

Doodle Recognition using Convolutional Neural Networks









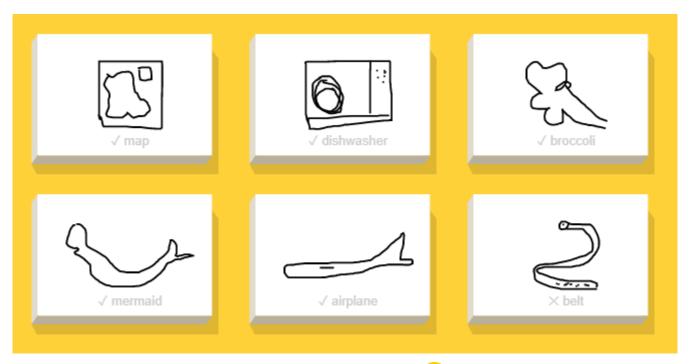
Hello!

We want to explore the Quick-Draw dataset.

Quick-draw is a 'neural network game, trying to guess what the user is drawing.

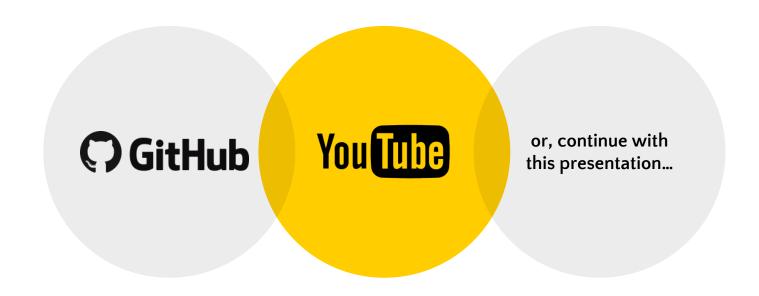


This is what Quick, Draw! Look Like





How would you like to explore our project?





First 2 inks will take you to external websites.

1.0 Business Objectives

Why are we interested in this project?

Discovering this doodle dataset will extend opportunities to explore implementations in real life projects like, handwritten text recognition, touch based complex interactions, etc.

Knowledge from this project work will help understand challenges for human computer interaction in touch-based applications.

2.0 The Dataset

What do 50 million drawings look like?



Quick, Draw! The Data

Millions of players have contributed huge doodle drawings playing this game! We decided to use these doodles to train our convolutional neural network.





Introduction to the Dataset

- 50 million drawings
- Classified into 345 classes
- 20 classes of drawings with first 10,000 image samples taken for data analysis and wrangling
- For CNN data modelling, we have used all 345 classes, but first 10,000 images



Where to get the data?

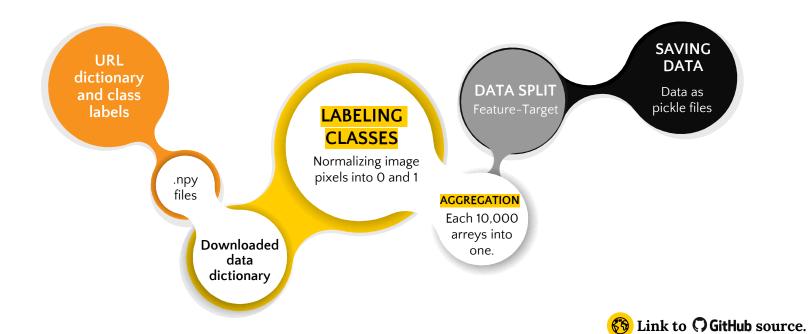
- Entire dataset is available in GitHub: https://github.com/googlecreativelab/quickdraw-dataset
- We are working with preprocessed dataset provided by Google Creative Lab.
- All the drawings have been rendered into a 28x28 px grayscale bitmap in numpy format.



How data cleansing and wrangling were done?

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Data Cleansing Process





- Created a dictionary for URL and class labels to download the entire dataset in .npy files.
- Then the dataset was downloaded into a dictionary.
- Normalized the image pixels between 0 and 1 and added class labels.



- Aggregated the first 10,000 arrays for every doodle into one array of doodles.
- Split the data into features and target labels.
- Save the train and test data as serialized data using pickle files.



Colab couldn't handle gigantic dataset!

Encountered a 'Memory Error' while trying to create a dictionary object using the downloaded data in Colab.

Memory Error

```
classes dict = {}
             for key, value in URL DATA.items():
                 response = requests.get(value)
                 classes_dict[key] = np.load(BytesIO(response.content))
                                                     Traceback (most recent call last)
             MemoryError
             <timed exec> in <module>
             ~\AppData\Local\Continuum\anaconda3\envs\nitin\lib\site-packages\requests\api.py in get(url, param
             s, **kwargs)
                  74
                         kwargs.setdefault('allow redirects', True)
                  75
                        return request('get', url, params=params, **kwargs)
             ---> 76
                  77
                  78
```

Running the code in Colab crashed the application and produced a RAM error as well. Then solved by looping through every .npy file and .png image data for every .npy file to set up data for 345 samples to create our CNN model.



Generating PNG by **Looping** all .npy

```
%%time
# Looping through every npy file and generating png image data for every npy file.
for filename in os.listdir(data file path):
   if filename.endswith('.npy'):
       data = np.load(data file path+"/"+filename)
       print(filename)
       data = data[0:,:]
   if not os.path.exists(train path+os.path.splitext(filename)[0]):
       try:
            os.makedirs(train_path+os.path.splitext(filename)[0])
       except OSError as exc:
            if exc.errno != errno.EEXIST:
   print(train path+os.path.splitext(filename)[0])
   if not os.path.exists(test path+os.path.splitext(filename)[0]):
            os.makedirs(test path+os.path.splitext(filename)[0])
       except OSError as exc:
            if exc.errno != errno.EEXIST:
                raise
   print(test_path+os.path.splitext(filename)[0])
   for i in range(0.5):
       x=np.reshape(data[i],(28,28))
       img = Image.fromarray(x)
       img = img.convert('L')
       if i<4:
            img.save(train_path+os.path.splitext(filename)[0]+"/"+os.path.splitext(filename)[0]+str(i)+".png")
       else:
            img.save(test path+os.path.splitext(filename)[0]+"/"+os.path.splitext(filename)[0]+str(i-4)+".png")
```

3.0 — Data Analysis

Exploring the hidden layer

Exploring Test Data

Exploring Test Data

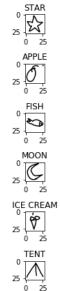
```
In [44]: ► # Test set
             unique, counts = np.unique(y_test, return_counts=True)
             dict(zip(unique, counts))
   Out[44]: {0.0: 2027,
              1.0: 2062,
              2.0: 2081,
              3.0: 2051,
              4.0: 2000,
              5.0: 2075,
              6.0: 1974,
              7.0: 2012,
              8.0: 1984,
              9.0: 1946,
              10.0: 2034,
             11.0: 1966,
              12.0: 1967,
              13.0: 1997,
              14.0: 1921,
              15.0: 1993,
              16.0: 1984,
              17.0: 1901,
              18.0: 2010,
              19.0: 2015}
```

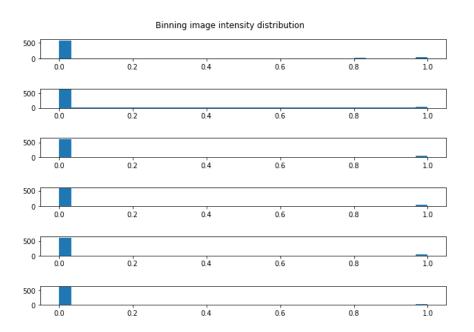


Plotting Intensity Histogram

```
# Image Intensity Histrogram for each class

fig, axs = plt.subplots(20, 2, figsize=(15,20))
plt.suptitle('Binning image intensity distribution', x=.7,y=1)
for i, (key,value) in enumerate(classes_dict.items()):
    axs[1,0].set_title(key.upper())
    axs[i,0].imshow(value[0,:784].reshape((28,28)), cmap="gray_r")
    axs[i,1].hist(value[0,:784].reshape((28,28)).flatten(), bins=30,)
plt.tight_layout()
```





4.0 Data Model

Building the CNN model



CNN Model Architecture for 345 Classes

```
In [110]: model = Sequential([Convolution2D(filters = 32,
                                  kernel size = (3,3),
                                  activation = "relu",
                                  input shape = img size),
                              Convolution2D(filters = 32,
                                  kernel size = (3,3),
                                  activation = "relu"),
                              MaxPooling2D(pool size=(2,2)),
                              Dropout(.20),
                              Convolution2D(filters = 64,
                                  kernel size = (3,3),
                                  activation = "relu"),
                              Convolution2D(filters = 64,
                                  kernel size = (3,3),
                                  activation = "relu"),
                              MaxPooling2D(pool size=(2,2)),
                              Dropout(.1),
                              Flatten(),
                              Dense(512, activation="relu"),
                              Dense(n_classes, activation="softmax")
```

Model Summary

Model: "sequential 7" Layer (type) Output Shape Param # conv2d 21 (Conv2D) (None, 26, 26, 32) 320 conv2d 22 (Conv2D) (None, 24, 24, 32) 9248 max pooling2d 11 (MaxPooling (None, 12, 12, 32) 0 dropout 11 (Dropout) (None, 12, 12, 32) 0 conv2d 23 (Conv2D) (None, 10, 10, 64) 18496 conv2d 24 (Conv2D) (None, 8, 8, 64) 36928 max pooling2d 12 (MaxPooling (None, 4, 4, 64) 0 dropout 12 (Dropout) (None, 4, 4, 64) 0 flatten 6 (Flatten) (None, 1024) 0 dense_15 (Dense) (None, 512) 524800 (None, 345) 176985 dense 16 (Dense)

Total params: 766,777 Trainable params: 766,777 Non-trainable params: 0

model.summary()

Model Training

```
In [99]: %%time
          training_set = train_datagen.flow_from_directory(
                  train path,
                  target size=(28, 28),
                  color mode="grayscale",
                  batch size=256,
                  class mode='categorical')
          Found 2760000 images belonging to 345 classes.
          Wall time: 1min 39s
In [100]: %%time
          test set = test datagen.flow from directory(
                  test path,
                  target size=(28, 28),
                  color mode="grayscale",
                  batch size=256,
                  class mode='categorical')
```

Found 690000 images belonging to 345 classes. Wall time: $28.6 \ \text{s}$

Model Optimizing

Model Fitting

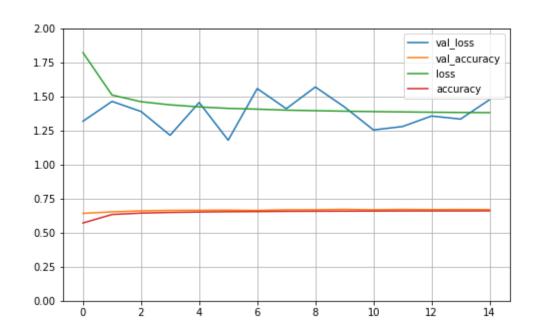
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Do You See the Wall Time?

```
10781/10781 [============= ] - 5197s 482ms/step - loss: 1.3964 - accuracy: 0.6578 - val lo
ss: 1.5704 - val accuracy: 0.6688
Epoch 10/15
10781/10781 [============= ] - 5212s 483ms/step - loss: 1.3928 - accuracy: 0.6584 - val lo
ss: 1.4241 - val accuracy: 0.6715
Epoch 11/15
10781/10781 [============ - 5153s 478ms/step - loss: 1.3897 - accuracy: 0.6591 - val lo
ss: 1.2549 - val accuracy: 0.6686
Epoch 12/15
10781/10781 [============= ] - 5066s 470ms/step - loss: 1.3874 - accuracy: 0.6597 - val lo
ss: 1.2798 - val accuracy: 0.6711
Epoch 13/15
10781/10781 [============== ] - 5166s 479ms/step - loss: 1.3851 - accuracy: 0.6601 - val lo
ss: 1.3570 - val accuracy: 0.6697
Epoch 14/15
10781/10781 [============= ] - 6328s 587ms/step - loss: 1.3834 - accuracy: 0.6601 - val lo
ss: 1.3347 - val accuracy: 0.6707
Epoch 15/15
10781/10781 [============== ] - 5627s 522ms/step - loss: 1.3821 - accuracy: 0.6606 - val lo
ss: 1.4774 - val accuracy: 0.6698
Wall time: 1d 50min 55s
```

Model fitting was running little more than a day. The machine did not have enough hardware to contribute to the processing time.

Model Performance



Our CNN model did not perform well enough. We ended up with a validation accuracy of ~70%. Which isn't very attractive. Inclusion of all 345 classes might have been too ambitious for 10,000 sample images.

5.0 Lessons Learned

What could have been better

Selecting less than 345 classes could have shown a better result with added opportunity of testing several models.

Touch based human computer interaction for handicapped users could be improved more with exploratory datasets from various world regions.

