



Handwritten Text Recognition using TensorFlow 2.0

Computer Vision

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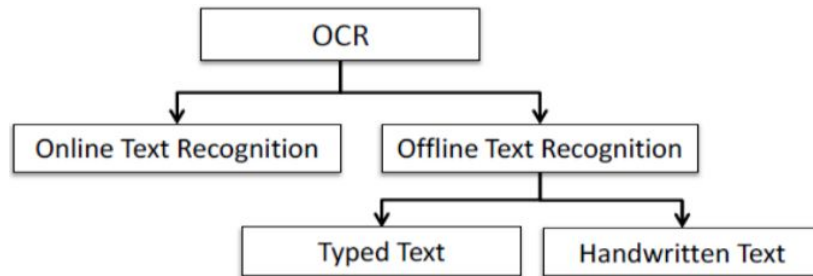
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Introduction

Offline Handwritten Text Recognition Systems (HTR) has the purpose of transcribing cursive text contained in images to the digital medium (ASCII, Unicode)

(BUNKE; ROTH; SCHUKAT-TALAMAZZINI, 1995)



*Classification of Optical Character Recognition.
(SONKUSARE; SAHU, 2016)*

Objectives

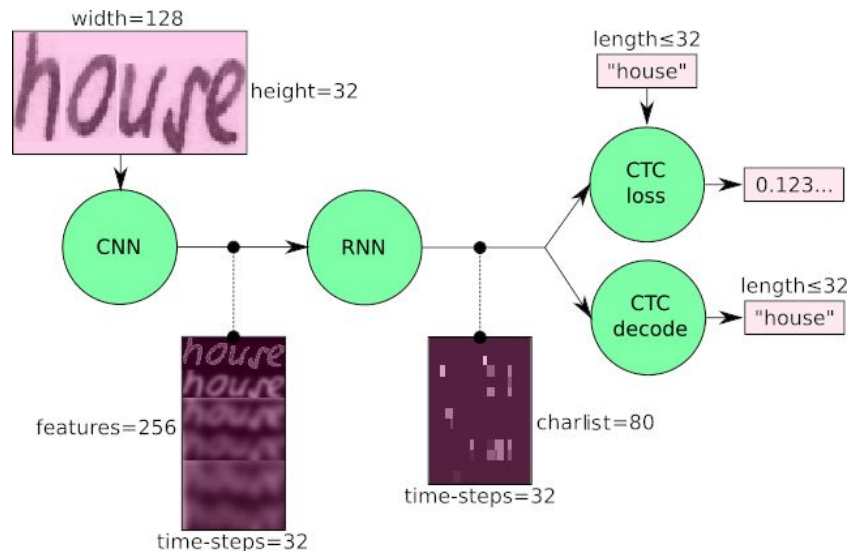
- To develop HTR system using TensorFlow 2.0;
- To implement optical models of the literature;
- To implement a new optical model inspired by the literature;
- To provide easy-to-use code (code, documentation, tutorial) for the development of HTR systems through TensorFlow 2.0 and Google Colab.

Handwritten Text Recognition System

CNN: these layers are trained to extract **relevant features** from the image.

RNN: these layers propagates relevant information through the CNN output. The output sequence is mapped to a matrix of size **time-steps x charlist**.

CTC: with the output of the RNN, calculates the **loss** and also **decodes** into final text.



Example of HTR system and the passage of data through the optical model (SCHEIDL, 2018)

Handwritten Text Recognition System

charlist is a character dictionary used to encode the ground truth into a sequence of numbers. The charlist is usually created from the characters of the dataset that will be trained.

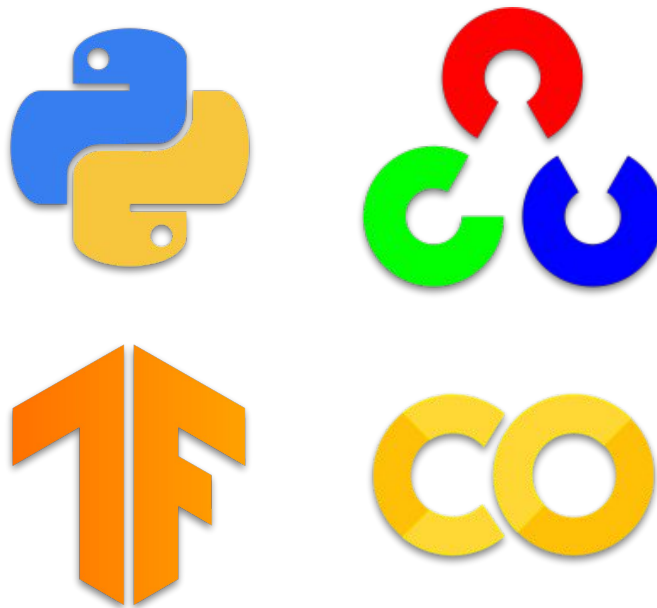
For example, IAM dataset has 80 characters (CTC blank label added):

!"#&'()*+,-./0123456789:;?ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz

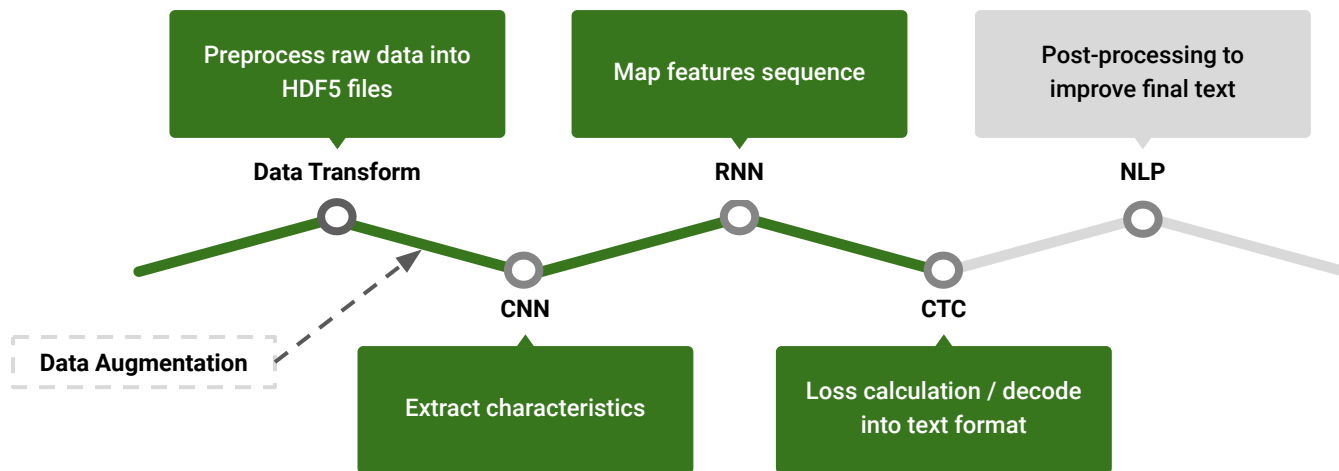
house = [60, 67, 73, 71, 57]

Tools

- Python 3.x
- OpenCV 4.x
- TensorFlow 2.x Beta
- Google Colaboratory/Drive



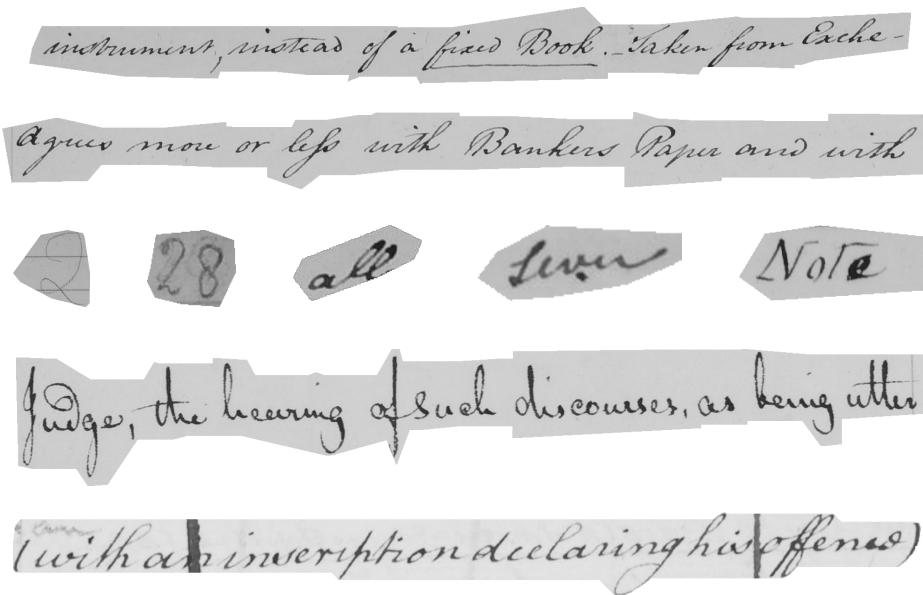
HTR Project Workflow



Datasets

- **Bentham** (DIEM et al., 2014)
<http://transcriptorium.eu/datasets/bentham-collection>
- **IAM** (MARTI; BUNKE, 2002)
<http://www.fki.inf.unibe.ch/databases/iam-handwriting-database>
- **Rimes** (GROSICKI et al., 2008)
<http://www.fki.inf.unibe.ch/databases/iam-historical-document-database/saint-gall-database>
- **Saint Gall** (FISCHER et al., 2010)
http://www.a2ialab.com/doku.php?id=rimes_database:start

Bentham



| Partitions | Characters | Words | Lines |
|------------|------------|---------|--------|
| Train | 424,199 | 86,015 | 9,195 |
| Validation | 64,679 | 12,958 | 1,415 |
| Test | 38,429 | 6,960 | 860 |
| Total | 527,307 | 105,933 | 11,470 |

Number of images per dataset partition

IAM

Though they may gather some Left-wing support, a
 Griffiths resolution. Mr. Foot's line will
 must have been worth a great deal to the proprietors
 He could hardly believe it and blinked several times.
 are highway payments, clearance payments (for clearing remains of
 on lands to the vital question of water

| Partitions | Characters | Words | Lines |
|------------|------------|--------|-------|
| Train | 274,964 | 53,728 | 6,161 |
| Validation | 40,770 | 7,899 | 900 |
| Test | 81,676 | 17,616 | 1,861 |
| Total | 397,410 | 79,246 | 8,922 |

Number of images per dataset partition

Rimes

Je vous remercie d'avance de toute l'attention que vous voudrez bien
 Mon numéro d'ent est le ETLZD 65
 Je vous remercie de me tenir au courant et,
 J'ai déjà fait part de la modification de mes
 quant au décalement de l'accident et aux dégâts
 le percepteur, je vous prie d'agréer, par la présente, mes plus

| Partitions | Characters | Words | Lines |
|------------|------------|--------|--------|
| Train | 458,737 | 73,798 | 10,193 |
| Validation | 51,968 | 8,404 | 1,133 |
| Test | 35,194 | 5,639 | 778 |
| Total | 545,899 | 87,841 | 12,104 |

Number of images per dataset partition

Saint Gall

didum ignei solis iubar singulari decore omnium in se prouoca
erant. admiratione cum & laude dignissimum iudicarent;
prodesse interim potuiss& ; Pergens ergo inde cum suis.
onis ostendat ; Et ille Sicut inquit soci sumus passionis. sic eri
sollemnus ; Cumq. stupatus agmine procerū introiss& ubi ipsa
rentib; consolationis praeberet medelam. nouitate miraculi pate

| Partitions | Characters | Words | Lines |
|------------|------------|--------|-------|
| Train | 26,909 | 3,933 | 468 |
| Validation | 13,107 | 1,982 | 235 |
| Test | 40,243 | 6,160 | 707 |
| Total | 80,259 | 12,075 | 1,410 |

Number of images per dataset partition

Preprocessing (Images)

- Resize with padding: 1024x128
- Illumination Compensation (CHEN et al., 2012)
- Deslant Cursive Images (VINCIARELLI; LUETTIN, 2001)

Preprocessing (Images)

a

6. The evidence of the engagement, consigned to a portable

b

6. The evidence of the engagement, consigned to a portable

c

6. The evidence of the engagement, consigned to a portable

Bentham example: original (a), normalization (b), illumination + deslanting + normalization (c)

Preprocessing (Images)

a 

b 

c 

IAM example: original (a), normalization (b), illumination + deslanting + normalization (c)

Note: memory allocation (int / float)

Preprocessing (Text)

1. **Accentuation normalization**
2. **charlist:** 95 printable characters from ASCII (letters of the latin alphabet, punctuation marks and math signs) + CTC blank label added:

!"#\$%&'()*+,-./0123456789:;<=>?@ABCDEFGHIJKLMNOPQRSTUVWXYZ[\]^_`abcdefghijklmnopqrstuvwxyz{|}~

GT: et les documents nécessaires à cette adhésion .

PP: et les documents necessaires a cette adhesion .

Sparse: [69, 84, 0, 76, 69, 83, 0, 68, 79, 67, 85, 77, 69, 78, 84, 83, 0, 78, 69, 67, 69, 83, 83,
65, 73, 82, 69, 83, 0, 65, 0, 67, 69, 84, 84, 69, 0, 65, 68, 72, 69, 83, 73, 79, 78, 0, 14]

Data Augmentation

- Rotation and Scale
- Height and width shift
- Morphological transformations

Note: *keras generator / openCV*

Optical Models (Related work)

2017 - Are Multidimensional Recurrent Layers Really Necessary for Handwritten Text Recognition

2017 - Gated Convolutional Recurrent Neural Networks for Multilingual Handwriting Recognition

2018 - Are 2D-LSTM really dead for offline text recognition

2018 - Word Beam Search A Connectionist Temporal Classification Decoding Algorithm

2018 - Desarrollo y experimentación de un sistema de aprendizaje profundo para redes neuronales convolucionales y recurrentes

2018 - Medicine Box, Doctor's Prescription Recognition Using Deep Machine Learning

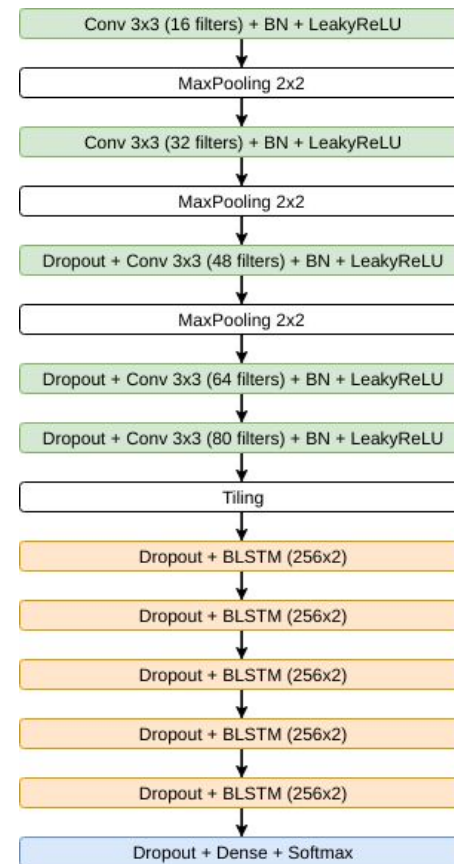
2018 - An Efficient End-to-End Neural Model for Handwritten Text Recognition

2019 - A Scalable Handwritten Text Recognition System

Puigcerver Model

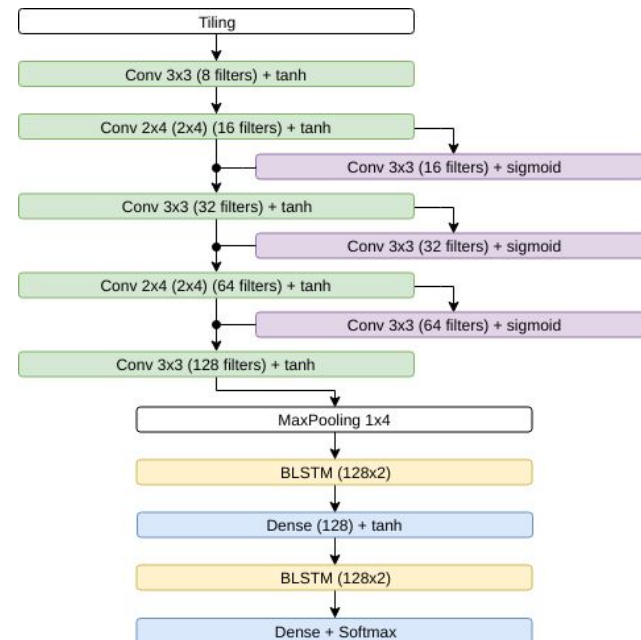
- 5 convolutional layers with LeakyReLU activations
- 5 BLSTM (256x2 units) with dropout (PHAM et al., 2014)
- Dense + Softmax

- 9,589,216 trainable parameters
- RMSProp optimizer with learning rate equal to $3e-4$

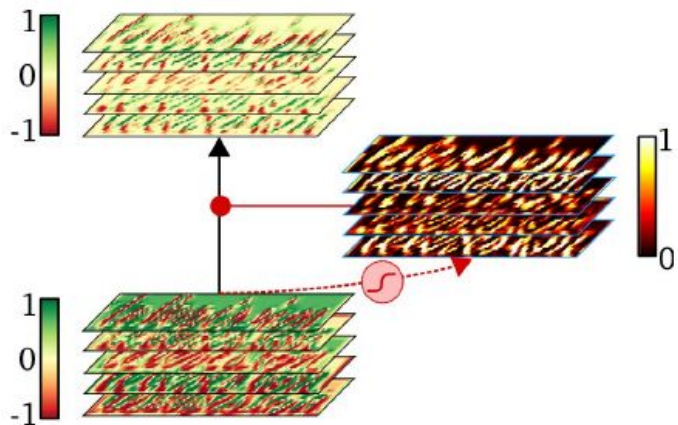


Bluche Model

- 8 convolutional layers (3 Gated) with tanh activations
 - Gated Convolutional by Bluche and Messina (2017)
 - 2 BLSTM (128x2 units)
 - Dense + Softmax
-
- 728,680 trainable parameters
 - RMSProp optimizer with learning rate equal to 4e-4



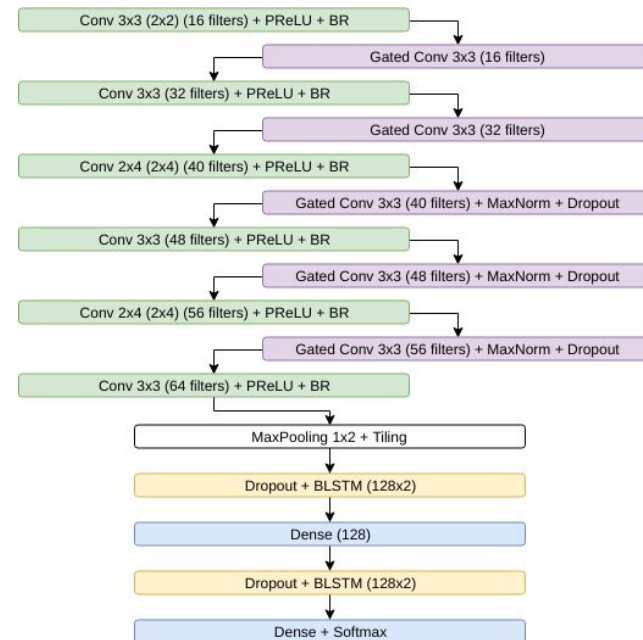
Gated Convolutional (Bluche and Messina)



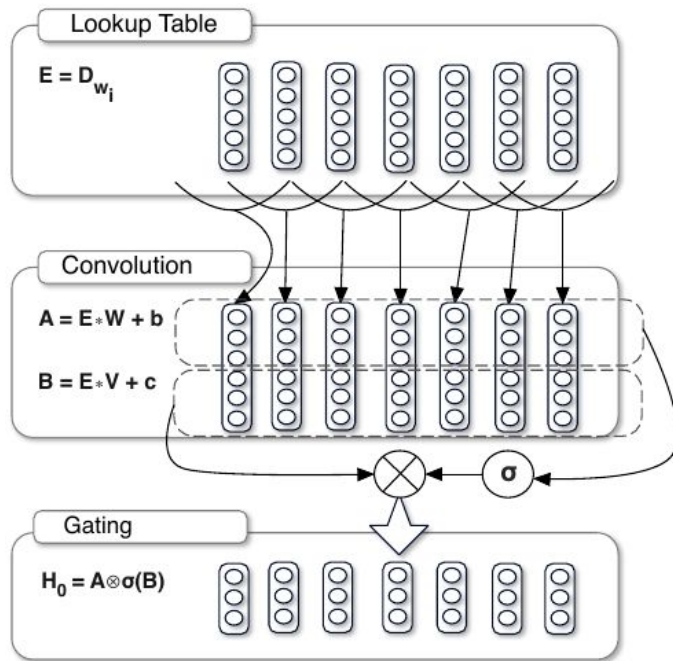
*Gated Convolutional Recurrent Neural Networks for
Multilingual Handwriting Recognition (BLUCHE; MESSINA, 2017)*

Flor Model

- 11 convolutional layers (5 Gated) with PReLU activations
 - Gated Convolutional by Dauphin et al. (2017)
 - 2 BLSTM (128x2 units) with dropout (PHAM et al., 2014)
 - Dense + Softmax
-
- 820,336 trainable parameters
 - RMSProp optimizer with learning rate equal to $5e-4$



Gated Convolutional (Dauphin et al.)



*Language Modeling with Gated Convolutional Networks
(DAUPHIN; FAN; AULI; GRANGIER, 2017)*

Connectionist Temporal Classification (CTC)

- Token Passing (GRAVES et al., 2009)
- **Vanilla Beam Search (HWANG; SUNG, 2016)**
- Word Beam Search (SCHEIDL; FIEL; SABLATNIG, 2018)

~ **No** language model applied in post-processing ~

Experiment Setup

- Default models and learning rates
- Mini-batch: 16
- Reduce Learning Rate on Plateau (10 epochs)
- EarlyStopping if validation loss doesn't improve after 20 epochs
- Metrics: Character Error Rate (CER) and Word Error Rate (WER)
- GPU: Nvidia Tesla T4 16gb (Google Colab default settings)

Bentham Results

860 images (test)

| Model | Default | | No punctuation | |
|------------|---------------|---------------|----------------|---------------|
| | CER | WER | CER | WER |
| Puigcerver | 0.1175 | 0.3931 | 0.0916 | 0.2443 |
| Bluche | 0.1658 | 0.4665 | 0.1424 | 0.3581 |
| Flor | 0.1131 | 0.3966 | 0.0849 | 0.2404 |

IAM Results

1,861 images (test)

| Model | Default | | No punctuation | |
|------------|---------------|---------------|----------------|---------------|
| | CER | WER | CER | WER |
| Puigcerver | 0.0939 | 0.2934 | 0.0932 | 0.3213 |
| Bluche | 0.1430 | 0.4117 | 0.1422 | 0.4452 |
| Flor | 0.0858 | 0.2790 | 0.0852 | 0.3058 |

Rimes Results

778 images (test)

| Model | Default | | No accentuation | | No punctuation | |
|------------|---------------|---------------|-----------------|---------------|----------------|---------------|
| | CER | WER | CER | WER | CER | WER |
| Puigcerver | 0.1050 | 0.3919 | 0.0856 | 0.3129 | 0.1053 | 0.3818 |
| Bluche | 0.1331 | 0.4640 | 0.1140 | 0.4054 | 0.1330 | 0.4527 |
| Flor | 0.0874 | 0.3781 | 0.0678 | 0.2975 | 0.0870 | 0.3657 |

Saint Gall Results

707 images (test)

| Model | Default | |
|------------|---------------|---------------|
| | CER | WER |
| Puigcerver | 0.0965 | 0.4199 |
| Bluche | 0.1267 | 0.5248 |
| Flor | 0.0906 | 0.4033 |

Conclusions

- Bluche model and dropout (MOYSSET; MESSINA, 2018)
- Flor model:
 - PReLU and LeakyReLU
 - Batch Renormalization and Batch Normalization
- Reduce LR on Plateau x Warm restarts x EarlyStopping
- Convolutional alternatives:
 - SeparableConv2D and DepthwiseConv2D (HOWARD et al., 2017)
 - Octave Convolution (CHEN et al., 2019)
- Repository with code, documentation and tutorial (Jupyter Notebook):
 - <https://github.com/arthurflor23/handwritten-text-recognition>

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