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 dataset is cleaned, explored through visualization, carefully prepared for investigation and finally the performances of AI approaches in classifying penguin species are compared.

| 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

Eleven records have missing values. The two missing both *sex* and all numerical features were removed as imputation is unlikely to be reliable. A further nine records are missing only a *sex* value and were considered for imputation. Figure 1 shows the physical attributes of the male and female of each species differ statistically, making it likely that imputing *sex* 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 is female [3]. Two of the records could be imputed as 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).
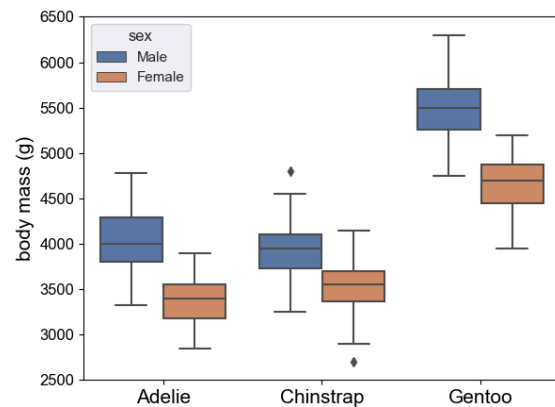
Figure 1: All numerical features (includig body mass shown here) show a significant statistical difference between sexes
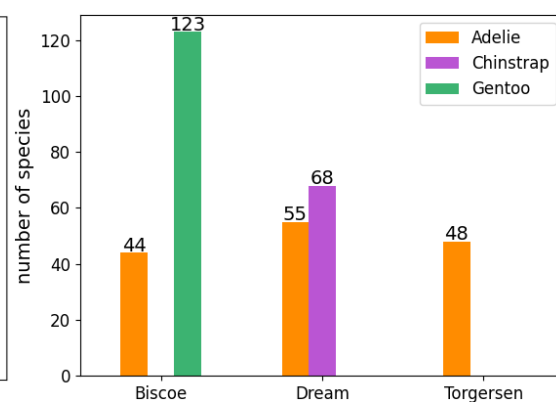
Figure 2: Adelie is found on all three islands, but Gentoo and Chinstrap samples are found on only one of the islands

Visualization of the dataset

Figure 2 shows Chinstrap and Gentoo penguins are each found on only one of the islands, making *island* a potential confounding factor since environmental factors may influence

physical characteristics. A Shapiro-Wilk test showed the numerical features of the Adelie penguins (found on all the islands) have a normal distribution and an ANOVA test confirmed Adelie features are not significantly influenced by the island inhabited. Thus *island* is unlikely to be a confounding factor.
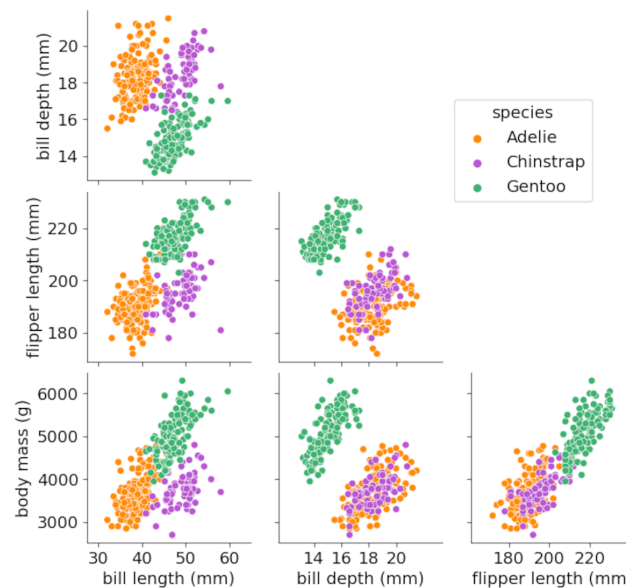
Pairwise scatterplots for the numerical features are shown in Figure 3. *Bill depth*, combined with either *flipper length* or *body mass*, yields a separable cluster of Gentoo penguins (shown in green) allowing them to be identified. No pairwise combination completely separates Adelie (orange) from 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. As 'narrower' distributions result if the *sex* of the species is considered rather than just the species itself, including *sex* in analysis is likely to improve species classification. This knowledge was able to improve performance for some AI methods, as discussed in 'results and analysis'.

Methodology

The categorical features in the dataset were encoded to numerical values as this is required for a num-

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

ber 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 the standardization itself was applied to all data, including test sets. If a dataset is imbalanced, AI predictions may be biased towards classes more frequently found in the training data. Although Adelie penguins are more populus in the dataset, all the methods adopted in the current work are known to be little affected by imbalanced data, so no modifications were made [5].

Predicting the penguin species from the given features is a classification problem. The code supporting this report is available on Github [6], was written in Python 3.11 [7] and used the `scikit-learn` libraries [8]. Results were obtained from two conventional classification approaches, namely k-Nearest Neighbour ($k$nn) [9] and random forest [10]. Classificaton was also carried out using unsupervised k-means (following cluster labelling) [11], as well as 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]. The values selected for the metaparameter grid are shown in Table 2 and are typical of those found in the literature [13]. Metaparameters giving the best performance

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

were selected to generate accuracy results (the percentage of correctly predicted species) from the test sets. The metrics 'precision' and 'recall' were calculated but not included here as measures of false positives or false negatives are not relevant to this study.

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.

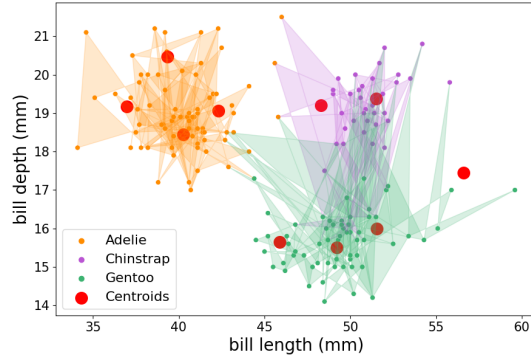| Method	Accuracy (range)
baseline, Adeleie species	43.49%
*k*nn, all features	99.24% (97.06%-100%)
*k*nn, no island	99.46% (97.06%-100%)
random forest, all features	98.57% (95.59%-100%)
random forest, no body mass	98.49% (92.65%-100%)
k-means, numerical features	97.03% (94.12%-97.06%)
k-means, two sex 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

In classification, the baseline 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 (Table 3). It appears that *island* did not provide any additional information and the larger value of *k* (compared to *k*=1 for all features) implies better generalization has been achieved during training.

Random forest When all features are inlcuded 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 mapping clusters to classes. Figure 4 illustrates such a mapping for two feature dimensions. Using the elbow method, the number of clusters (k) was suggested to be two, but three was identified by the silhouette method. By trial and error, accuracy was found to improve when $k \geq 4$, as otherwise clusters were not reliably formed for all three species. Accuracy was also greatly improved by creating a separate set of clusters for each *sex*.
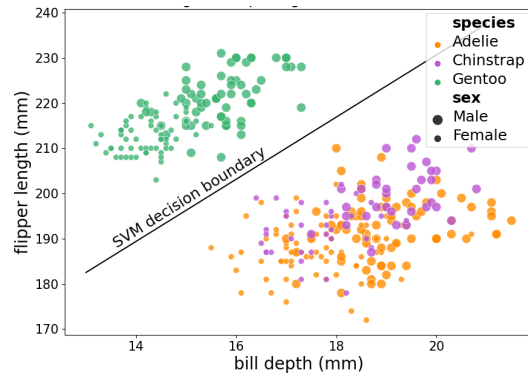

Figure 4: k-means clusters mapped to species using majority voting. Mappings are shown by polygon colour (k=10, 50 samples included).

CVA requires manual identification of suitable pairs of features for SVM classification. Given features **x**, SVM finds a decision boundary that maximizes class separation

$$\mathbf{w}^T\mathbf{x} = b, \tag{1}$$

where **w** is a weight vector perpendicular to the boundary and b is the intercept. SVM training finds **w** and b to specify an optimal hyperplane (and hence the boundary). 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 the SVM decision boundary separates Gentoo from the other two species. Figure 5(b) plots *bill length* against *bill depth* and shows the SVM boundary to best distinguish Adelie from Chinstrap. Accuracy was improved by implementing separate SVM models for each *sex*.

(a) Gentoo distinguished from the other species
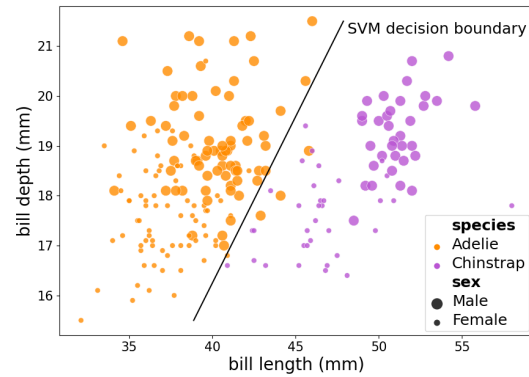
(b) Adelie and Chinstrap partially separated

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

Conclusions

With careful data preparation, selection of metaparameters and robust application of training and testing methods, $k$nn and random forest both produced high-quality results. k-means training does not take advantage of target information and this resulted in comparatively poor accuracy, but training separate clusters for each sex did improve performance significantly. The novel CVA approach needs to be tailored anew to each

problem and is not well-suited to high-dimensional data, but it was found to produce results comparable to those of general-purpose classification methods and has the advantage that its internal operations are easy to visualize, understand and explain.

That CVA makes a series of decisions using chosen feature pairs led the author to consider SVMs in place of entropy at random forests nodes - but this has been done [14]!

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 [15], [16]. Through the application of a series of test data sets, Obermeyer *et al.* [17] 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 [18], [19]. 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 [20], [21]. 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 [22], [23], care needs to be taken that the removal of bias doesn't significantly affect the performance of the model in its application domain [24].

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 [25]. With such advancements comes the risk that AI systems whose decision-making does not prioritise human welfare may pose a threat to life [26].

A specific example of a military AI system posing an existential risk [27], [28], is one that decides maximising human casualties would be the best strategy to achieve a high-level battlefield objective [29]. Recent deployments of automated missiles that activate on target acquisition [30], [31], have raised ethical concerns over the use of AI in situations where human beings are potential targets [32]. 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 [33].

Addressing these existential threats requires international cooperation to guarantee the transparency of AI algorithms [34], [35]. A potential future safeguard is to include a human-controlled override in all military AI systems [36], although Russell [37] 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.

References

[1] A. M. Horst, A. P. Hill, and K. B. Gorman, "Palmerpenguins: Palmer archipelago (antarctica) penguin data," 2020, [Online]. Available: `https://allisonhorst.github.io/palmerpenguins/` [Accessed 27/4/2024].

[2] S. S. Shapiro and M. B. Wilk, "An analysis of variance test for normality (complete samples)," *Biometrika*, vol. 52, no. 3/4, pp. 591–611, 1965.

[3] D. Freedman, R. Pisani, and R. Purves, *Statistics*. W.W.Norton & Company, 2007, ISBN: 978-0393929720.

[4] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, 2009, ISBN: 978-0387848570.

[5] H. He and Y. Ma, "Learning from imbalanced data," *Knowledge and Data Engineering, IEEE Transactions on*, vol. 21, no. 9, pp. 1263–1284, 2009.

[6] T. Mulvaney, *Ai coursework repository*, [Online]. Available: `https://github.com/timmulvaney/AI/` [Accessed 10/5/2024], 2024.

[7] Python Software Foundation, "Python 3.11 documentation," 2022, [Online]. Available: `https://docs.python.org/3.11/` [Accessed 28/4/2024].

[8] scikit-learn contributors, "Scikit-learn: Machine learning in python," version 1.2.2, 2023, [Online]. Available: `scikit-learn.org/` [Accessed 27/4/2024].

[9] C. M. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2006.

[10] L. Breiman and A. Cutler, "Random forests," in *Machine Learning*, Springer, vol. 45, 2001, pp. 5–32.

[11] P.-N. Tan, M. Steinbach, and V. Kumar, *Introduction to Data Mining*. Pearson Addison Wesley, 2005.

[12] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning: with Applications in R*. Springer, 2013.

[13] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Sebastopol, CA, USA: O'Reilly Media, 2019.

[14] M. Law, I. Cohen, and C.-L. Liu, "Support vector decision trees for classification," *Neural Information Processing - Letters and Reviews*, vol. 2, no. 4, pp. 71–76, 2003.

[15] S. Jemielity, "Health care prediction algorithm biased against black patients, study finds," 2019, [Online]. Available: `https://news.uchicago.edu/story/health-care-prediction-algorithm-biased-against-black-patients-study-finds`. [Accessed 27/4/2024].

[16] H. Ledford, "Millions affected by racial bias in health-care algorithm," *Nature*, vol. 574, pp. 608–609, Oct. 2019.

[17]   Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," *Science*, vol. 366, pp. 447–453, Oct. 2019.

[18]   B. Séroussi, K. F. Hollis, and L. F. Soualmia, "Transparency of health informatics processes as the condition of healthcare professionals' and patients' trust and adoption: The rise of ethical requirements," *Yearbook of Medical Informatics*, vol. 29, no. 01, pp. 007–010, 2020.

[19]   P. D. Winter and A. Carusi, "(de)troubling transparency: Artificial Intelligence (AI) for clinical applications," *Medical Humanities*, vol. 49, no. 1, pp. 17–26, 2023.

[20]   E. Parliament, "Eu AI act: First regulation on artificial intelligence," 2023, [Online]. Available: `https://www.europarl.europa.eu/topics/en/article/20230601ST093804/eu-ai-act-first-regulation-on-artificial-intelligence`. [Accessed 27/3/2024].

[21]   L. Edwards, "The EU AI act: A summary of its significance and scope," *Artificial Intelligence (The EU AI Act)*, vol. 1, 2021.

[22]   J. Donovan, J. Matthews, R. Caplan, and L. Hanson, "Algorithmic accountability: A primer," 2018, [Online]. Available: `https://datasociety.net/library/algorithmic-accountability-a-primer/`. [Accessed 27/3/2024].

[23]   T. Lawry, *AI in Health*, 1st. Boca Raton: CRC Press, Taylor & Francis Group, 2020.

[24]   M. Kearns and A. Roth, *The Ethical Algorithm*, 1st. New York: Oxford University Press, 2020.

[25]   K. Grace, J. Salvatier, A. Dafoe, B. Zhang, and O. Evans, "When will AI exceed human performance? evidence from AI experts," *Journal of Artificial Intelligence Research*, vol. 62, pp. 729–754, Jul. 2018.

[26]   T. Ord, *The Precipice: Existential Risk and the Future of Humanity*, 1st. New York: Hachette Books, 2020.

[27]   R. Yampolskiy, "Taxonomy of pathways to dangerous artificial intelligence," in *Workshops at the Thirtieth AAAI Conference on Artificial Intelligence*, Phoenix, Arizona, Mar. 2016.

[28]   M. L. Cummings, *Artificial Intelligence and the Future of Warfare*. London: Chatham House for the Royal Institute of International Affairs, 2017.

[29]   J. Barrat, *Our Final Invention*, 1st. New York: Thomas Dunne Books, 2013.

[30]   K. Atherton, "Brookings: Loitering munitions preview the autonomous future of warfare," 2021, [Online]. Available: `https://www.brookings.edu/articles/loitering-munitions-preview-the-autonomous-future-of-warfare`. [Accessed 30/3/2024].

[31]   I. Bode and T. Watts, "Loitering munitions and unpredictability: Autonomy in weapon systems and challenges to human control," 2023.

[32] R. J. Emery, "Algorithms, AI, and ethics of war," *Peace Review: A Journal of Social Justice*, vol. 33, pp. 205–212, 2021.

[33] M. Tegmark, *Life 3.0: Being Human in the Age of Artificial Intelligence*, 1st. Toronto: Alfred A. Knopf, 2017.

[34] P. Cihon, "Standards for AI governance: International standards to enable global coordination in AI research & development," Future of Humanity Institute, University of Oxford, Tech. Rep., 2019.

[35] D. Leslie, "Understanding Artificial Intelligence ethics and safety," *CoRR*, vol. abs 1906.05684, 2019.

[36] A. Critch and D. Krueger, "AI research considerations for human existential safety," *Computing Research Repository, Cornell University*, 2020, [Online]. Available: `https://arxiv.org/abs/2006.04948`. [Accessed 30/3/2024].

[37] S. Russell, *Human Compatible: Artificial Intelligence and the Problem of Control*, 1st edition. New York: Viking.