Drawing: A New Way To Search

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OVERVIEW

Motivation: Using words can be limited when communicating across cultures and literacy levels. Images are a shared medium of communication that can beneficially bridge those divides.

We want to develop an efficient system that recognizes labels of hand-drawn images based on Google's QuickDraw dataset. We implemented a variety of models and found that an altered CNN was best for this task.

DATA

Google's QuickDraw is the world's largest doodling dataset, consisting of hand-drawn images from over 15 million people all over the world.

Examples:

Data features: We used the npy bitmap version of the data. Each drawing consists of raw pixel inputs with values from 0 to 255. We are take advantage of the fact that each image has only two colors, black and white to binarize the pixels.

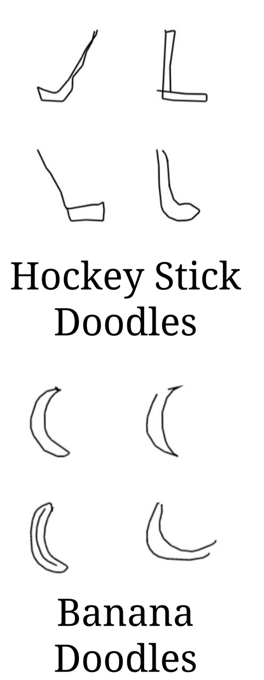
MODEL RESULTS

LOGISTIC REGRESSION

- For baseline, we used Logistic Regression, a simple and fast to train model using numpy bitmap of raw image pixels.

	Accuracy (%)		Training Time (s)	
Classes	10	50	10	50
Baseline	64.64	43.89	122	1089

Table 1. Results for linear regression



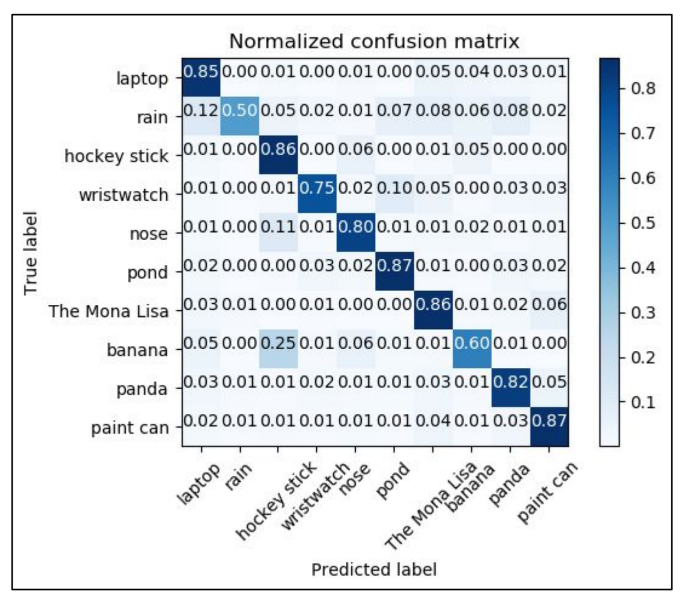


Figure 1. The confusion matrix for linear regression

- Linear Regression performs relatively well
- Banana is often confused with hockey stick which shows that there is a need for a more sophisticated model to make up for drawing quality

SUPPORT VECTOR MACHINE

- In Support Vector Machine with Kernel, some kernels may be more suited for the task of doodle classification, thus we implemented a SVM with four different kernels (Linear, RBF, Polynomial, Sigmoid) to identify the best one for this task empirically.

Model on 10 classes	Accuracy (%)	Training Time (s)
Linear Kernel	22.22	1831
RBF Kernel	61.01	2842
Polynomial Kernel	50.89	6673
Sigmoid Kernel	11.72	6971

Parameters: polynomial degree of 5, RBF coefficient of 1 and RBF gamma of 1, sigmoid coefficient of 1

Table 2. Results for SVMs

- Surprisingly SVMs performed worse than linear regression overall
- Suspect it is due to lack of parameter tuning: For the sigmoid kernel, if the chosen parameters are not well tuned, the algorithm can perform worse than random [1]
- Simultaneously, we found that our CNN was performing with an acceptable accuracy so we decided to focus on CNNs

CONVOLUTIONAL NEURAL NET

- A doodle is a simple image, thus some components of a CNN may be removed. We implemented a CNN, then simplified it by progressively removing layers and dense units to analyze the impact on accuracy and runtime.

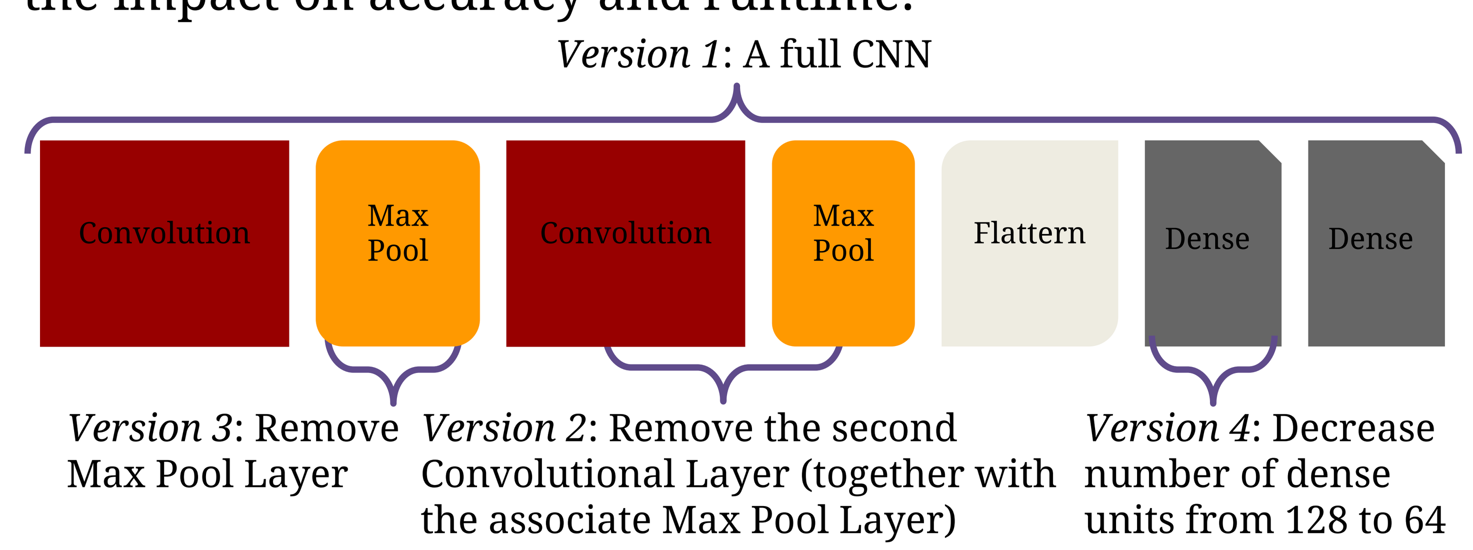


Figure 2. A sketch of how we progressively simplified CNN for doodle classification

	Accuracy (%)		Training Time (s)		Binarized
Number of classes	10	50	10	50	
v1: full CNN	86.59	82.12	3047	14949	No
	83.86	77.28	5391	13856	Yes
v2: remove 2nd convLayer	85.5	76.1	2450	11524	No
	82.16	70.27	2332	16617	Yes
v3: v2 + remove 1st maxPool	86.55	77.17	560	2455	Yes
v4: v2 with a dense layer of 64 units	85.6	70.29	628	3043	Yes

Table 3. Results for CNNs

TRANSFER LEARNING

- Training a deep-learning model from scratch is time-intensive. Transfer learning is one way to leverage pre-trained models for our task. We explored whether using pre-trained winning models from the ImageNet competition could help save time and improve accuracy for our task of doodle classification.

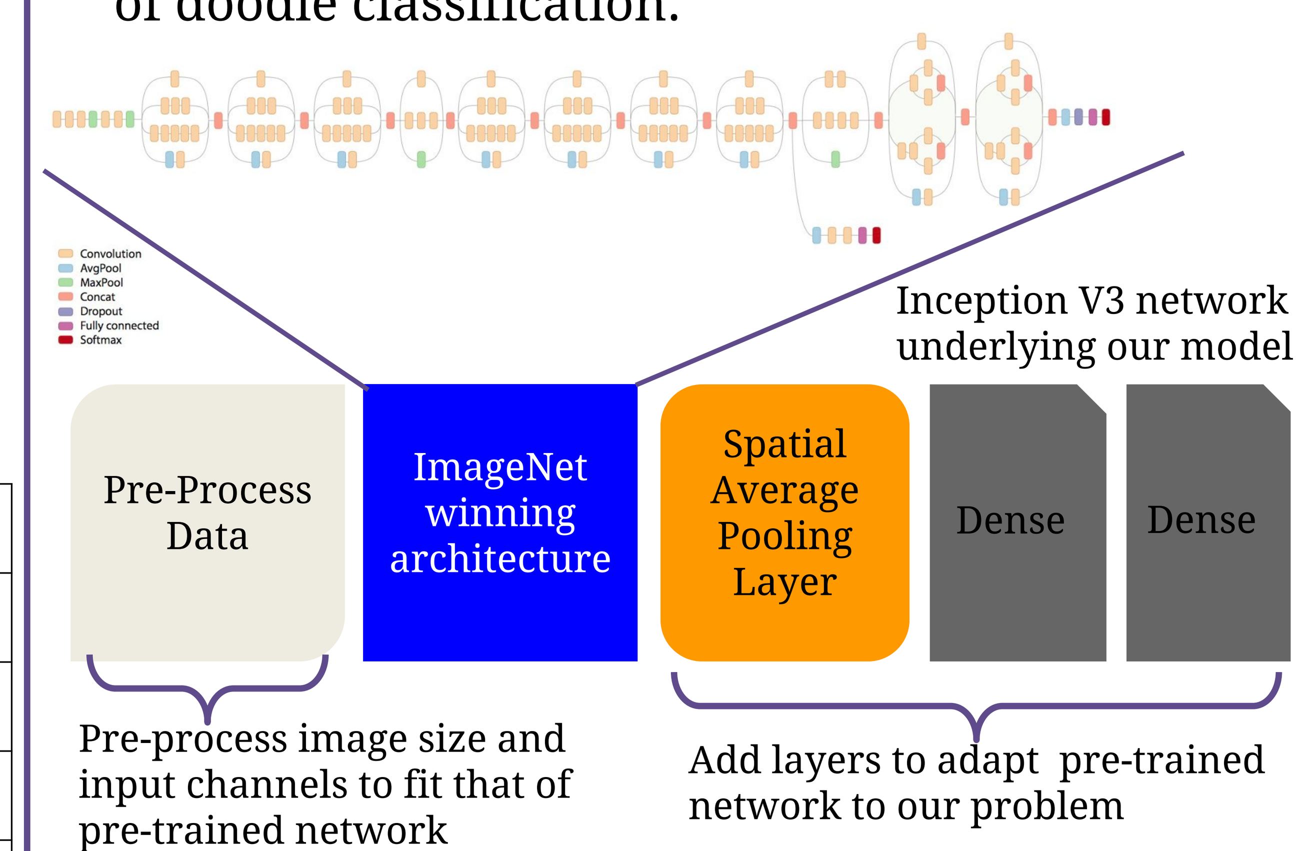


Figure 3. A sketch of how we carried out transfer learning

Models on 3 classes	Accuracy (%)	Training Time (s)
Inception v3	48.77	(stopped at 20 epochs)
MobileNet	75.4	10290
VGG	N/A	(Ran out of memory)
ResNet50	62.72	15232

Table 4. Results for transfer learning

DISCUSSION

Training Time Vs Accuracy tradeoff

- Judging purely on the basis of training time / training resources, Logistic regression was the fastest with a training time of about half an hour.
- However, assuming one has more resources available to train more sophisticated models, we find that CNN does the best for this task with a training time of O(hours) ~ 4+ hours.

Transfer Learning

- Transfer learning model was also expensive to train/tune due to the deep nature of the source models that we were only able to run it on 3 classes.
- Getting Transfer learning to work well likely requires more extensive model tuning.
- In our case, we find transfer learning not optimal if the goal is to optimize training time and accuracy.

FUTURE WORK

- Develop our most promising approach: More extensive experiments to determine the effect of each layer in CNN
- Explore a different approach of transfer learning: using transfer learning as a fixed feature extractor for logistic regression
- Develop other efficiency metrics: data efficiency - working on efficiency in conjunction with smaller datasets

REFERENCES

[1] R. Amami, D. B. Ayed, and N. Ellouze. Practical selection of svm supervised parameters with different feature representations for vowel recognition. arXivpreprint arXiv:1507.06020, 2015.
[2] Simon Kornblith, Jonathon Shlens, and Quoc V. Le. Do better imagenet models transfer better? CoRR, abs/1805.08974, 2018. URL http://arxiv.org/abs/1805.08974