

# Predicting Pictionary Sketches



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# Kaggle result






We have considered a range of models including:

 Random Forest (80% accuracy)

 XGBoost (???% accuracy)

 **Neural Network (92% accuracy)**

# Approach


-  Assign one model to each member to work on
-  Tune hyperparameters, submit predictions, record accuracy
-  Improve on model's performance to its maximum potential
-  Summarise each model's overall performance
-  Pick one model with highest accuracy

# Model overview

**Our best model was a **Convolutional Neural Network model** that was then further improved through **bagging** and **boosting**.**

# Convolutional Neural Network - CNN

 CNN is a type of Neural Network that specialises in **image recognition**.

 Instead of applying a simple pixel to pixel comparison, it applies a series of learned filters to create **feature maps, e.g. lines and shapes**.

# Convolutional Neural Network - CNN

 There are **3 main types of layers in a CNN**:

- . **Convolution layer**: allows certain features of the image to be recognised such as lines and shapes
- . **Pooling layer**: summarises the presence of a feature in each small areas of the feature map and reduce dimension to limit memory and improve speed of the model.
- . **Fully connected layer**: is connected after a series of convolution and pooling layer to support the image classification.

# Genetic algorithm

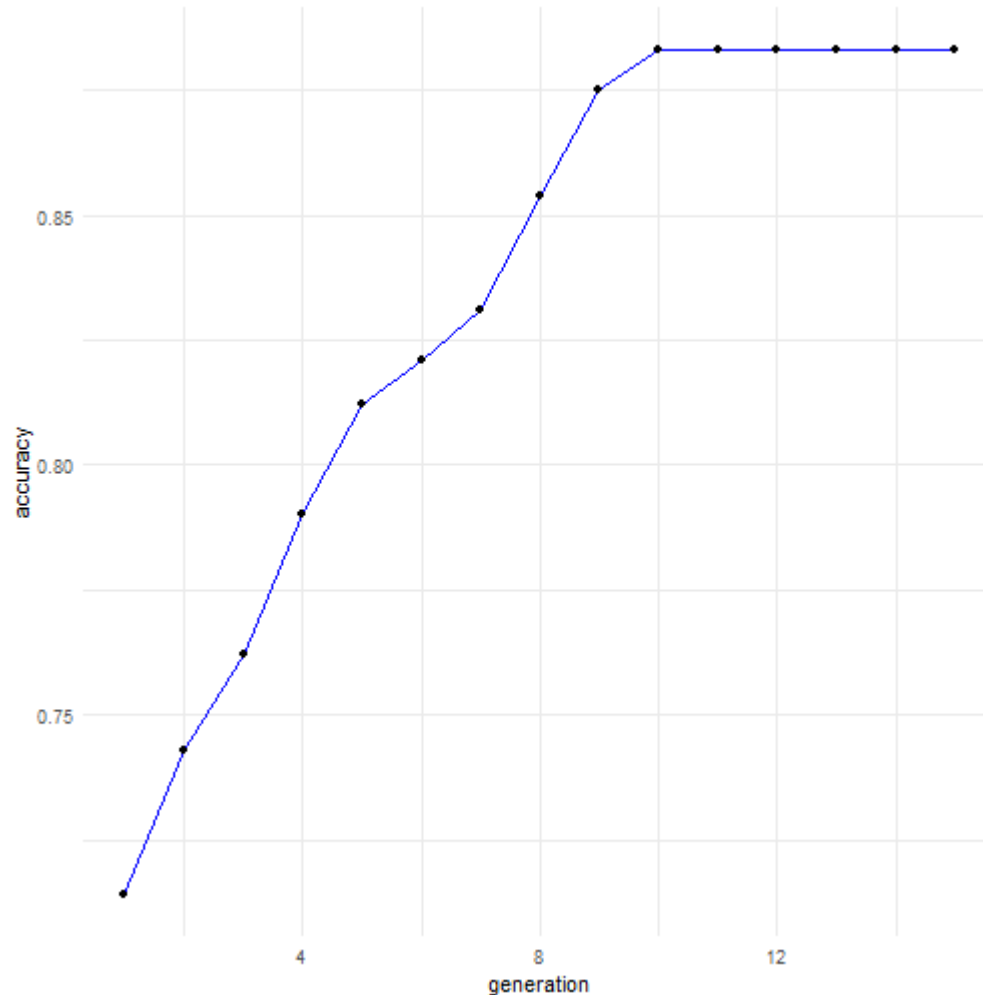


Was used to determine the **optimal configuration for the hyperparameters of our dense layers**, i.e. found the **optimal combination** of:


- 🕒 the loss function,
- 🕒 optimiser,
- 🕒 the number of layers,
- 🕒 the number of nodes and activation function of each layer.

 The genetic algorithm runs through the selection and scoring of models for a **number of iterations, i.e. generations**.

# Generations vs. Accuracy:

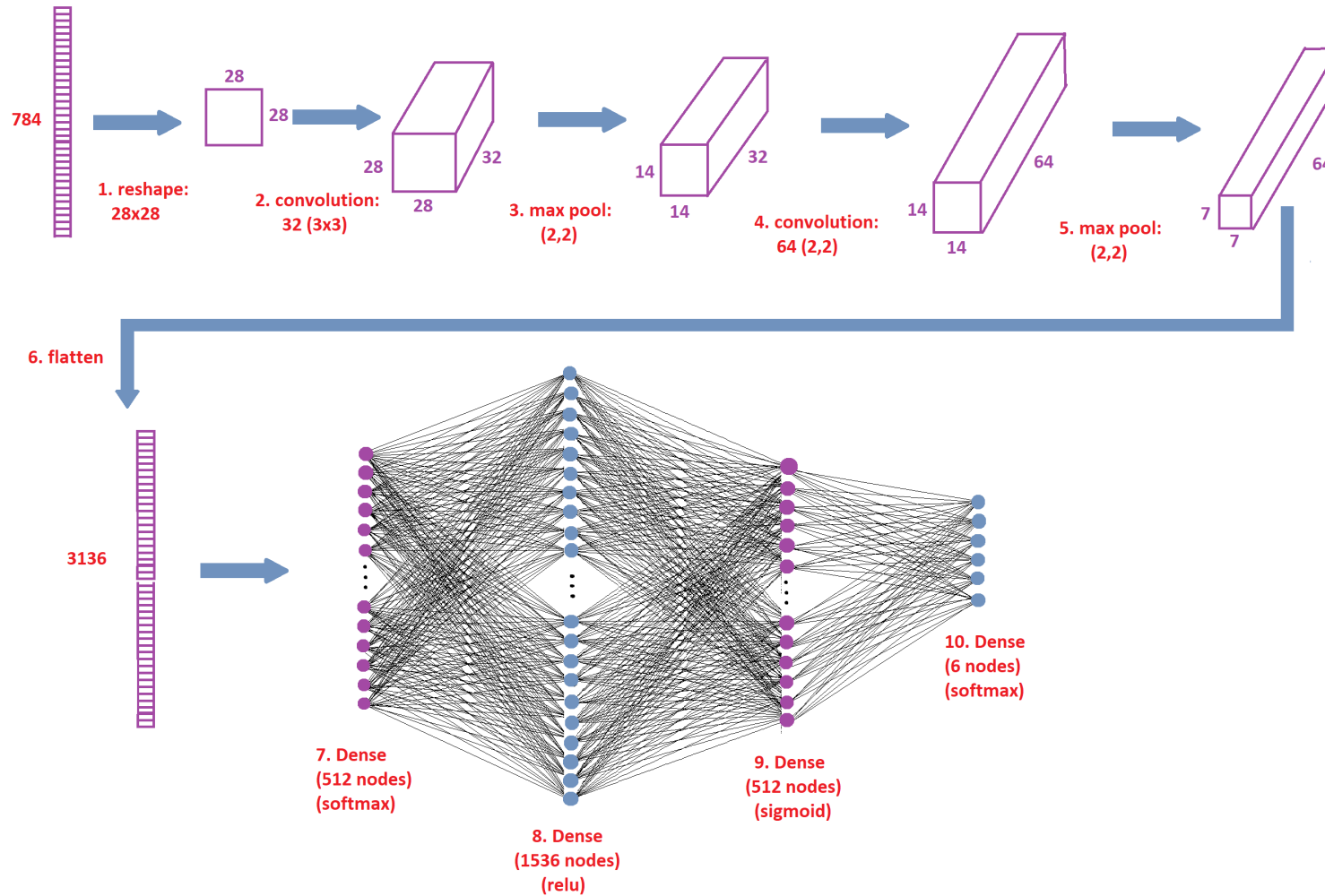


 After 9 generations, the models stop getting better.

 This is because the population were almost all identical at this point because an optimal model had been discovered.



# Full architecture of our model



# Ensemble methods

## Bagging



Train multiple models on different bootstrapped samples of the training dataset



Calculate the average value for the responses from each model to obtain an output



Improvement: reduce bias

## Boosting:



Create and train a model on a bootstrapped sample of the training set.



Calculate model's accuracy with test set.

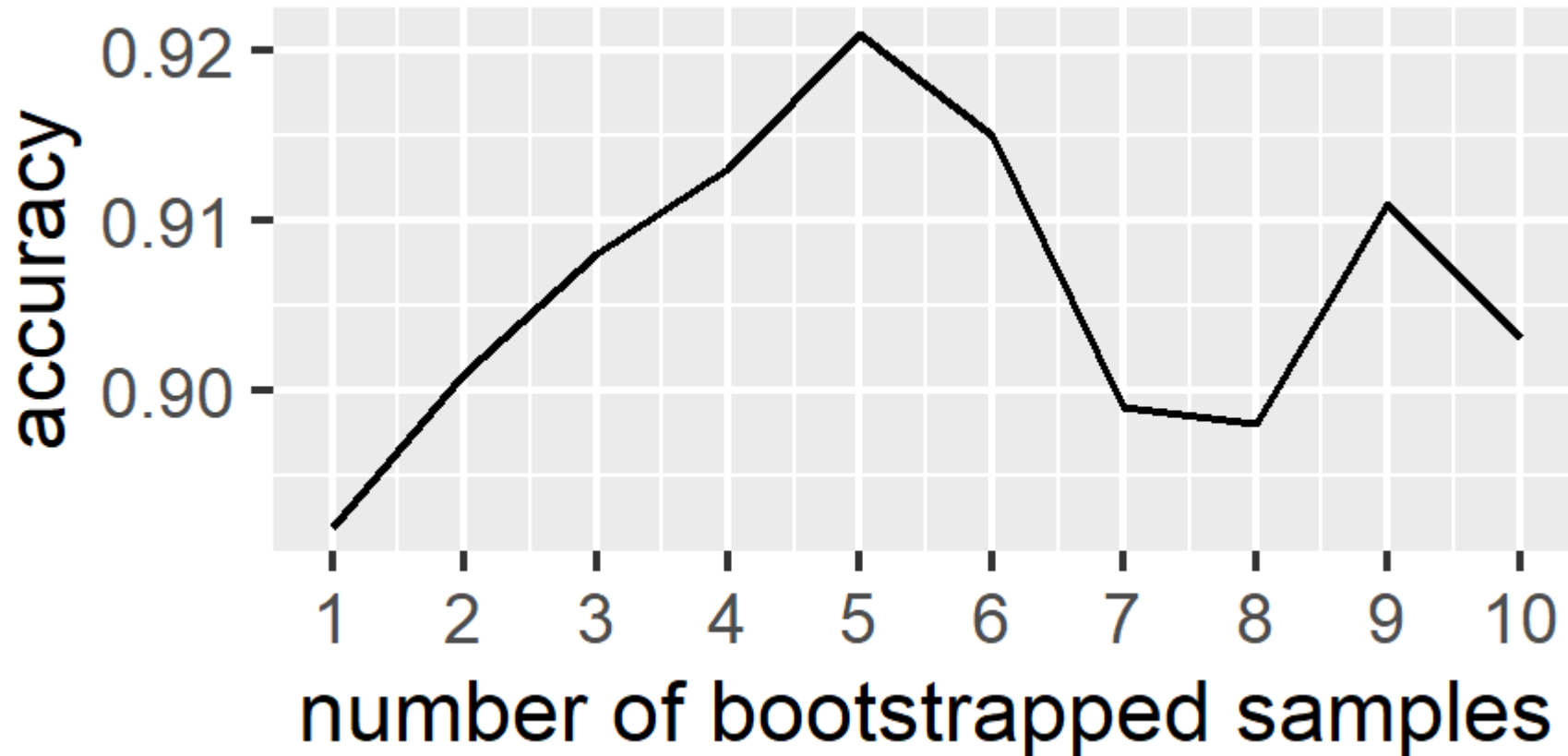


Determine hard-to-predict observations and add them into the training set twice.



Repeat for multiple iterations and average out the results of the first 5 boosted models.

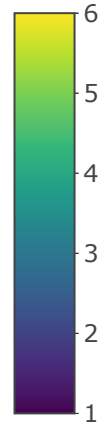
# Accuracy of the ensemble method



# Confusion table

Boosted + Bagged		Predicted								
		banana	boomerang	cactus	crab	flip flops	kangaroo	Total	sensitivity	specificity
Actual	banana	120	2	1	2	2	2	129	93%	99%
	boomerang	5	120	2	4	1	3	135	89%	98%
	cactus	0	0	128	3	4	3	138	93%	99%
	crab	0	1	4	125	2	2	134	93%	99%
	flip flops	1	2	1	3	120	3	130	92%	99%
	kangaroo	2	1	4	2	2	127	138	92%	98%
Accuracy	0.921							804		

# Principal Component



# Interesting observations



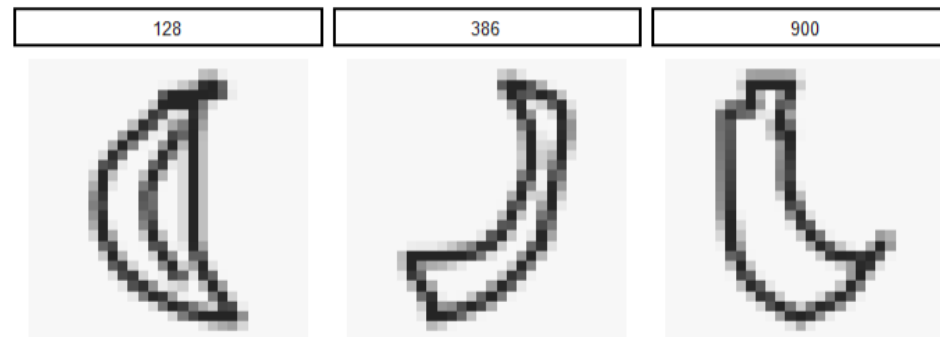
The two most often confused classes are **bananas** and **boomerangs**, which were constantly misclassified by both RF and XGB



CNN, however, had little difficulty



Some examples where only CNN correctly recognised to be bananas, whereas RF and XGB labeled as boomerangs:



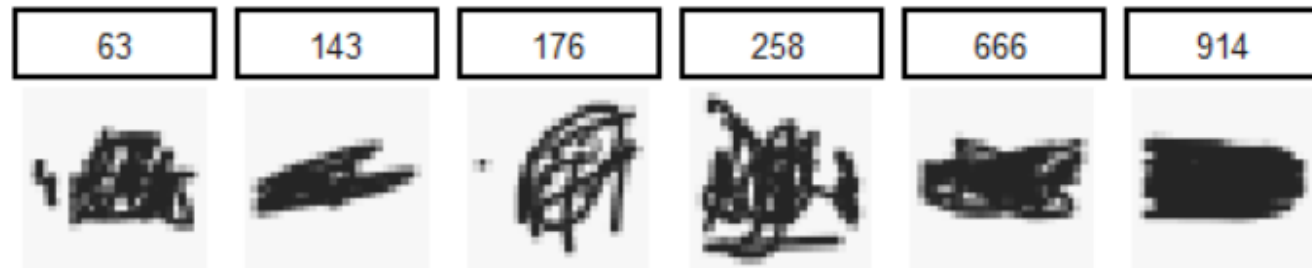
# Interesting observations: scribbles



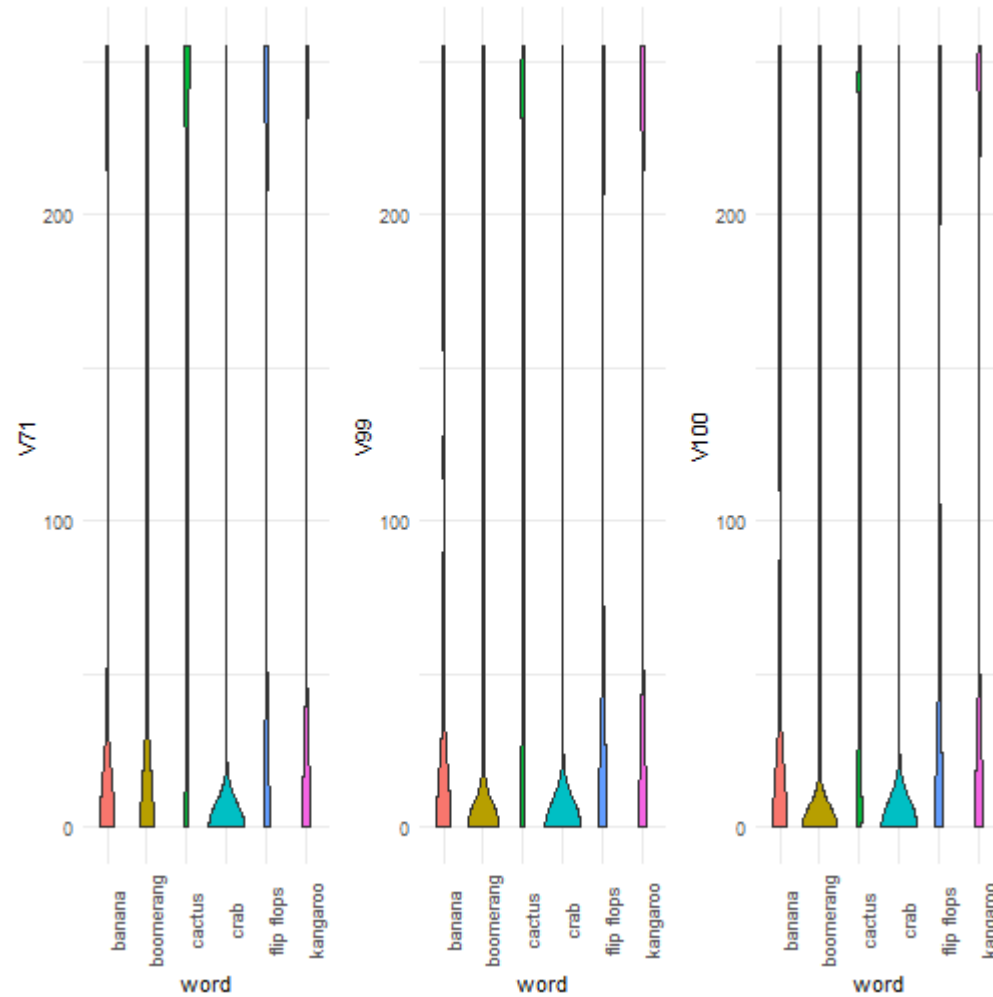
There were some observations where it looks like the player just gave up on the game and decided to make **random scribbles**.



These sketches are indecipherable even with human eyes and **all three models could not decide on a unanimous answer**.



# Important variables





# Acknowledgements

Slides produced using Rmarkdown with xaringan styling.

## Questions?



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