Q1 - Visualization and analysis of the Palmer penguin dataset

The Palmer penguin dataset consists of 344 records of the physical attributes of three species of penguin living on three islands in Antarctica (Table 1) [1]. In this report, the the data are cleaned and carefully prepared for analysis, the dataset is then explored through visualization and finally analysis is carried out to compare the accuracy of a small number of AI approaches in classifying penguin species.

Feature	Type	Values in the dataset	Importance
island	categorical	Torgersen, Biscoe, Dream	0.12 (4)
bill length	numerical	32.1mm - 59.6mm	0.37 (1)
bill depth	numerical	13.1mm - 21.5mm	0.17 (3)
flipper length	numerical	172mm - 231mm	0.23 (2)
body mass	numerical	2700g - 6300g	0.11 (5)
sex	categorical	Male, Female	0.01 (6)
species	categorical	Adelie, Chinstrap, Gentoo	class

Table 1: Palmer penguin dataset features. Importance was calculated using random forest and a ranking is shown.

Data cleaning - missing values, encoding, standardization and imbalance

The two records missing sex and all numerical features were removed as imputation is unlikely to be reliable. The remaining nine records are missing only the sex attribute. Figure 1 shows the physical attributes of the male and female of each species differ statistically, making it reasonable to consider imputing sex for those records would be reliable. Following standardization, a Shapiro-Wilk test confirmed all the numerical attributes have a normal distribution [2] and Z-tests were applied to assess the hypotheses that the missing sex value is male or female [3]. Two of the records could be imputed as

Figure 1: All numerical features show a significant statistical difference between male and female, as in the body mass example above. Shown are median values, upper and lower quartiles, and outliers.

male and three as female; the remaining four records were removed. The cleaned dataset has 338 records, 147 Adelie (74 male, 73 female), 68 Chinstrap (34 male, 34 female) and 123 Gentoo (62 male, 61 female).
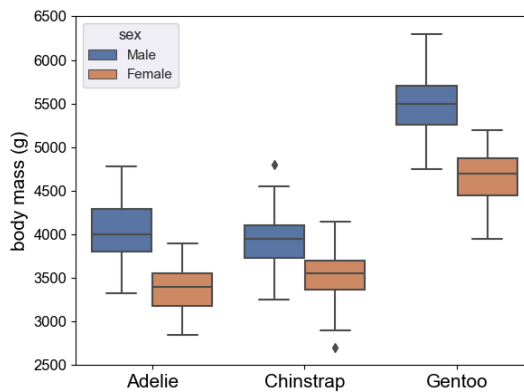
The categorical features in the dataset were encoded to numerical values as this is required for a number of the AI methods. Some AI methods are known to be biased in favour of numerical features with smaller standard deviations [4], but this bias can be reduced by the standardization of features to zero mean and unity standard deviation. Standardization statistics were calculated only from training sets, but were applied to all data. If a dataset is imbalanced, AI predictions may be biased towards classes more frequently found in the training data. All the methods adopted in the current work are known to be little affected by imbalanced data [5], so no modifications were made.

Visualization of the dataset

Figure 2 shows Chinstrap and Gentoo penguins are found only on one island, making it a potential confounding factor since environmental factors may influence physical characteristics. A Shapiro-Wilk test showed the numerical features of the Adelie penguins have a normal distribution and an ANOVA test confirmed Adelie features are not significantly influenced by the island inhabited. Island is thus unlikely to be a confounding factor.

Figure 2: Adelie is on all three islands, but Gentoo and Chinstrap samples are from only one.

Pairwise scatterplots for the numerical features are shown in Figure 3. Bill depth, combined with either flipper length or body mass, yields a separable cluster of Gentoo penguins (shown in green) allowing them to be identified. No pairwise combination completely separates Adelie (orange) from Chinstrap (purple) clusters, but the best candidate feature for doing so is bill length.

Figure 1 above shows the normative body masses of the male and female differ for all the species. Differences between the sexes for the other three numerical physical characteristics were also apparent. Since narrower distributions are extracted if the sex of the species is considered rather than just the species itself, sex is likely to provide a finer grained distinction for species classification. This knowledge was able to improve performance in some cases, as discussed in 'results and analysis'.

Methodology

The code is available on Gitub [6] and was written in Python 3.11 [7]

Figure 3: Pairwise distributions of numerical features. Gentoo can be distinguished, but Adelie and Chinstrap may not be completely separable from one another

using 'scikit-learn' libraries [8]. Predicting the penguin species from the given features is a classification problem. Results are obtained from two conventional classification approaches, namely k-Nearest Neighbour ($k$nn) [9] and random forest [10], unsupervised k-means (following cluster labelling) [11] and a novel combined visualization and analysis
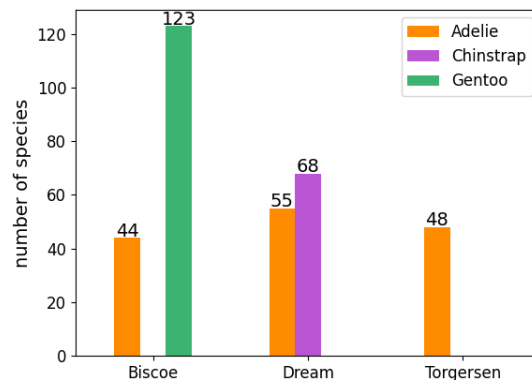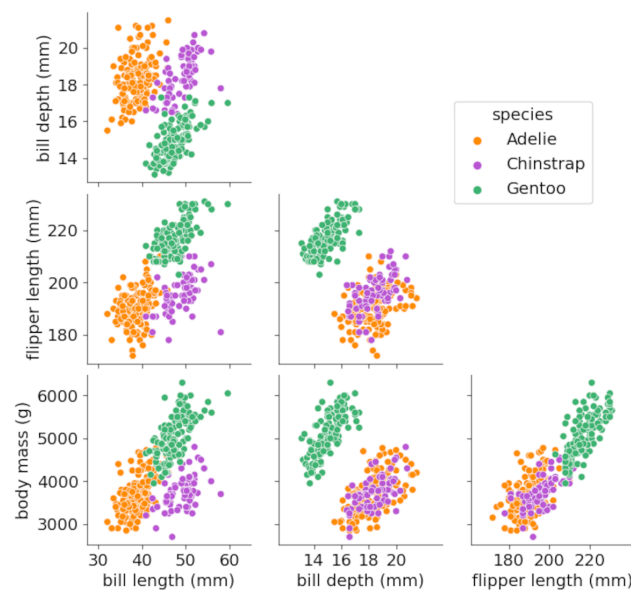
(CVA) approach that is a mix of practical visualizations and Support Vector Machine (SVM) classification.

To reduce the potential for overfitting, the classification methods were trained using 'hold-out validation', where 80% of the dataset was used in a five-fold cross-validation configuration [12]. The remaining 20% was kept for a test set. For all methods, the scikit-learn function GridSearchCV was employed to tune metaparameters [8]. Table 2 shows the values selected for the metaparameter grid. Those giving the best performance were selected to generate accuracy re-

Method	Metaparameters	Values considered
$k$nn	nearest neighbours k prediction function distance metric	***1***, 2, 3, 4, 5, 6, 8, 10 ***uniform***,distance ***Manhattan***,Euclid
random forest	number of trees maximum depth min samples to split min samples at leaf split function	5, ***10***, 15, 20, 25 ***no max***, 10, 20 ***2***, 5, 10 ***1***, 2, 4 ***gini***,entropy
k-means	number of clusters k centroid initialize runs for centroid maximum iterations	2, 3, ***4***, 5, 6, 7, 8, 10 ***k-means++***,random 2, ***5***, 10, 20 5, ***10***, 20, 50
CVA	regularization kernel coefficient kernel type	0.1, 1, ***10***, 100 ***1***, 0.1, 0.01, 0.001 rbf, ***linear***,poly

Table 2: Metaparameters values shown in italics most consistently produced training results of best accuracy during validation and were selected for generating results

sults (the percentage of correctly predicted species) from the test set. The metrics 'precision' and 'recall' were also calculated, but as these are only relevant if false positives or false negatives (respectively) are of interest, they are not included in this report.

Results and analysis

The scikit-learn pseudo-random procedure was used for selecting validation and test set values and 100 (indices 1 to 100) of these were used both when selecting metaparameters and when deriving accuracy results. The results in Table 3 include a baseline to demonstrate the performance improvements achieved by the AI methods. In classification, the baseline

Method	Accuracy (range)
baseline, Adeleie species	43.49%
kNN, all features	99.24% (97.06%-100%)
kNN, no island	99.46% (97.06%-100%)
random forest, all features	98.57% (95.59%-100%)
random forest, no body mass	98.49% (92.65%-100%)
k-means, numerical features	97.03% (94.12%-97.06%)
k-means, two sex clusters	99.18% (94.12%-100%)
CVA, three main features	98.98% (95.35%-100%)
CVA, separate sex models	99.25% (90.91%-100%)

Table 3: Classification accuracy mean value and range for 100 pseudo-random test sets and using the metaparameters identified in Table 2

method is often simply to select the most frequent class in the observations. Here, this is the Adelie penguins, giving an accuracy of 43.49% (147/338).

$k$nn The accuracy of $k$nn obtained using the dataset could be improved by removing certain features (particularly those shown as less important in Table 1). The best improvement was found when island was omitted and when k=3. It appears that island did not provide any additional information and the larger value of k implies better generalization may have been achieved.

Random forest Including all of the features in the analysis, the accuracy of random forest was marginally worse than achieved using $k$nn. No performance improvement was found using fewer features, indicating that random forest may be less influenced by

superfluous information in the training data.

k-means Although a clustering method, k-means can be used for classification by matching clusters to classes. Figure 4 illustrates the mapping of classes to clusters for two feature dimensions. k-means is normally applied to numerical features and only they were included in this work. Using the elbow approach, the number of clusters (k) was recommended to be two, but three was suggested using the silhouette method. Empirically, accuracy improved when $k \geq 4$, as otherwise clusters were not reliably formed for all three species. An accuracy improvement was achieved by creating a separate set of clusters for each sex.
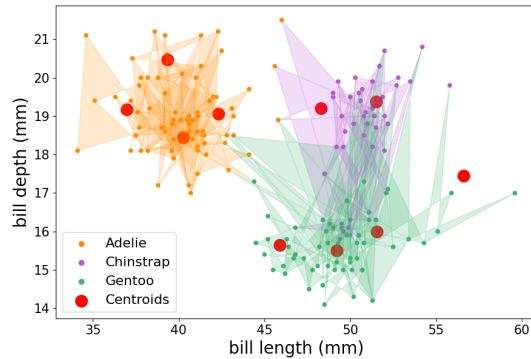

Figure 4: k-means clusters mapped to species using majority voting. Mappings are shown by polygon colour (k=10, 50 samples coloured).

CVA requires manual inspection of pairwise feature plots to identify suitable sets of two-dimensional SVM classifiers. An application of CVA to the Penguin dataset is given in Figure 5. Figure 5(a) shows the relationship between bill depth and flipper length, and SVM determines finds a suitable 'decision boundary' to separate Gentoo from the other two species. Figure 5(b) plots bill length against bill depth and shows the SVM boundary that best separates Adelie and Chinstrap. An improvement in accuracy was apparent when separate SVM models were developed for each sex.
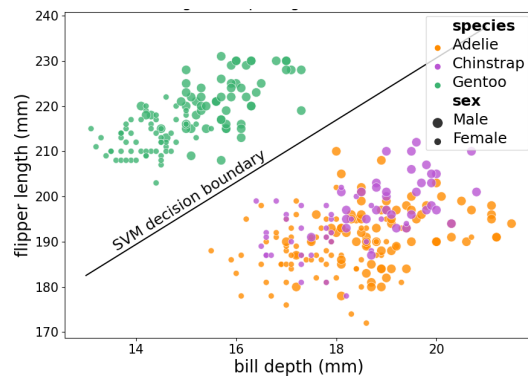
(a) Gentoo can be distinguished from other species
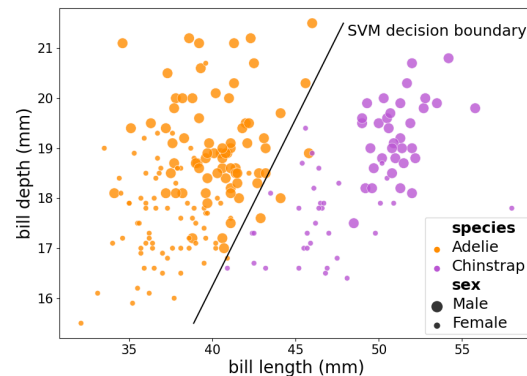
(b) Adelie and Chinstrap can be partially separated

Figure 5: Two-stage CVA approach with boundaries fitted using SVM to training data of feature pairs

Conclusions

With careful data preparation, optimization of metaparameters and robust application of training and testing methods, the $k$nn and random forest classification methods produced high-quality results. As expected, the k-means accuracy results were comparatively worse as training does not take advantage of target data information, but its

performance was improved significantly by producing a cluster for each sex. The novel CVA approach was able to produce accuracy results similar to those of other classification methods. Although needing to be tailored to each problem and not well-suited to high-dimensional data, in contrast with many general-purpose classification methods its internal operations are easy to visualize, understand and explain.

Question 2 - Ethical challenges and threats in AI

Racial Bias in Medical Algorithms

In 2019, a widely used US healthcare algorithm was found to discriminate by prioritising hospital services based on historical spending records, resulting in the allocation of relatively less future funding and fewer referrals for black patients [13, 14]. Through the application of a series of test data sets, Obermeyer *et al.* [15] identified this inadvertent bias and the team was able to mitigate against it by adjusting the model's training labels.

    The fact that this third-party assessment and adjustment were possible, demonstrates how exposing a model's internal operations can aid bias identification and removal [16, 17]. Ensuring greater transparency of AI models is becoming the subject of legislation, for example the 2023 EU AI Act aims to enforce transparency principles by requiring developers to disclose an algorithm's variables, data sources, and selection logic [18, 19]. While ensuring that organisations building AI systems are held accountable for the processes used in their development may lead to algorithmic changes that reduce bias [20, 21], care needs to be taken that the removal of bias doesn't significantly affect the performance of the model in its application domain [22].

AI system safety and existential risks in warfare

Recent developments in AI have led many researchers to believe that AI systems capable of directly acting in the real world based on decisions they have taken autonomously will become available later this century [23]. With such advancements comes the risk that AI systems whose decision-making does not prioritise human welfare may pose a threat to life [24].

    A specific example of a military AI system posing an existential risk [25, 26], is one that decides maximising human casualties would be the best strategy to achieve a high-level battlefield objective [27]. Recent deployments of automated missiles that activate on target acquisition [28, 29], have raised ethical concerns over the use of AI in situations where human beings are potential targets [30]. If such advanced AI was given control of powerful military weapons and applied more widely, the ramifications for the human race's survival could be profound [31].

    Addressing these existential threats requires international cooperation to guarantee the transparency of AI algorithms [32, 33]. A potential future safeguard is to include a human-controlled override in all military AI systems [34], although Russell [35] warns that super-intelligent AI may be capable of removing such safety measures. Ultimately, a global strategy that prioritises human wellbeing in all areas of AI usage will be essential.

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