the Gaussian naïve Bayes, this KDE naïve Bayes implementation should be your own and should not just call a pre-existing function.)

4. Instead of using an arbitrary kernel bandwidth for the KDE naïve Bayes classifier, use random hold-out or cross-validation to choose the kernel bandwidth. Discuss how this changes the model performance compared to using an arbitrary kernel bandwidth.

5. Naïve Bayes ignores missing values, but in pose recognition tasks the missing values can be informative. Missing values indicate that some part of the body was obscured and sometimes this is relevant to the pose (e.g., holding one hand behind the back). Are missing values useful for this task? Implement a method that incorporates information about missing values and demonstrate whether it changes the classification results.

6. Engineer your own pose features from the provided keypoints. Instead of using the (x,y) positions of keypoints, you might consider the angles of the limbs or body, or the distances between pairs of keypoints. How does a naïve Bayes classifier based on your engineered features compare to the classifier using (x,y) values? Please note that we are interested in explainable features for pose recognition, so simply putting the (x,y) values in a neural network or similar to get an arbitrary embedding will not receive full credit for this question. You should be able to explain the rationale behind your proposed features. Also, don't forget the conditional independence assumption of naïve Bayes when proposing new features – a large set of highly-correlated features may not work well.

If you are in a group of 1, you will respond to two questions of your choosing (two responses in total). If you are in a group of 2, you will respond to four questions of your choosing (four responses in total). A response to a question should take about 150–250 words, and make reference to the data wherever possible. We strongly recommend including figures or tables to support your responses.

Submission

Submission will be made via the LMS. Please submit your code and written report separately:

- Your code submission should be a .zip or .tar.gz file which includes your code, results files, and any additional files we would need to run your code and replicate your results. (You don't need to include the dataset that we provided, but if you created separate train/validation sets you should include those or provide the code to recreate your train/validation splits.) Please also include a README file that tells us how to run your code and recreate your results.
- Your written report should be uploaded separately as a .pdf, using the Turnitin submission link.

If you are working in a group, please include both group members' student id numbers on the written report and in your code file (in the README file or a group.txt file).

Late submission

The submission mechanism will stay open for one week after the submission deadline. Late submissions will be penalised at 10% per 24-hour period after the original deadline. Submissions will be closed 7 days (168 hours) after the published assignment deadline, and no further submissions will be accepted after this point.

Assessment

8 of the marks available for this assignment will be based on the implementation of the naïve Bayes classifier, specifically the four Python functions specified above. Any other functions you've implemented will not be directly assessed, unless they are required to make these four functions work correctly.

Each question is worth 4 marks. We will be looking for evidence that you have an implementation that allows you to explore the problem, but also that you have thought deeply about the data and the behaviour of the relevant classifier(s).

Because the number of questions depends on the group size, individual projects can receive a total of 16 marks and group projects can receive a total of 24 marks. In both cases, the project will contribute 20% of the final mark in this subject. In group projects, both members of the group will receive the same mark.

Updates to the assignment specifications

If any changes or clarifications are made to the project specification, these will be posted on the LMS.

Academic misconduct

You are welcome — indeed encouraged — to collaborate with your peers in terms of the conceptualisation and framing of the problem. For example, we encourage you to discuss what the assignment specification is asking you to do, or what you would need to implement to be able to respond to a question.

However, sharing materials beyond your group — for example, plagiarising code or colluding in writing responses to questions — will be considered cheating. We will invoke University's Academic Misconduct policy (`http://academichonesty.unimelb.edu.au/policy.html`) where inappropriate levels of plagiarism or collusion are deemed to have taken place.