Part 1/2

No Mercy for Manual Entry

29/Sep/2021
Workshop @ AMLD2021

ONE swiss bank

SamurAI

AMLD EPFL

Wifi Info

Network:	Free_STCC
User ID :	2317791957
Password:	5197

ONE swiss bank SamurAI

AMLD EPFL

Authors

Valerio Rossetti, PhD
Co-founder of SamurAI
Senior Data Scientist

Giulio Grossi, PhD
Senior Quantitative Portfolio Manager
at ONE swiss bank

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AMLD EPFL

Get to know the audience

- Knowledge in Supervised Learning and Computer Vision
- Your coding skills in Python
- Do you have practical applications of the techniques in this workshop?

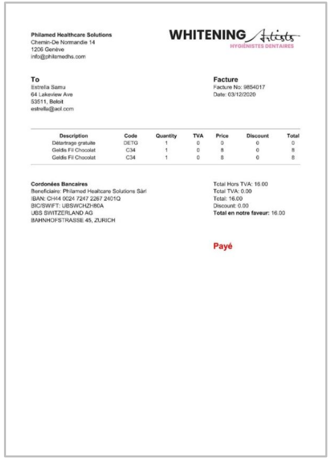
Manual Entry

- A lot of information in paper/pdf documents: invoices, contracts, personal information, surveys …

Manual Entry

- A lot of information in paper/pdf documents: invoices, contracts, personal information, surveys ...
- These documents are then treated manually:
    - costly,
    - time-consuming and
    - error-prone

Manual image-to-data process



Philamed Healthcare Solutions
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1206 Genève
info@philamedhs.com

WHITENING Artists
HYGIÉNISTES DENTAIRES

To
Estrella Samu
64 Lakeview Ave
53511, Beloit
estrella@aol.com

Facture
Facture No: 9854017
Date: 03/12/2020

Description	Code	Quantity	TVA	Price	Discount	Total
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Cordonées Bancaires
Beneficiaire: Philamed Healtcare Solutions Sàrl
IBAN: CH44 0024 7247 2267 2401Q
BIC/SWIFT: UBSWCHZH80A
UBS SWITZERLAND AG
BAHNHOFSTRASSE 45, ZURICH

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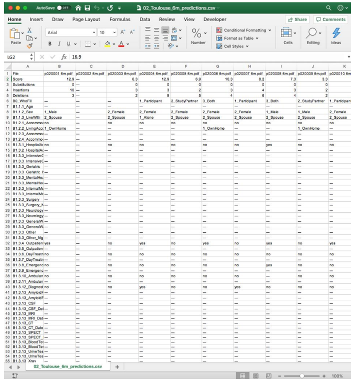

LG2 16.9

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2	Score	12.9	—	6.3	12.9	6.9	10.3	8.2	7.3	3.3	
3	Substitutions	0	—	0	0	0	0	0	0	0	
4	Insertions	10	—	3	3	2	3	4	3	2	
5	Deletions	3	—	2	9	5	4	6	4	2	
6	B0_WhoFill	—	—	—	1_Participant	2_StudyPartner	3_Both	1_Participant	3_Both	2_StudyPartner	1_Participan
7	B1.1.1_Age	—	—	—	—	—	—	—	—	—	—
8	B1.1.2_Sex	1_Male	—	2_Female	2_Female	2_Female	2_Female	2_Female	1_Male	1_Male	2_Female
9	B1.1.3_LiveWith	2_Spouse	—	2_Spouse	1_Alone	2_Spouse	2_Spouse	2_Spouse	2_Spouse	2_Spouse	2_Spouse
10	B1.2.1_Accommo	no	—	no	no	no	no	no	no	no	no
11	B1.2.2_LivingAcc	1_OwnHome	—	—	—	—	1_OwnHome	—	—	1_OwnHome	—
12	B1.2.3_Accommo	—	—	—	—	—	—	—	—	—	—
13	B1.2.4_Accommo	—	—	—	—	—	—	—	—	—	—
14	B1.3.1_HospitalAc	no	—	no	no	no	no	no	yes	no	no
15	B1.3.2_HospitalAc	—	—	—	—	—	—	—	—	—	—
16	B1.3.3_IntensiveC	—	—	—	—	—	—	—	—	—	—
17	B1.3.3_IntensiveC	—	—	—	—	—	—	—	—	—	—
18	B1.3.3_Geriatric	—	—	—	—	—	—	—	—	—	—
19	B1.3.3_Geriatric_N	—	—	—	—	—	—	—	—	—	—
20	B1.3.3_MentalHea	—	—	—	—	—	—	—	—	—	—
21	B1.3.3_MentalHea	—	—	—	—	—	—	—	—	—	—
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23	B1.3.3_InternalMe	—	—	—	—	—	—	—	—	—	—
24	B1.3.3_Surgery	—	—	—	—	—	—	—	—	—	—
25	B1.3.3_Surgery_N	—	—	—	—	—	—	—	—	—	—
26	B1.3.3_Neurology	—	—	—	—	—	—	—	—	—	—
27	B1.3.3_Neurology	—	—	—	—	—	—	—	—	—	—
28	B1.3.3_GeneralW	—	—	—	—	—	—	—	—	—	—
29	B1.3.3_GeneralW	—	—	—	—	—	—	—	—	—	—
30	B1.3.3_Other	—	—	—	—	—	—	—	—	—	—
31	B1.3.3_Other_Nig	—	—	—	—	—	—	—	—	—	—
32	B1.3.4_Outpatient	yes	—	no	yes	no	yes	no	yes	no	yes
33	B1.3.5_Outpatient	—	—	—	—	—	—	—	—	—	—
34	B1.3.6_DayTreatn	no	—	no	no	no	no	no	no	no	no
35	B1.3.7_DayTreatn	—	—	—	—	—	—	—	—	—	—
36	B1.3.8_Emergenc	no	—	no	no	no	no	no	yes	no	no
37	B1.3.9_Emergenc	—	—	—	—	—	—	—	—	—	—
38	B1.3.10_Ambulan	no	—	no	no	no	no	no	—	no	no
39	B1.3.11_Ambulan	—	—	—	—	—	—	—	—	—	—
40	B1.3.12_Diagnost	no	—	no	yes	no	no	yes	no	no	no
41	B1.3.13_AmyloidP	—	—	—	—	—	—	—	—	—	—
42	B1.3.13_AmyloidP	—	—	—	—	—	—	—	—	—	—
43	B1.3.13_CSF	—	—	—	—	—	—	—	—	—	—
44	B1.3.13_CSF_Dat	—	—	—	—	—	—	—	—	—	—
45	B1.3.13_MRI	—	—	—	—	—	—	—	—	—	—
46	B1.3.13_MRI_Dat	—	—	—	—	—	—	—	—	—	—
47	B1.3.13_CT	—	—	—	—	—	—	—	—	—	—
48	B1.3.13_CT_Date	—	—	—	—	—	—	—	—	—	—
49	B1.3.13_SPECT	—	—	—	—	—	—	—	—	—	—
50	B1.3.13_SPECT_	—	—	—	—	—	—	—	—	—	—
51	B1.3.13_BloodTes	—	—	—	—	—	—	—	—	—	—
52	B1.3.13_BloodTes	—	—	—	—	—	—	—	—	—	—
53	B1.3.13_UrineTes	—	—	—	—	—	—	—	—	—	—
54	B1.3.13_UrineTes	—	—	—	—	—	—	—	—	—	—
55	B1.3.13_Xray	—	—	—	—	—	—	—	—	—	—

ONE swiss bank

SamurAI

AMLD EPFL

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- A lot of information in paper/pdf documents: invoices, contracts, personal information, surveys ...
- These documents are then treated manually:
  - costly,
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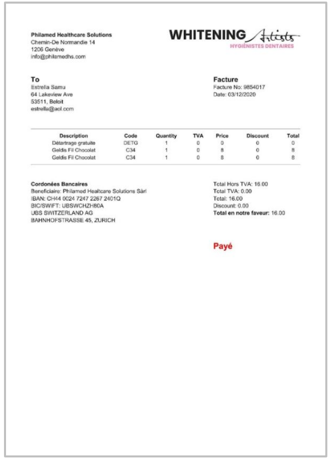
- Main solution: go fully digital and eliminate the paper document!

Manual image-to-data process



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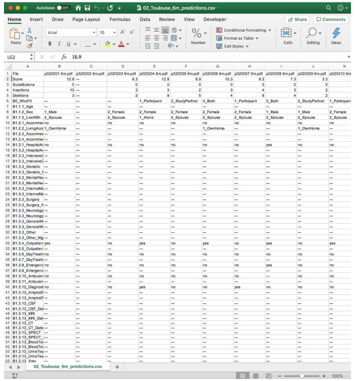

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02_Toulouse_6m_predictions.csv

ONE swiss bank

SamurAI

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Manual Entry: a zombie among us

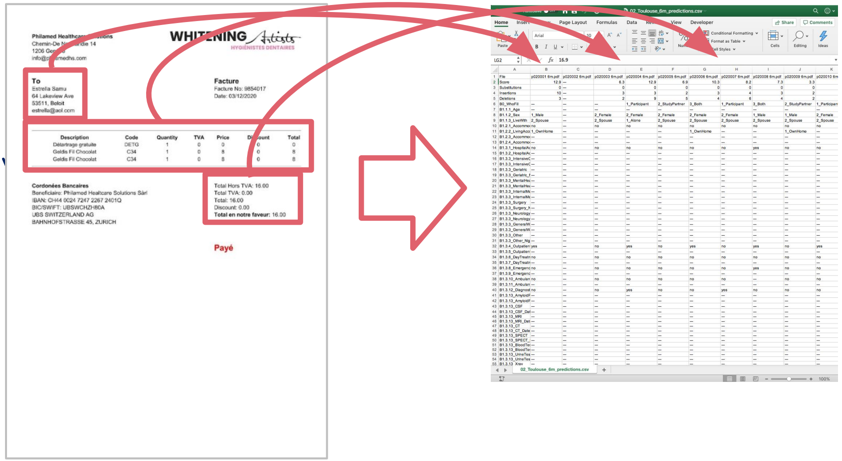
- In some cases we don't manage to eliminate the paper/pdf document

- Examples:
    - Traders send emails with pdf documents treated by the back-office
    - Commodity trading dealing with letters of credit
    - Banks dealing with client documents (passport, ID, scanned contract, ...)
    - Medical research dealing with huge volumes of paper documents from patients
    - Auditors oftentimes compare tables in pdf documents to Excel spreadsheets

This workshop: the goal

- ML can help you to automate processes with scanned paper documents
- This workshop presents few selected techniques to:
  - Classify documents
  - Extract information from documents
- Disclaimer:
  - This workshop doesn’t present the fanciest / more powerful techniques to do these tasks
  - This workshop shows you few techniques that are easy to understand, implement and deploy as a beginner data scientist

Automated image-to-data process



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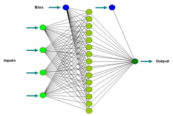
This workshop

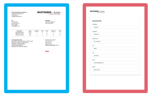
- For beginners
- Get your hands dirty in code
- Adding levels of complexity

Part 1
(~1h30)

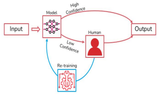
Supervised Learning & ANNs



Document Classification

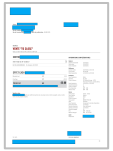


Human In The Loop

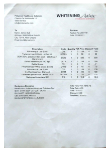


Part 2
(~2h00)

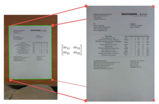
Document with items in fixed position



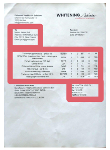
Scanned Documents



Documents from Camera



Document with items in variable position



Workshop: Schedule

Session	Duration	Start - End	Subjects
Part 1	~1:30	13:30 – 15:00	Intro + Document Classification + HITL
Break	0:30	15:00 – 15:30	
Part 2	~2:00	15:30 – 17:30	Information Extraction

ONE swiss bank

SamurAI

AMLD EPFL

Your questions are welcomed!

Your 1st question

=

Swiss chocolate bar

«I don’t get the big picture»

«I didn’t understand what this code does»

«Why are we doing this?»

ONE swiss bank SamurAI

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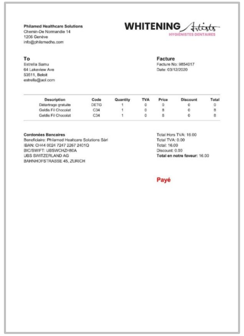
Supervised Learning

Attributes/
Features



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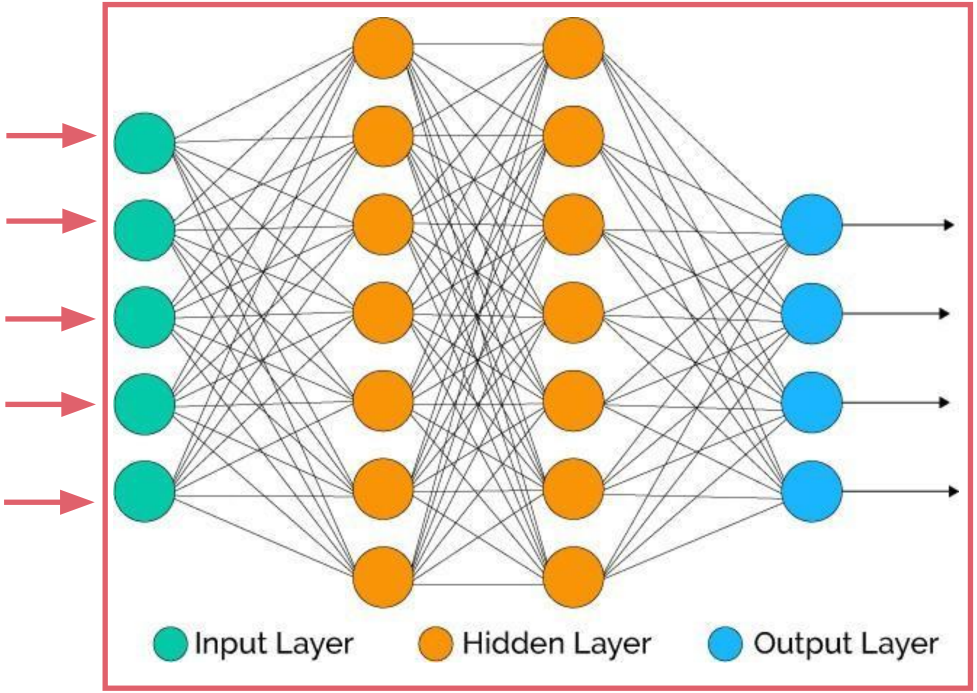
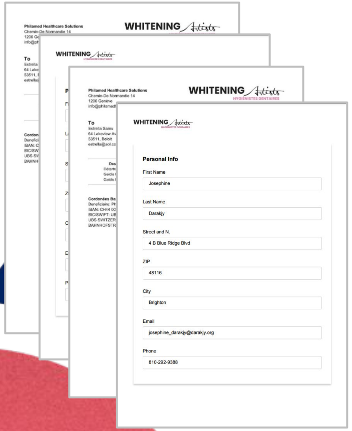


Predictions

It's a
document
Invoice!

Supervised Learning

Attributes/ Features



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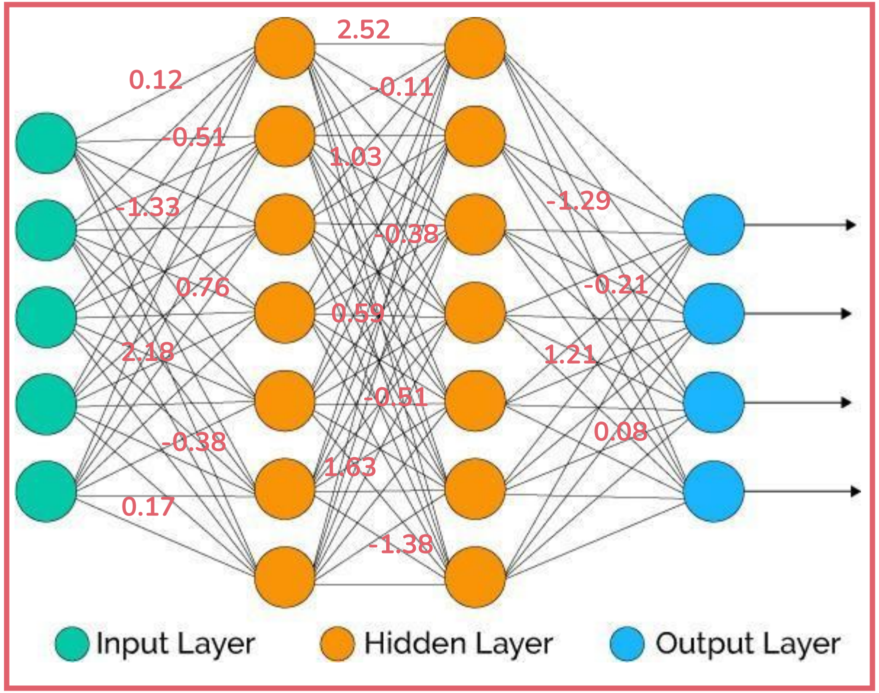
WHITENING Artists
HYGIÉNISTES DENTAIRES

Personal Info

First Name	Josephine
Last Name	Darakjy
Street and N.	4 B Blue Ridge Blvd
ZIP	48116
City	Brighton
Email	josephine_darakjy@darakjy.org
Phone	810-292-9388

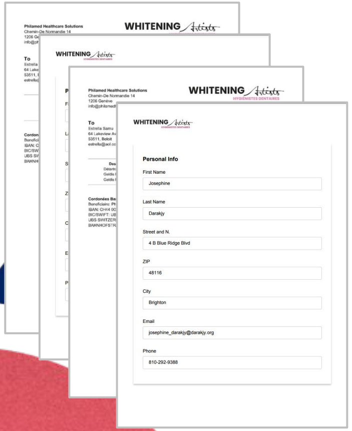


Predictions		Labels
invoice	🟢	invoice
invoice	🔴	registration
registration	🔴	invoice
invoice	🔴	registration
registration	🟢	registration
registration	🔴	invoice
invoice	🔴	registration
invoice	🟢	invoice
invoice	🟢	invoice
registration	🟢	registration

Loss/CostFunction:	1000
Accuracy:	50%

Supervised Learning

Attributes/
Features



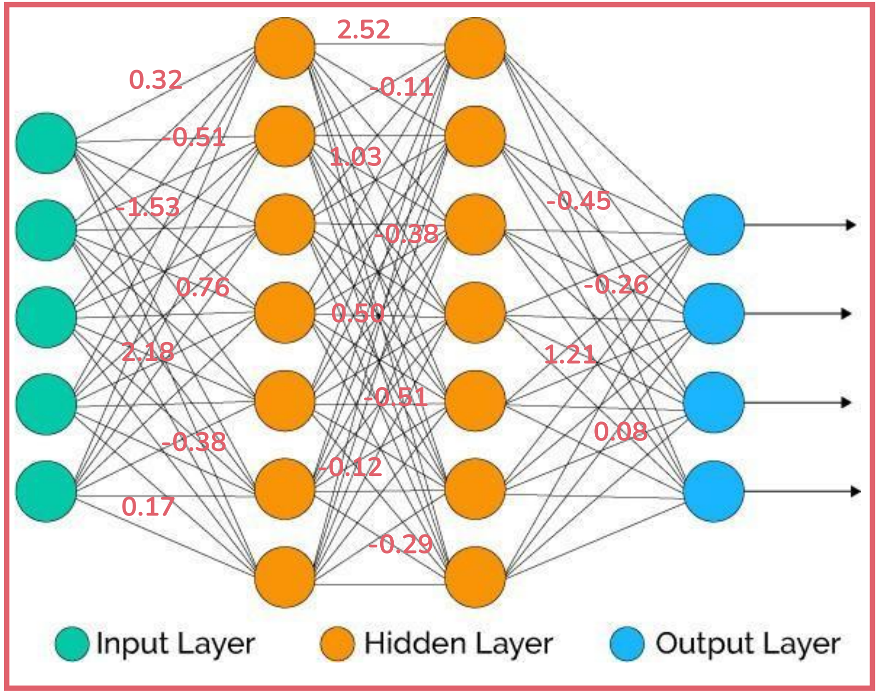
WHITENING Artists
HYGIÉNISTES DENTAIRES

Philamed Healthcare Solutions
Chemin-De Normandie 14
1206 Genève

To
Estrella Samu

Personal Info

First Name	Josephine
Last Name	Darakjy
Street and N.	4 B Blue Ridge Blvd
ZIP	48116
City	Brighton
Email	josephine_darakjy@darakjy.org
Phone	810-292-9388



Predictions		Labels
invoice	🟢	invoice
registration	🟢	registration
registration	🔴	invoice
invoice	🔴	registration
registration	🟢	registration
invoice	🟢	invoice
invoice	🔴	registration
invoice	🟢	invoice
invoice	🟢	invoice
registration	🟢	registration

Loss/CostFunction: 600
Accuracy: 70%

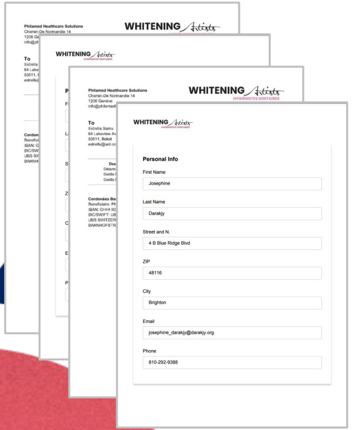
ONE
swiss bank

SamurAI

AMLDEPFL

Supervised Learning

Attributes/ Features



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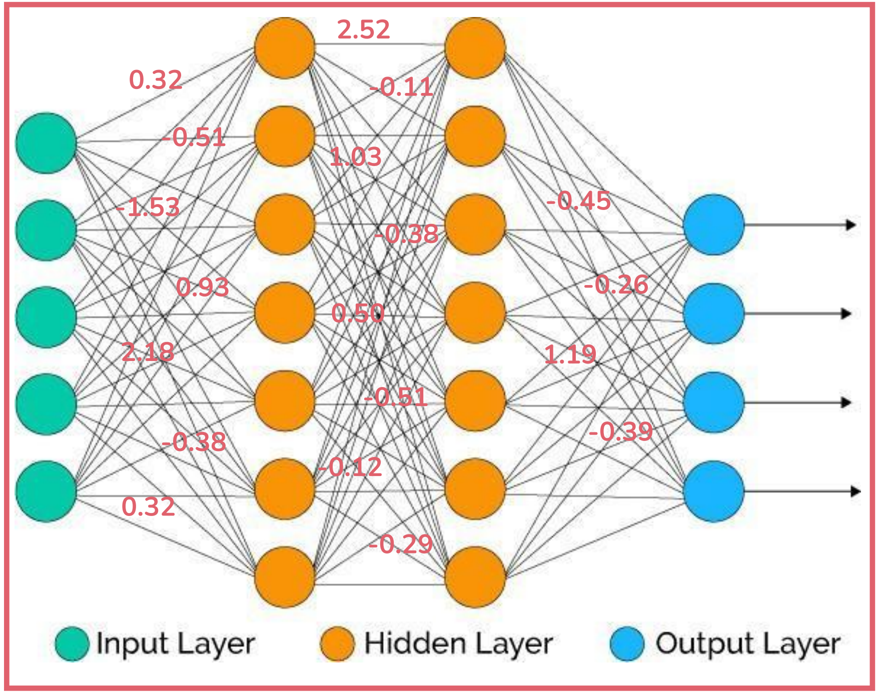

Predictions		Labels
invoice	🟢	invoice
registration	🟢	registration
invoice	🟢	invoice
registration	🟢	registration
registration	🟢	registration
invoice	🟢	invoice
invoice	🔴	registration
invoice	🟢	invoice
invoice	🟢	invoice
registration	🟢	registration

Loss/CostFunction:	300
Accuracy:	90%

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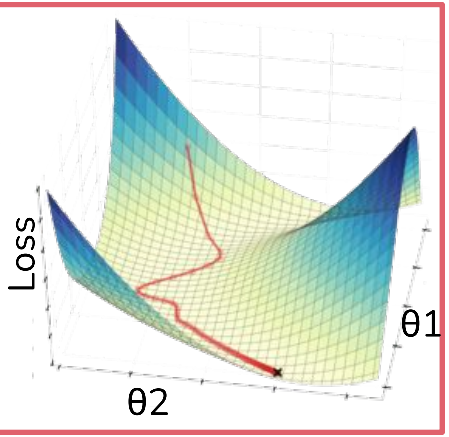
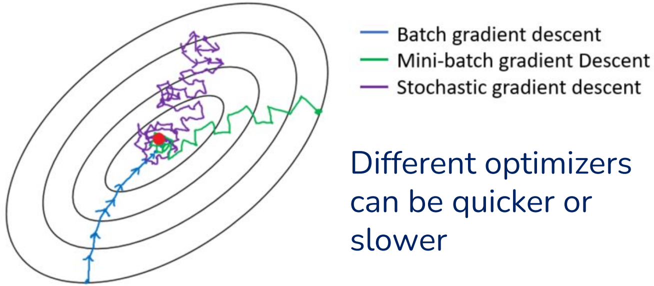
Training as a loss minimization

- The loss quantifies the spread between labels and predictions
- The optimizers are algorithms that find the (possibly absolute) minimum of the loss

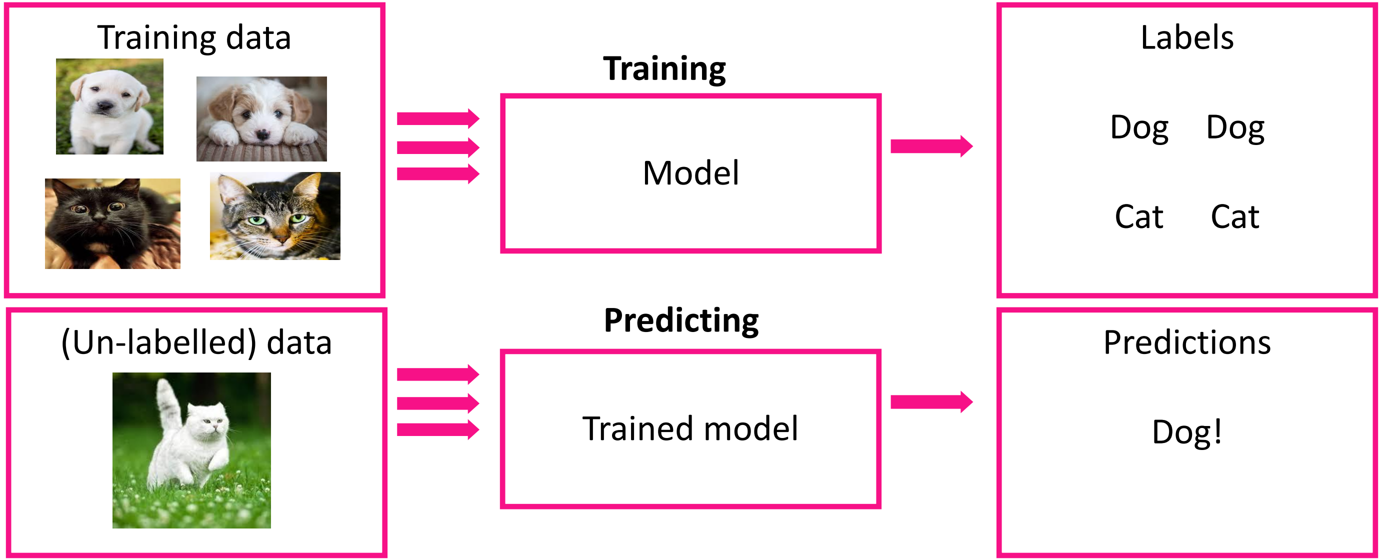
During the training the optimizer finds the path to minimize the loss, like a river flowing downhill





Different optimizers can be quicker or slower

Learning is hard



Training data

Training

Model

Labels

Dog Dog

Cat Cat

(Un-labelled) data

Predicting

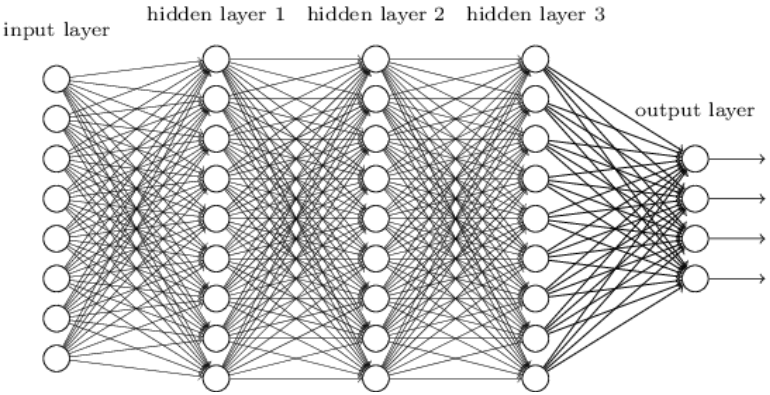
Trained model

Predictions

Dog!

ANN: Dense Layers

- Multi-Layer Perceptrons are the simplest ANN
- Every node of a layer is connected with all the nodes in the previous and in the following layer
- These layers are called Fully connected or Dense

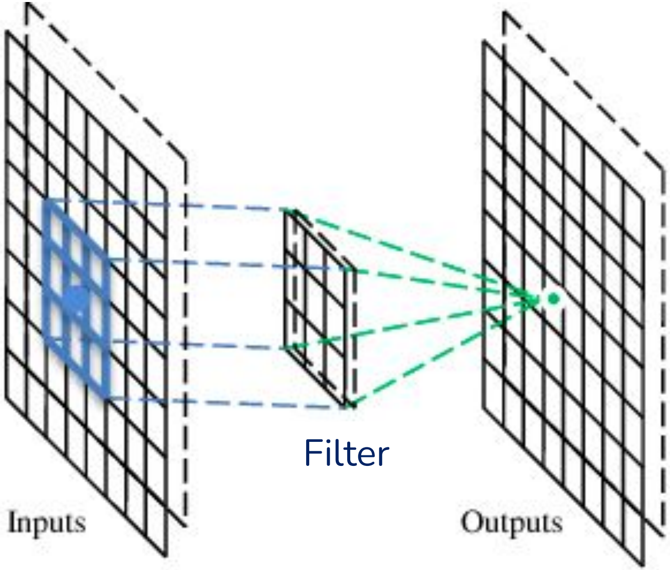


- Image of 500 x 500 x 3 pixels
- First layer 100 nodes
- Already for the first layer we need ~750k parameters

The MLP is great, but too many parameters!

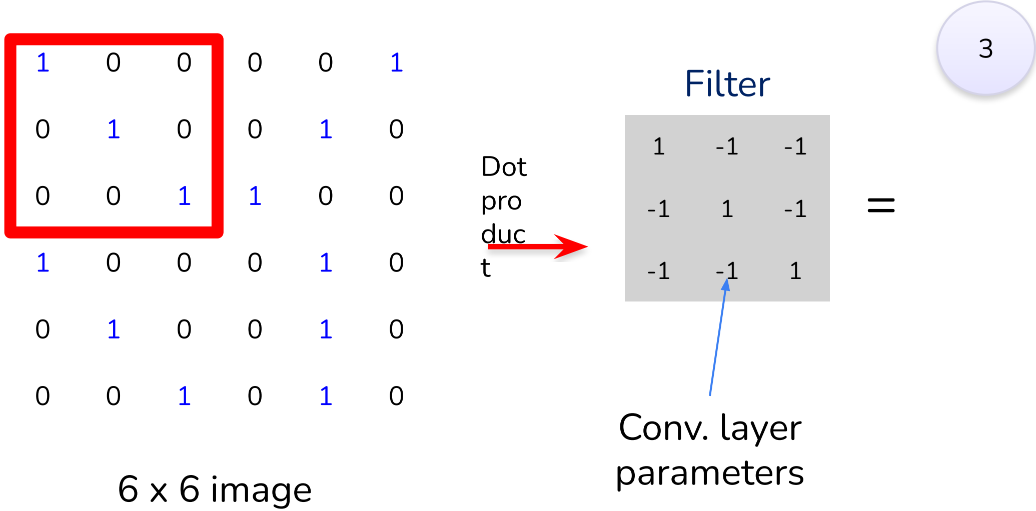
ANN: Convolutional Layers

- We want to reduce the model parameters
- We introduce the concept of filter



ANN: Convolutional Layers

- We want to reduce the model parameters
- We introduce the concept of filter



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

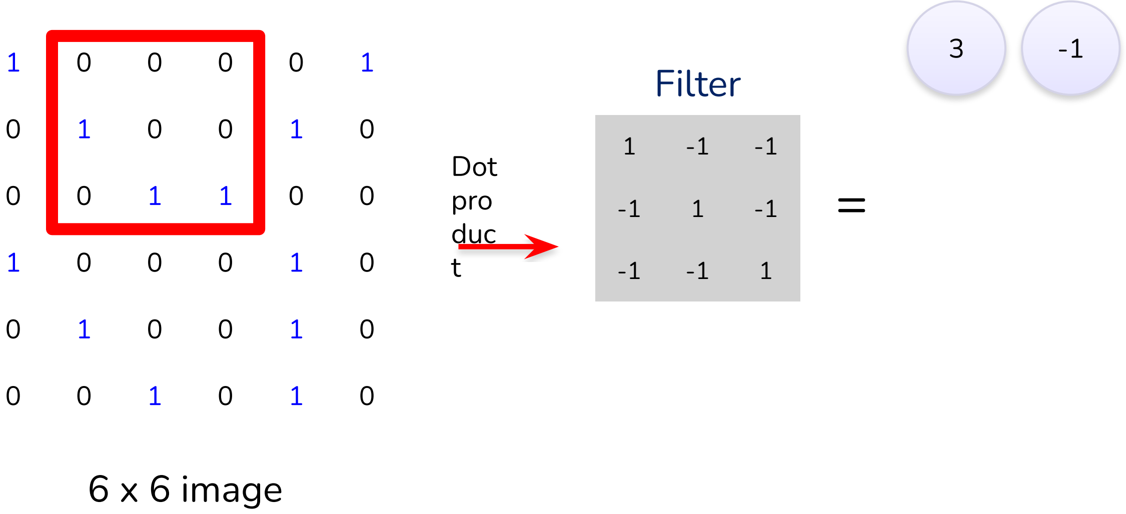
Filter

1	-1	-1
-1	1	-1
-1	-1	1

Conv. layer parameters

ANN: Convolutional Layers

- We want to reduce the model parameters
- We introduce the concept of filter



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Dot product

Filter

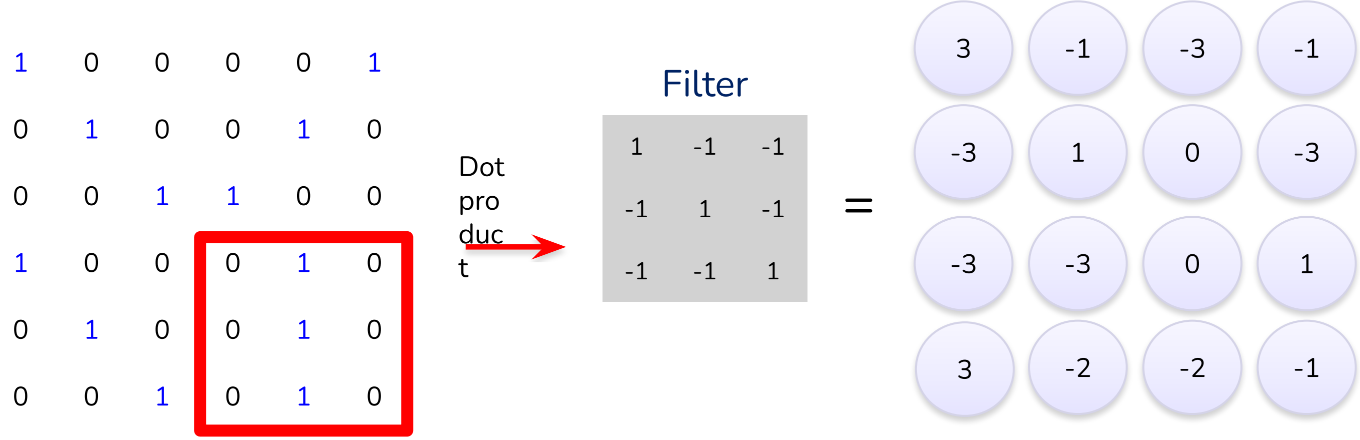
1	-1	-1
-1	1	-1
-1	-1	1

=

3 -1

ANN: Convolutional Layers

- We want to reduce the model parameters
- We introduce the concept of filter



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

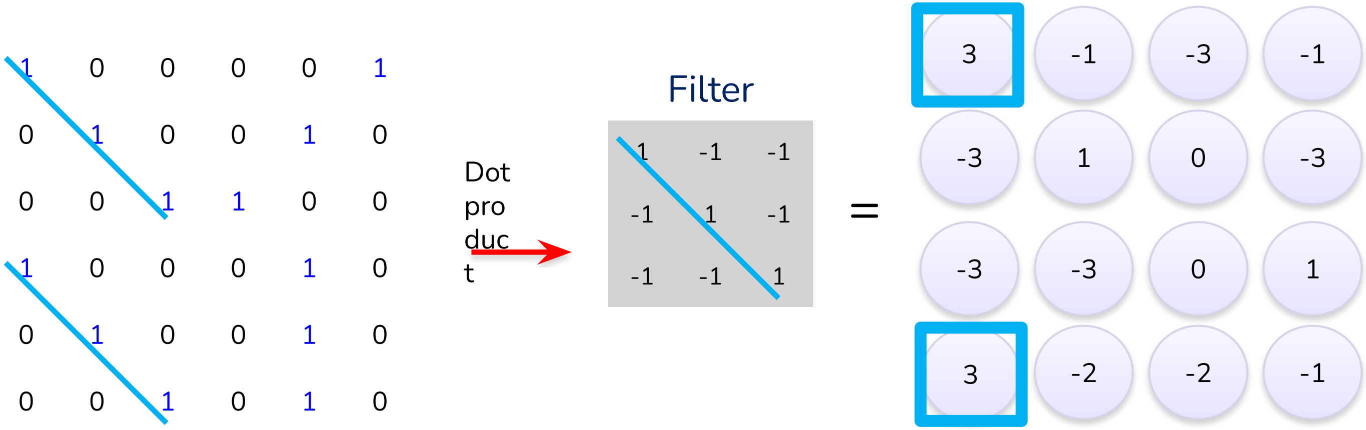
Filter

1	-1	-1
-1	1	-1
-1	-1	1

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

ANN: Convolutional Layers

- We want to reduce the model parameters
- We introduce the concept of filter



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Dot product

Filter

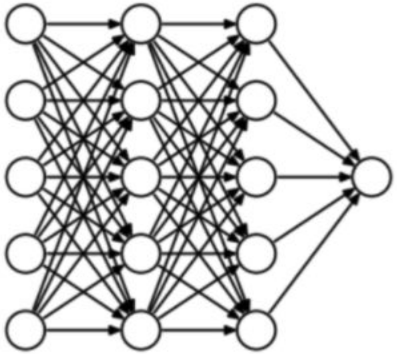
1	-1	-1
-1	1	-1
-1	-1	1

=

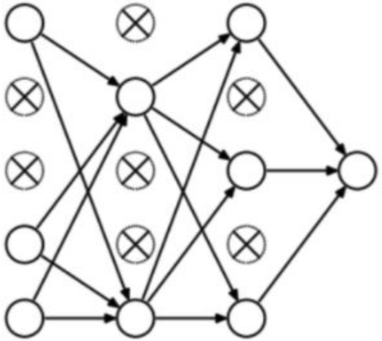
3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Dropout

- Regularization technique
- A fraction of the nodes are not considered in a training step
- This forces the network to have several "routes" in the nodes to ensure good performances



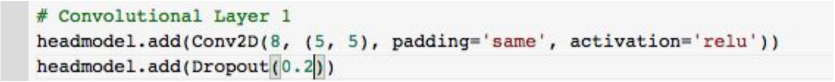
Standard Training



Training with Droupout

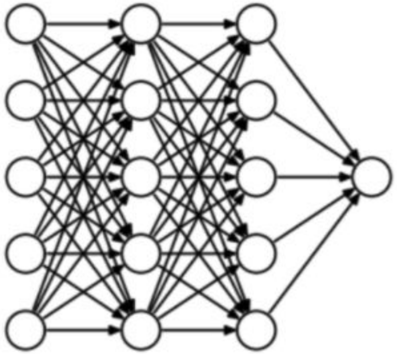
Dropout

- Regularization technique
- A fraction of the nodes are not considered in a training step
- This forces the network to have several “routes” in the nodes to ensure good performances

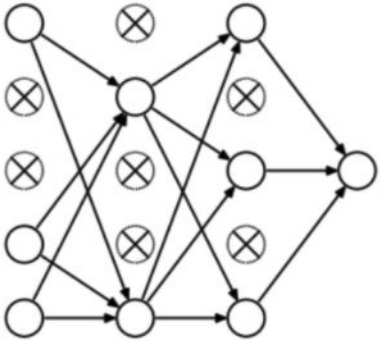


```
# Convolutional Layer 1
headmodel.add(Conv2D(8, (5, 5), padding='same', activation='relu'))
headmodel.add(Dropout(0.2))
```

This means “drop 20% of the nodes in the previous layer while training



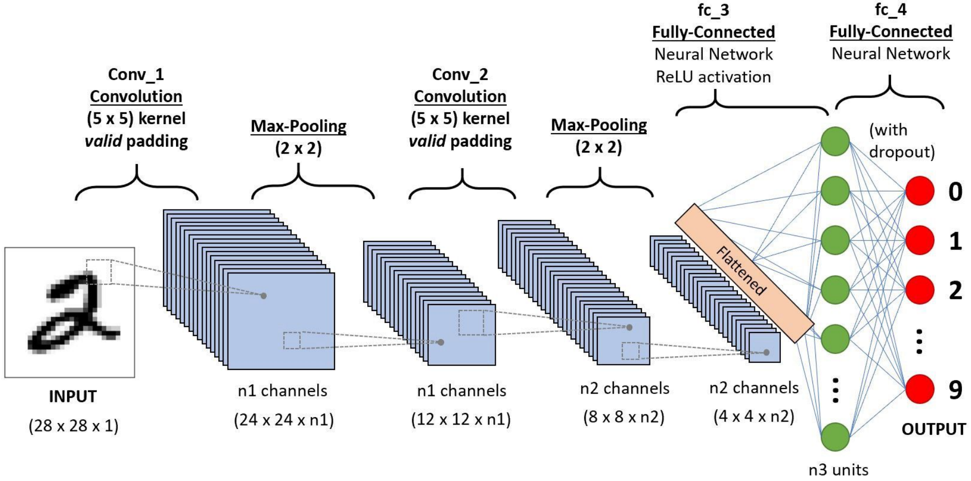
Standard Training



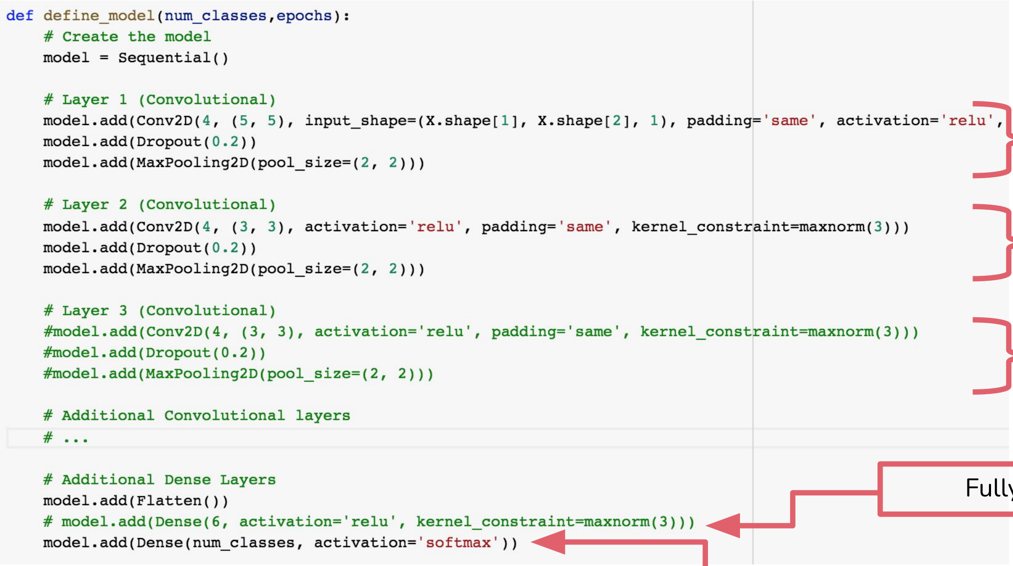
Training with Droupout

Typical CNN structure

- Typical CNNs are made of :
  - A series of convolutional layer + dropout + max-pooling
  - Fully-connected layers at the end
- Many parameters are subject to tuning:
  - Number and type of layer
  - Number of filters
  - Size of filters



CNN in Keras



```
def define_model(num_classes,epochs):
    # Create the model
    model = Sequential()

    # Layer 1 (Convolutional)
    model.add(Conv2D(4, (5, 5), input_shape=(X.shape[1], X.shape[2], 1), padding='same', activation='relu',
    model.add(Dropout(0.2))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    # Layer 2 (Convolutional)
    model.add(Conv2D(4, (3, 3), activation='relu', padding='same', kernel_constraint=maxnorm(3)))
    model.add(Dropout(0.2))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    # Layer 3 (Convolutional)
    #model.add(Conv2D(4, (3, 3), activation='relu', padding='same', kernel_constraint=maxnorm(3)))
    #model.add(Dropout(0.2))
    #model.add(MaxPooling2D(pool_size=(2, 2)))

    # Additional Convolutional layers
    # ...

    # Additional Dense Layers
    model.add(Flatten())
    # model.add(Dense(6, activation='relu', kernel_constraint=maxnorm(3)))
    model.add(Dense(num_classes, activation='softmax'))
```

Conv. Layer + Dropout + Max-Pooling

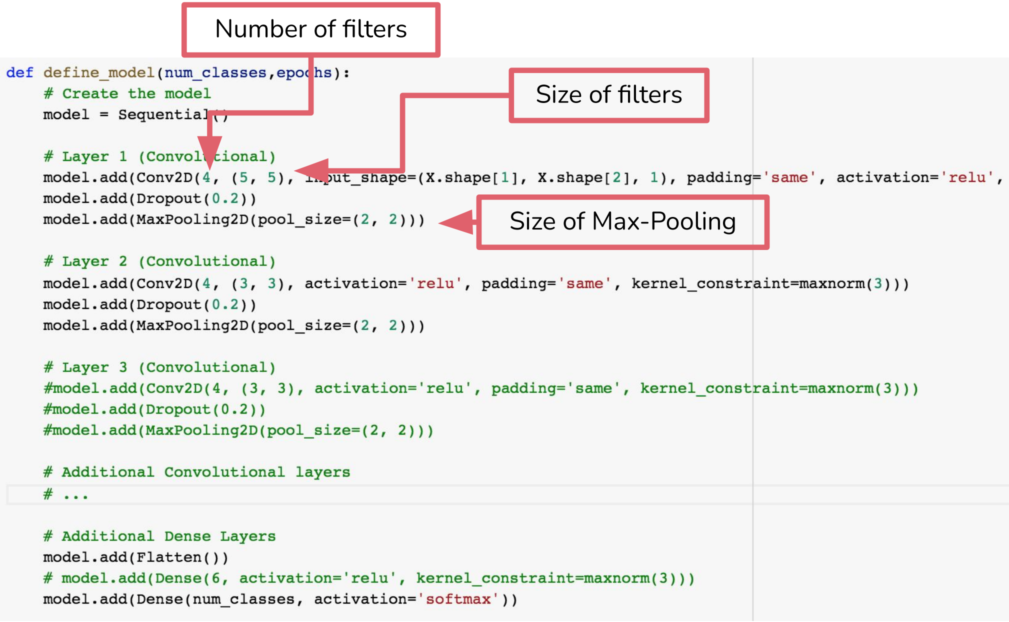
Conv. Layer + Dropout + Max-Pooling

Conv. Layer + Dropout + Max-Pooling

Fully Connected Layers

Output

CNN in Keras



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    # ...

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    model.add(Flatten())
    # model.add(Dense(6, activation='relu', kernel_constraint=maxnorm(3)))
    model.add(Dense(num_classes, activation='softmax'))
```

Number of filters

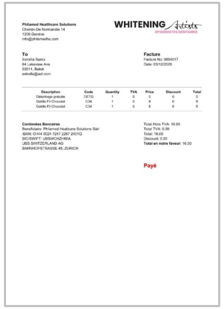
Size of filters

Size of Max-Pooling

Document Classification

- We are going to train an algorithm to discriminate between different types of documents, <u>only using their images</u>
- The dataset:
  - ~400 invoices
  - ~400 registration
  - ~600 other
- We want the model to be robust enough to use images taken from a phone

invoice



Philamed Healthcare Solutions
Chemin-De Normandie 14
1206 Genève
info@philamedhs.com

WHITENING Artists
HYGIÉNISTES DENTAIRES

To
Estrella Samu
64 Lakeview Ave
53511, Beloit
estrella@aol.com

Facture
Facture No: 9854017
Date: 03/12/2020

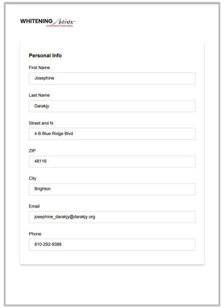
Description	Code	Quantity	TVA	Price	Discount	Total
Détartrage gratuite	DETG	1	0	0	0	0
Geldis Fil Chocolat	C34	1	0	8	0	8
Geldis Fil Chocolat	C34	1	0	8	0	8

Cordonées Bancaires
Beneficiaire: Philamed Healtcare Solutions Sàrl
IBAN: CH44 0024 7247 2267 2401Q
BIC/SWIFT: UBSWCHZH80A
UBS SWITZERLAND AG
BAHNHOFSTRASSE 45, ZURICH

Total Hors TVA: 16.00
Total TVA: 0.00
Total: 16.00
Discount: 0.00
Total en notre faveur: 16.00

Payé

registration



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First Name
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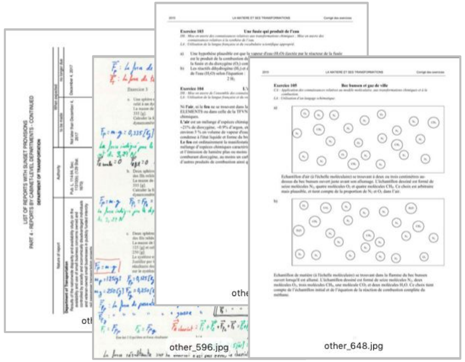
ZIP
48116

City
Brighton

Email
josephine_darakjy@darakjy.org

Phone
810-292-9388

other

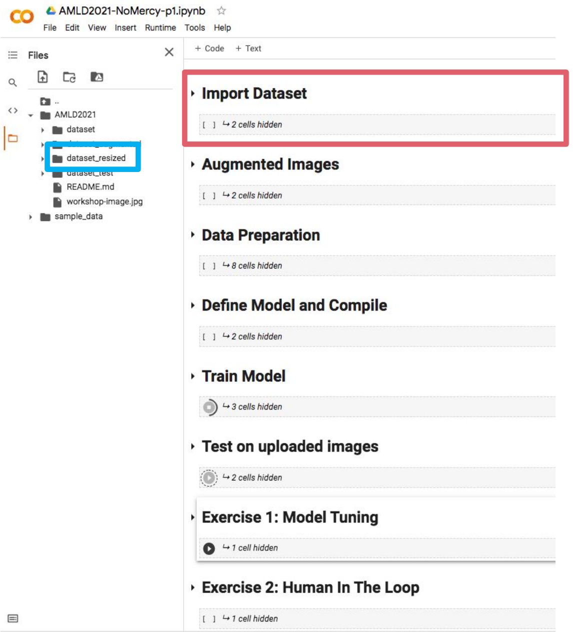


ONE swiss bank

SamurAI

AMLD EPFL

Notebook structure



AMLD2021-NoMercy-p1.ipynb

- ..
- AMLD2021
  - dataset
  - dataset_resized
  - dataset_test
  - README.md
  - workshop-image.jpg
- sample_data

Import Dataset
[ ] ↳ 2 cells hidden

Augmented Images
[ ] ↳ 2 cells hidden

Data Preparation
[ ] ↳ 8 cells hidden

Define Model and Compile
[ ] ↳ 2 cells hidden

Train Model
↳ 3 cells hidden

Test on uploaded images
↳ 2 cells hidden

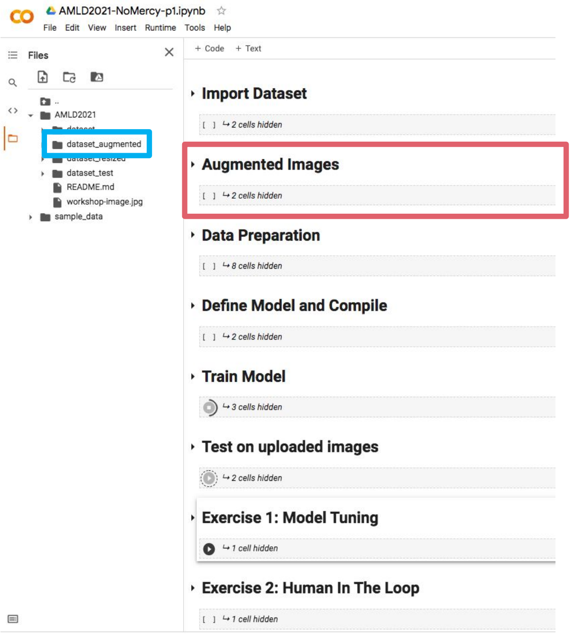
Exercise 1: Model Tuning
↳ 1 cell hidden

Exercise 2: Human In The Loop
[ ] ↳ 1 cell hidden

- Import images from github
- On the left, you will see the folder AMLD2021 appear
- The main dataset used for this notebook is in AMLD2021/dataset_resized/
- ~1600images of 708x500 pixels

ONE swiss bank SamurAI AMLD EPFL

Notebook structure



Import Dataset
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Train Model
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Exercise 1: Model Tuning
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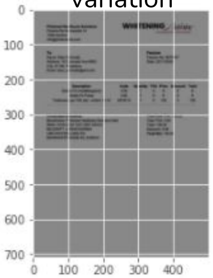
Exercise 2: Human In The Loop
[ ] ↳ 1 cell hidden

- More augmented images are created with distortions, brightness variations, tilt, ...

(un)zoom

rotation

brightness variation



- Augmented images are moved to AMLD2021/dataset_augmented/

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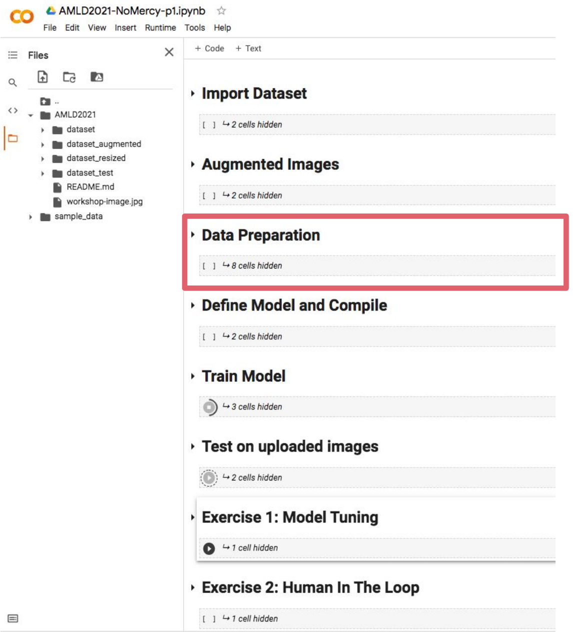
Notebook structure



AMLD2021-NoMercy-p1.ipynb

Import Dataset

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Augmented Images

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Define Model and Compile

[ ] ↳ 2 cells hidden

Train Model

↳ 3 cells hidden

Test on uploaded images

↳ 2 cells hidden

Exercise 1: Model Tuning

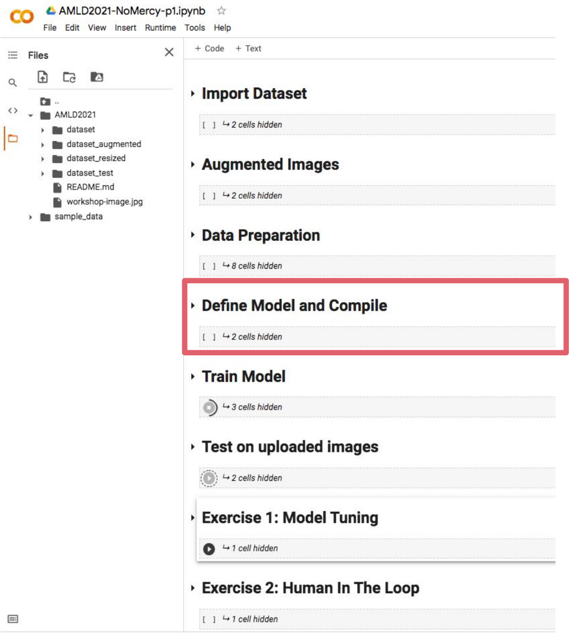
↳ 1 cell hidden

Exercise 2: Human In The Loop

[ ] ↳ 1 cell hidden

- Images are resized to a smaller size
- Dataset is created
- Train-test split

Notebook structure



Import Dataset
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Augmented Images
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Data Preparation
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Define Model and Compile
[ ] ↳ 2 cells hidden

Train Model
↳ 3 cells hidden

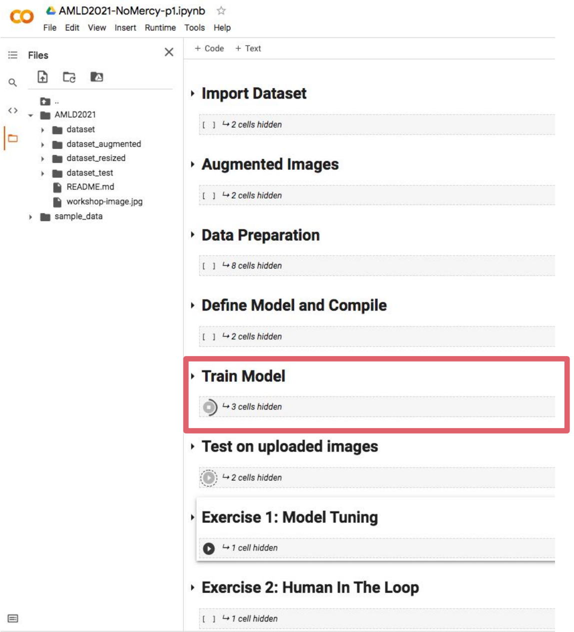
Test on uploaded images
↳ 2 cells hidden

Exercise 1: Model Tuning
↳ 1 cell hidden

Exercise 2: Human In The Loop
[ ] ↳ 1 cell hidden

- Model is defined as a Keras ANN with Conv and Dense layers

Notebook structure



AMLD2021-NoMercy-p1.ipynb

Import Dataset

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Define Model and Compile

[ ] ↳ 2 cells hidden

Train Model

↳ 3 cells hidden

Test on uploaded images

↳ 2 cells hidden

Exercise 1: Model Tuning

↳ 1 cell hidden

Exercise 2: Human In The Loop

[ ] ↳ 1 cell hidden

- Training and evaluation of performance

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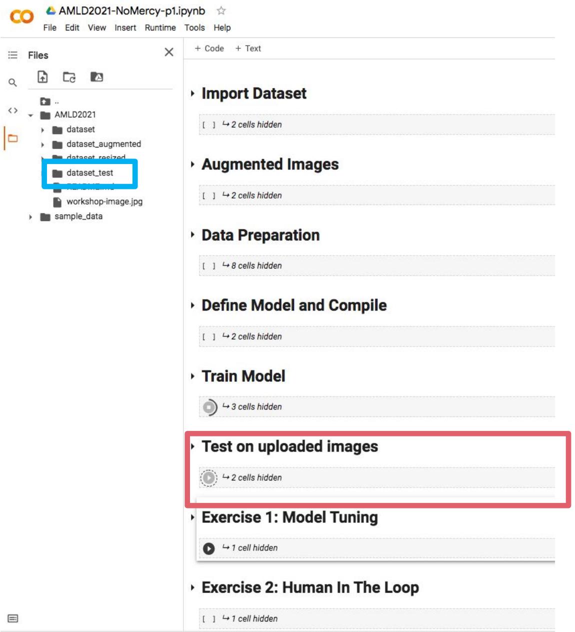
Notebook structure



Import Dataset
[ ] ↳ 2 cells hidden

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Train Model
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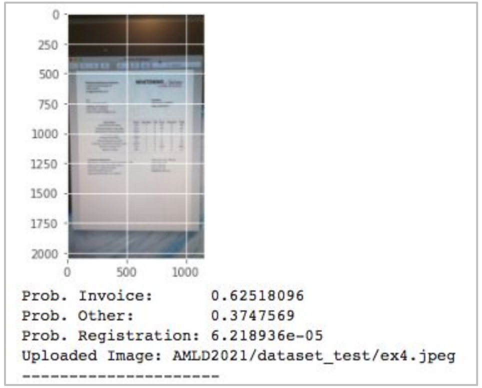
Test on uploaded images
↳ 2 cells hidden

Exercise 1: Model Tuning
↳ 1 cell hidden

Exercise 2: Human In The Loop
[ ] ↳ 1 cell hidden

- You can take a picture of a document and test the model on it
- Upload your picture to Colab and in the folder AMLD2021/dataset_test/
- The code will make predictions on all pictures in this folder



```
Prob. Invoice:      0.62518096
Prob. Other:        0.3747569
Prob. Registration: 6.218936e-05
Uploaded Image: AMLD2021/dataset_test/ex4.jpeg
---------------------
```

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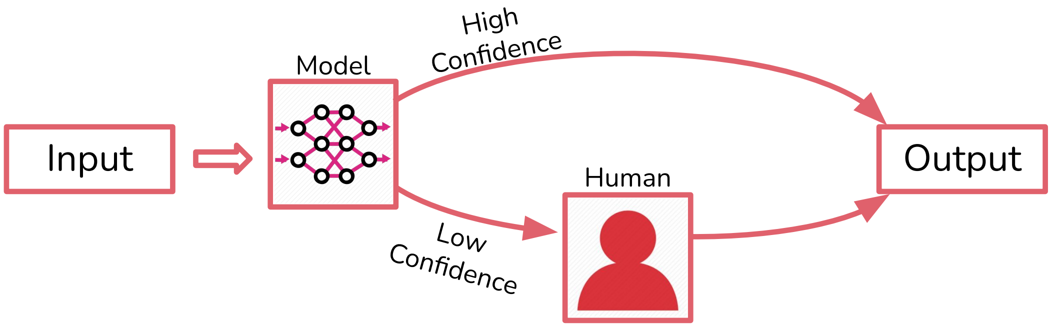
Exercise 1: Tuning the model

- Hyper-parameter tuning and feature engineering:
  - CNN layers, filters, dropout
  - Dense layers, number of nodes, dropout
  - Optimizer, Batch size, Num. of Epochs
  - Resize of the images (up in the data preparation)
- Goal: reach an accuracy of > 99% on the training and validation sets

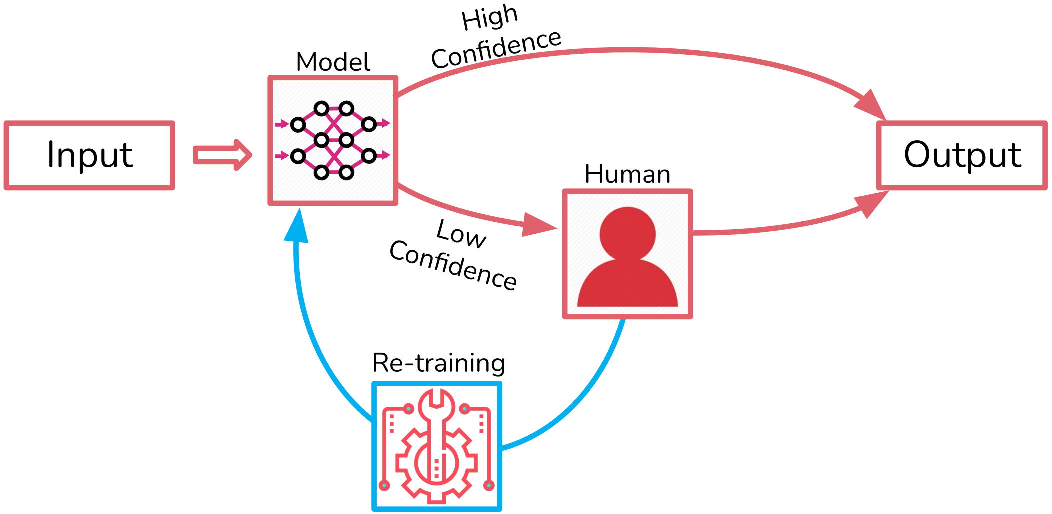
Human in the loop (HITL)

- AI systems are typically <100% accurate
- We can keep a HITL to mitigate for mistakes
    - ○ Manually do the tasks for which the model has low confidence (low h)
    - ○



Human in the loop (HITL)

- AI systems are typically <100% accurate
- We can keep a HITL to mitigate for mistakes
  - Manually do the tasks for which the model has low confidence (low h)
  - Prepare data to retrain the model



Exercise 2: Human in the loop

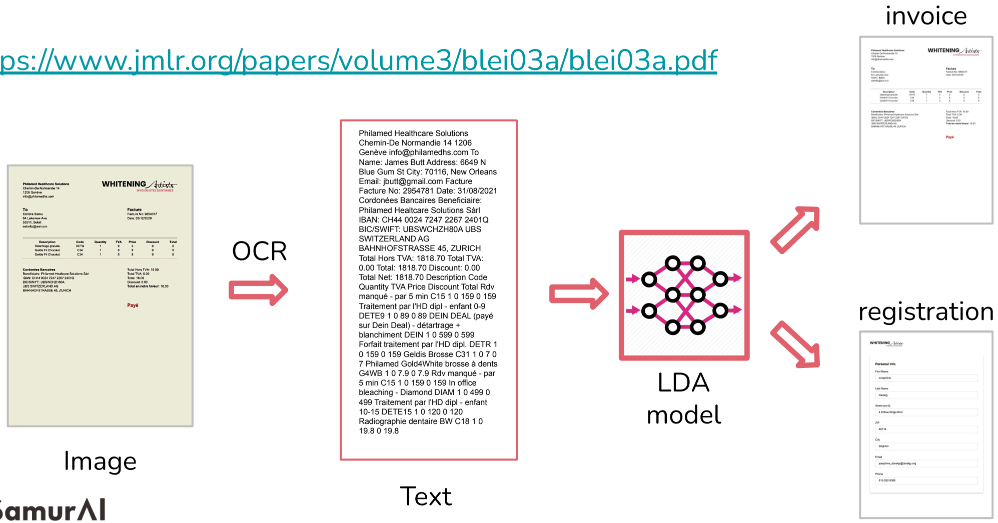
- Make photos of several documents (~5-10 per class)
  - Jpeg format is perfect
  - Advice: name the images according to their class (ex: my_invoice_1.jpg). This will help for the rest of the exercise
- Upload them on Colab and copy them to the right folder for re-training (for example AMLD2021/dataset_resize/invoice/ for invoices)
  - example: !cp my_invoice_* AMLD2021/dataset_resize/invoice/
- Re-build augmented images, retrain the model, and re-evaluate performance

ONE swiss bank SamurAI

AMLD EPFL

Possible Extensions: OCR

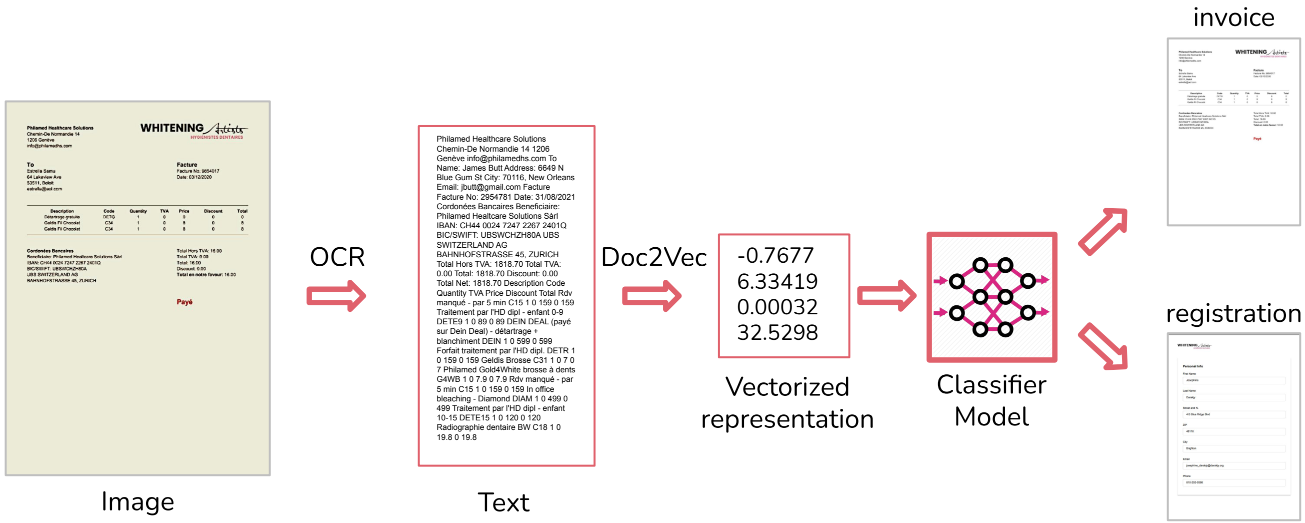
- In our classification we used only the images of our documents. We didn’t use the text within the document
- Here an example of how to do document classification using only the text extracted with OCR: link
  - Using an LDA model: https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf



Philamed Healthcare Solutions Chemin-De Normandie 14 1206 Genève info@philamedhs.com To Name: James Butt Address: 6649 N Blue Gum St City: 70116, New Orleans Email: jbutt@gmail.com Facture Facture No: 2954781 Date: 31/08/2021 Cordonées Bancaires Beneficiaire: Philamed Healtcare Solutions Sàrl IBAN: CH44 0024 7247 2267 2401Q BIC/SWIFT: UBSWCHZH80A UBS SWITZERLAND AG BAHNHOFSTRASSE 45, ZURICH Total Hors TVA: 1818.70 Total TVA: 0.00 Total: 1818.70 Discount: 0.00 Total Net: 1818.70 Description Code Quantity TVA Price Discount Total Rdv manqué - par 5 min C15 1 0 159 0 159 Traitement par l'HD dipl - enfant 0-9 DETE9 1 0 89 0 89 DEIN DEAL (payé sur Dein Deal) - détartrage + blanchiment DEIN 1 0 599 0 599 Forfait traitement par l'HD dipl. DETR 1 0 159 0 159 Geldis Brosse C31 1 0 7 0 7 Philamed Gold4White brosse à dents G4WB 1 0 7.9 0 7.9 Rdv manqué - par 5 min C15 1 0 159 0 159 In office bleaching - Diamond DIAM 1 0 499 0 499 Traitement par l'HD dipl - enfant 10-15 DETE15 1 0 120 0 120 Radiographie dentaire BW C18 1 0 19.8 0 19.8

Possible Extensions: OCR + Doc2Vec

- Document classification using OCR and transforming the text of a whole page into a vector: link



Philamed Healthcare Solutions
Chemin-De Normandie 14
1206 Genève
info@philamedhs.com

WHITENING Artists
HYGIÉNISTES DENTAIRES

To
Estrella Samu
64 Lakeview Ave
53511, Beloit
estrella@aol.com

Facture
Facture No: 9854017
Date: 03/12/2020

Description	Code	Quantity	TVA	Price	Discount	Total
Détartrage gratuite	DETG	1	0	0	0	0
Geldis Fil Chocolat	C34	1	0	8	0	8
Geldis Fil Chocolat	C34	1	0	8	0	8

Cordonées Bancaires
Beneficiaire: Philamed Healtcare Solutions Sàrl
IBAN: CH44 0024 7247 2267 2401Q
BIC/SWIFT: UBSWCHZH80A
UBS SWITZERLAND AG
BAHNHOFSTRASSE 45, ZURICH

Total Hors TVA: 16.00
Total TVA: 0.00
Total: 16.00
Discount: 0.00
Total en notre faveur: 16.00

Payé

Image

OCR

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Text

Doc2Vec

-0.7677
6.33419
0.00032
32.5298

Vectorized representation

Classifier Model

invoice

registration