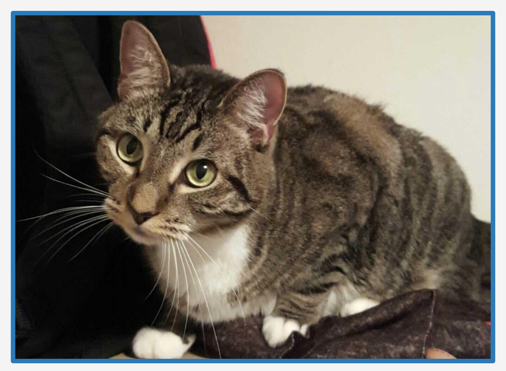
An Evaluation of Machine Learning Algorithms for Classification of Shelter Animal Outcomes

Mikayla Timm and Eman El-Sheikh, Ph.D.
Department of Computer Science
University of West Florida

University of West Florida
Computer Science

Introduction

Background



- Every year, **animal shelters** across the U.S. give approximately **7.6 million animals** a chance at finding a forever home and starting a new life [1].
- **Certain attributes** of the animals recorded at shelter intake may **affect their outcomes**.
- Shelters can **focus their efforts** on animals who are less likely to be adopted if they know the animal is at risk of having a **negative outcome**.

Goals

- Develop a system utilizing **machine learning** algorithms to **predict the outcomes** of animals brought to shelters based on the attributes recorded about them.

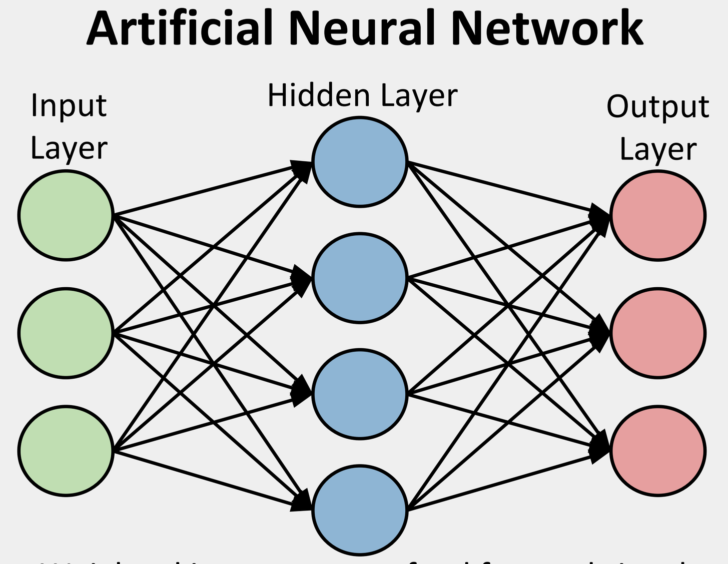
Approach

Data

- Data taken from Austin Animal Shelter from October, 2013, to March, 2016.
- **Attributes:** Name, Animal Type, Sex, Intactness, Age, Breed, Color, Date/Time
- **Possible Outcomes:** Adoption, Return to Owner, Transfer, Euthanasia, Died
- **Number of Animals in Training Set (outcomes recorded):** 26729
- **Number of Animals in Testing Set (outcomes not recorded):** 11456

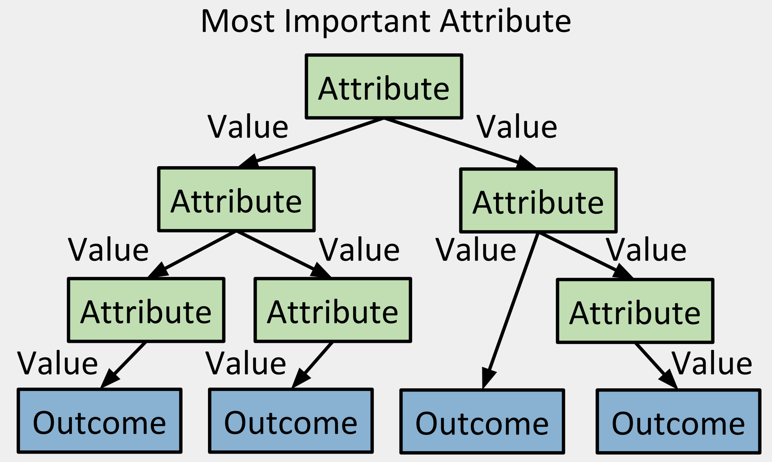
Classification

Artificial Neural Network



- Weighted input **neurons** feed forward signals through **axons** when input weights surpass a threshold in an **activation function** [2], [3]
- **Output layer** represents all possible **outcomes**
- **Many parameters** can be altered, including learning rate, momentum, number of epochs, and number of hidden layers and neurons
- **Relatively slow** - large datasets require a much longer training time for accurate classification
- More **complex** structure and algorithm

Decision Tree Learning

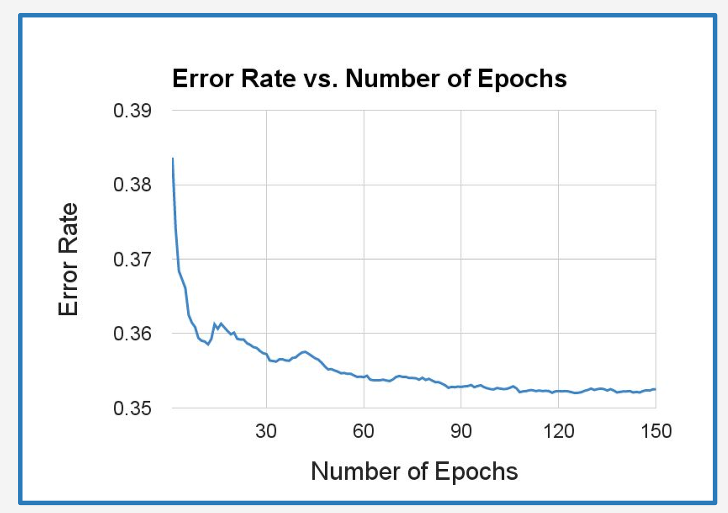


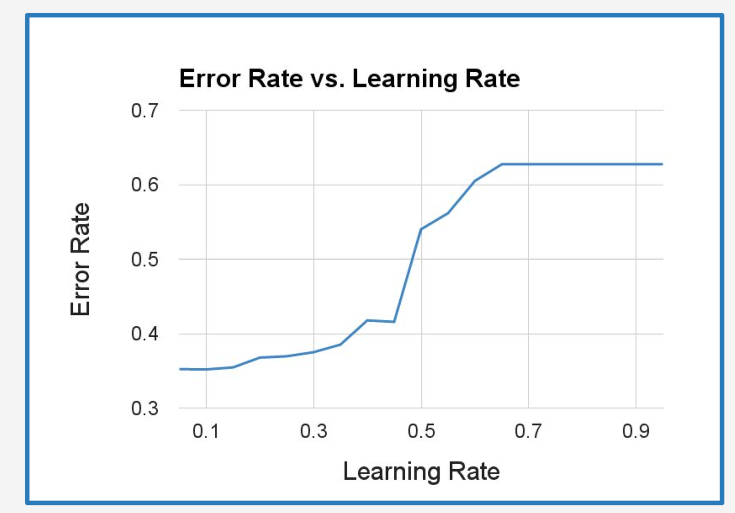
- **Split instances** by the values of the **most important attribute**, creating **subtrees** that continue to split until all instances in each leaf have the **same classification** [2], [3]
- Most important attribute determined by measuring **information gain** for each attribute - **difference in entropy** between parent and child
- **Relatively fast** - can sometimes classify accurately without looking at all attributes
- **Simpler** structure and algorithm

Results

Artificial Neural Network Parameterization

- By altering the **learning rate** and **number of epochs** for the neural network, we can observe changes in the **total error** for classification of the training set.



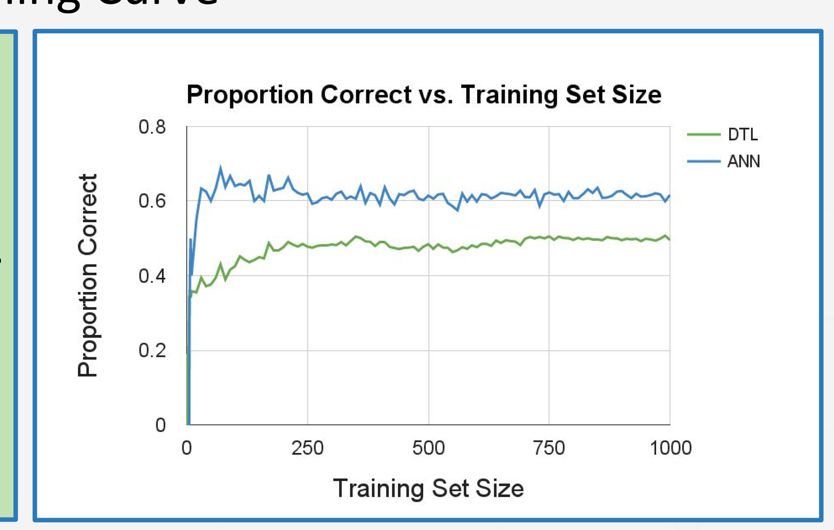


- Increasing the **number of epochs** leads to a **lower error rate** for the ANN.
- Increasing the **learning rate** to a point leads to a **higher error rate** for the ANN.

Artificial Neural Network (ANN) vs. Decision Tree Learning (DTL)

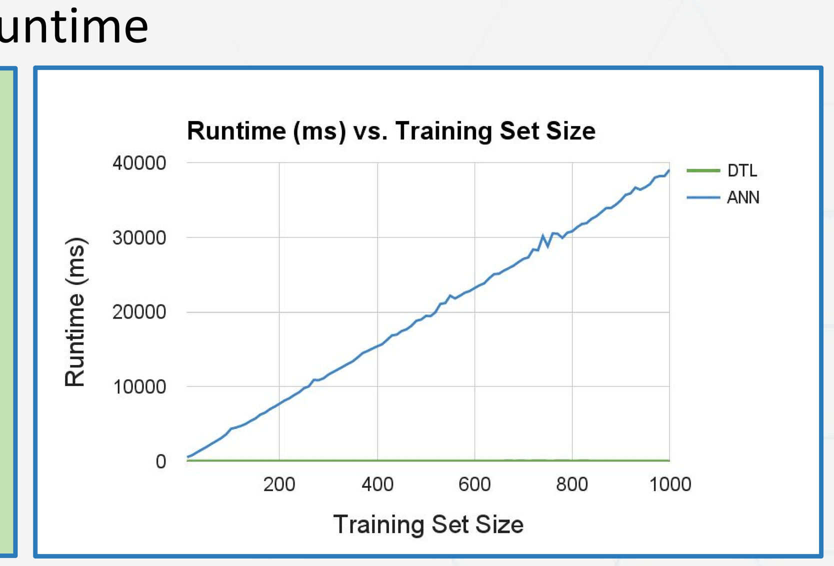
Learning Curve

- Comparative **learning curves** show the proportion of the training set **classified correctly** by each algorithm as the **training set grows**.
- From the graph, it appears that the **ANN** outperforms the DTL algorithm in terms of **accuracy**. The DTL grows at a slower initial rate.



Runtime

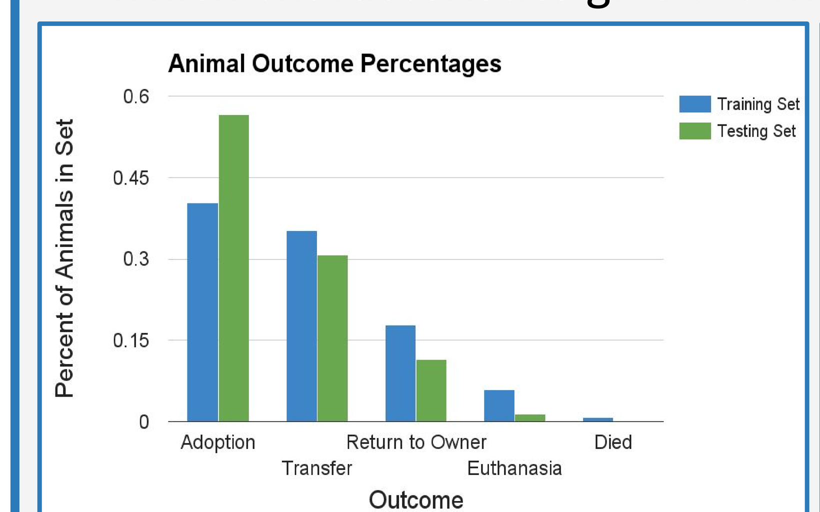
- This graph compares the **runtime** (in milliseconds) of each algorithm as the **training set size increases**.
- The **ANN's** runtime **increases** at a **linear** rate as the dataset grows.
- The **DTL's** runtime appears to not increase at all, staying **close to 0ms** even as the dataset grows large.

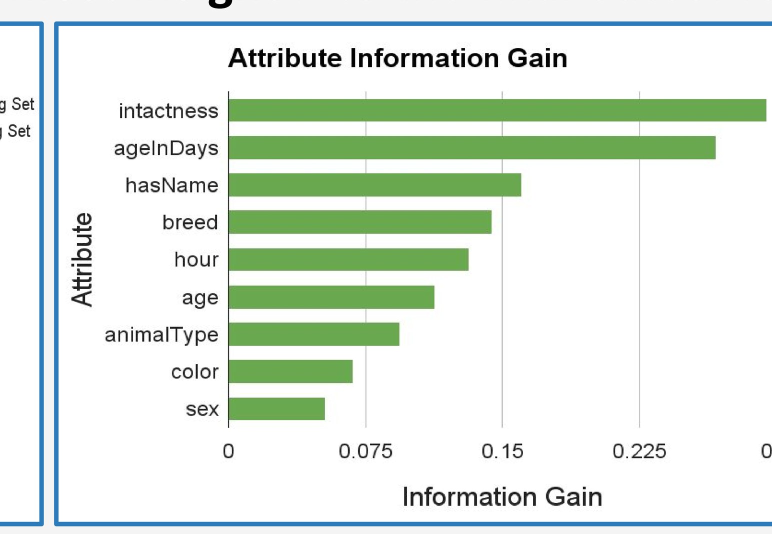


- It is apparent that there is a **trade-off** between algorithms' **accuracy** and **speed**.
- While the **ANN** takes a **longer time to run** on larger datasets compared to the DTL, it also reaches a relatively **high accuracy** given few examples. The **DTL** is significantly **faster**, but requires many **more examples** to reach a high accuracy.
- The **ANN** also has a **more complex** implementation than the **DTL** algorithm.

Results (cont.)

- The percentage of each outcome **predicted** in the **testing** set is relatively **similar** to the percentages found in the **training** set.
- By ranking the attributes by their information gain, we can see **which characteristics** give the **most insight** into the final outcome.





Conclusion

Discussion

- The **ANN** classifies a **higher percentage of correct instances** than the DTL, but takes a **much longer time** to run (no free lunch).
- Some **attributes** of the animals **do not matter much** (sex, color), while some make a **big difference** (intactness, ageInDays) in determining the outcomes.
- Given a greater number of **examples**, both algorithms **improve** in **accuracy**, though the runtime increases significantly for the ANN.
- Some attributes cannot be controlled, but **adoption rates** may **increase** by **spaying/neutering** the shelter animals and giving each one a **name**.

Future Directions

- Add decision tree **pruning** to combat overfitting issues
- Implement **GUI** for viewing visualizations of attributes/outcomes
- Test **other algorithms**, such as Naive Bayes, and compare results

References

1. **ASPCA**. Pet Statistics. http://www.aspca.org/animal-homelessness, 2016.
2. **M. Aly.** Survey on Multiclass Classification Methods. 2005.
3. **S. Russell and P. Norvig.** Artificial Intelligence A Modern Approach, Third Edition. 2010.

Acknowledgements

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