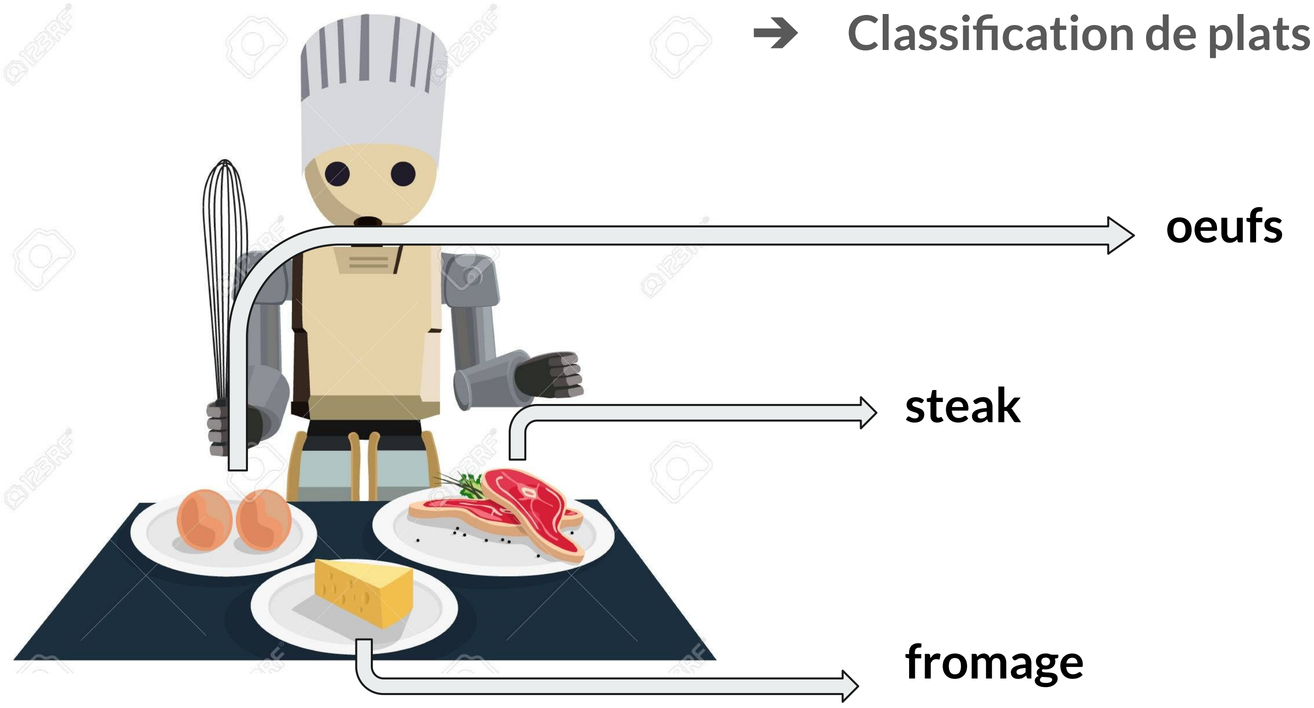
FOODVISOR

Nguyen Tu Anh Abdel Wedoud Mohamed Malick Ba

FoodVisor

➔ Classification de plats



Les données

UPMC Food-101

- 100,000 images de 101 Food categories: Apple pie, Foie gras, Spring rolls,...

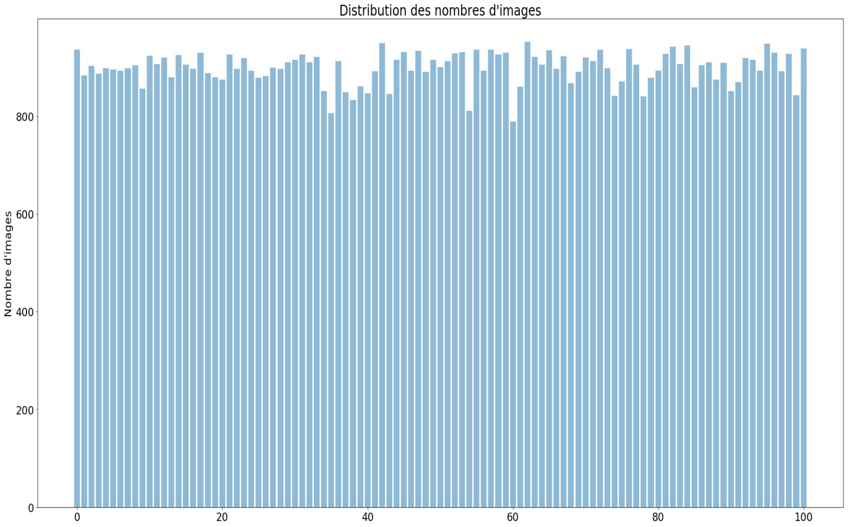
apple_pie_22.jpg

apple_pie_980.jpg

Les données

UPMC Food-101

- 100,000 images de 101 Food categories: Apple pie, Foie gras, Spring rolls,...
- 800-1000 images pour chaque catégorie



Les données

UPMC Food-101

- Il existe également les textes depuis les sites où ils viennent

Organic Apple Pie All Made From Scratch

14 comments | Print | ADD TO RECIPE BOX

Let me start by making your stomach ache for a slice of this heavenly apple pie recipe. Are your cheeks filling up with saliva? Do you wish you could pick off that bit of crumble that has fallen to the side? Look at those chunks of tender apple suspended in the brown sugary glaze, reclining on the thin and tender buttery pie crust. The crumble topping with fresh heavy cream baked right in, will make you think you're eating an apple crumble with melted ice cream. I'll let you in on something right now before you run off to the store.

- Buy enough ingredients to MAKE TWO PIES!

The first pie will be history after one meal. If you're family can manage to restrain themselves to save half of the pie for the next dinner, they will no doubt race through that dinner just so they can be first to get the next slice. I've seen it happen. *You should have see me go. I've never eaten so fast in my life.* ;D

Okay, now one note on my use of the word 'organic' in this recipe. The apples, the fresh heavy cream, and butter used in the crust were as close to organic as I had on hand. I have no idea where someone finds organic cinnamon, nutmeg and brown sugar. As for organic flour, I haven't come around to buying it. It's not easily available to me and I honestly forget that it exists. I used the term 'organic' in the recipe because my apples were organic. So I didn't lie, but I want to be clear that I couldn't make the entire recipe strictly an organic one. If you have all the organic ingredients on hand, then you know what to do. Enough said.

FIRST THINGS FIRST, PIE CRUST MADE FROM SCRATCH

I've already written to you about making pie crust that won't let you down. Go ahead and measure out enough ingredients for two 10-inch crusts. Even if you don't plan to make two apple pies, you'll have an extra crust ready for the next time. Go here to print off the pie crust recipe…

- Simple Homemade Pie Crust That Won't Let You Down

La tâche

- Bien classifier les images et les textes
- Benchmark (dans la publication des données) : 40.21 %

Visual				Textual	Fusion
BoW	Bossanova	Deep	Very Deep	TF-IDF	TF-IDF + Very Deep
23.96%	28.59%	33.91%	40.21%	82.06%	85.10%

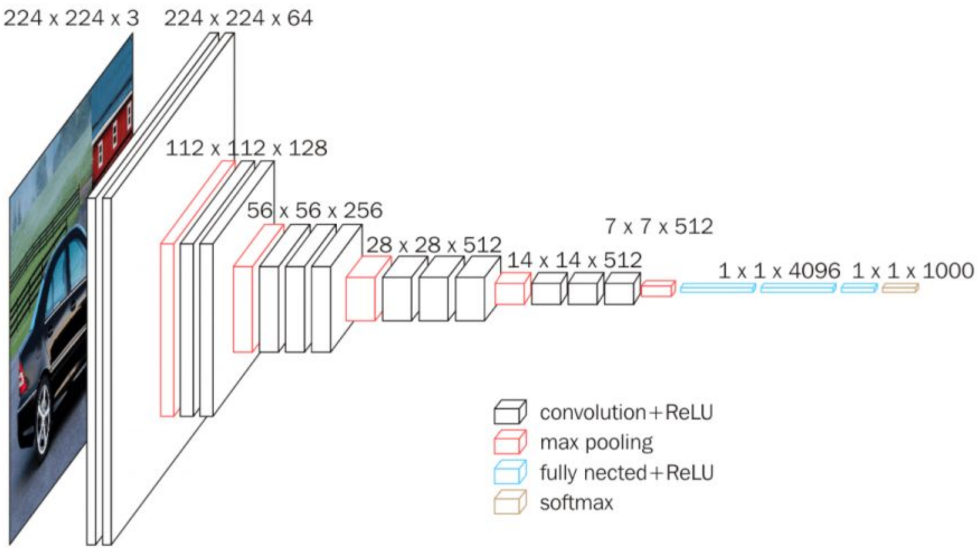
Table 2: Classification results (Ave. Precision %) on UPMC Food-101 for Visual, Textual and Combined features.

Transfer learning

- Fine-tuning les réseaux profonds
  - VGG-16
  - Resnet
  - Inception V3

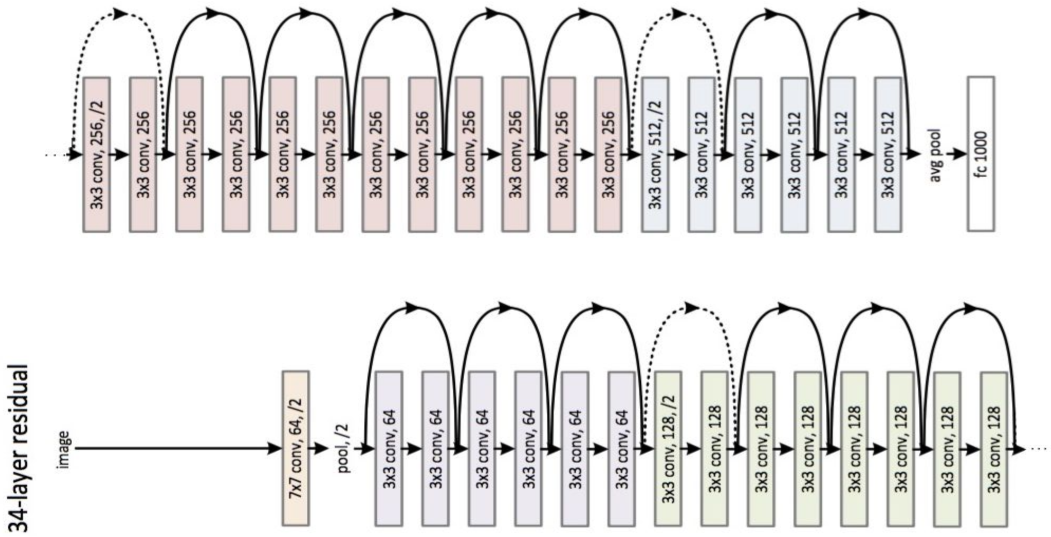
Fine-tuning le VGG-16

- Changer la dernière couche : de 1000 à 101 output
- Fine tune que les couches fully connected



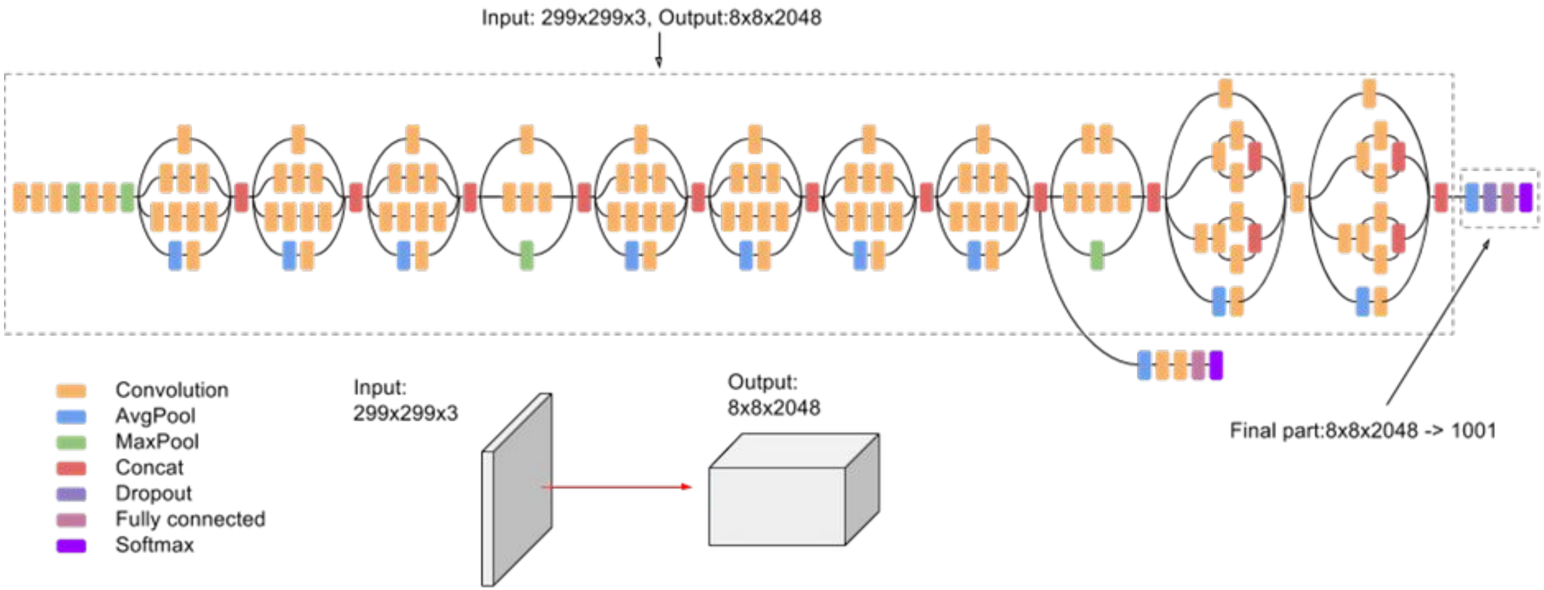
Fine-tuning le Resnet

- Changer la dernière couche : de 1000 à 101 output
- Fine tune tous les paramètres



Fine-tuning l'Inception

- 2 outputs : principale et auxiliaire
- Fine tune tous les paramètres



Les premiers résultats

- VGG16 :
  - fine tune que la dernière couche : 0.4333
  - fine tune les couches de classifier : 0.4842
- Resnet :
  - fine tune toutes les couches : 0.4524
- InceptionV3 :
  - fine tune toutes les couches : 0.5578

Classification de textes

- Preprocess les textes
  - Stem les mots, ex :
    - love/lovely/loves -> love
    - programs/programer/programing -> program
  - Enlever les chiffres, caractères spéciaux, ... et les mots courants/rares
- Transform les documents en TF-IDF vecteurs
- Appliquer une classifier ou bien un réseau de neurones

Classification de textes - Results

- ★ LinearSVC : 0.8730
- ★ Réseau de neurones avec 5 couches : 0.7734

```python
class myNet(nn.Module):
    def __init__(self, n_inputs, num_classes):
        super(myNet, self).__init__()
        self.classifier = nn.Sequential(
            nn.Linear(n_inputs, 1024),
            nn.ReLU(True),
            nn.Dropout(0.3),
            nn.Linear(1024, 512),
            nn.ReLU(True),
            nn.Dropout(0.3),
            nn.Linear(512, 256),
            nn.ReLU(True),
            nn.Dropout(0.3),
            nn.Linear(256, num_classes),
        )

    def forward(self, x):
        x = self.classifier(x)
        return x
```

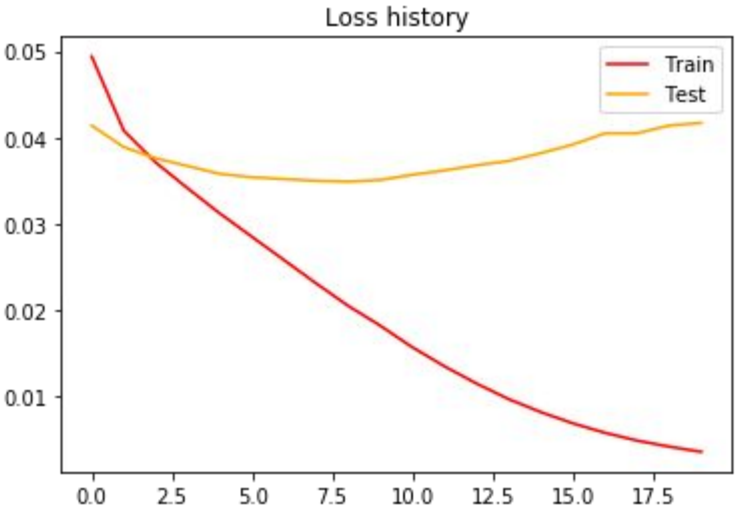
Classification de textes - Results

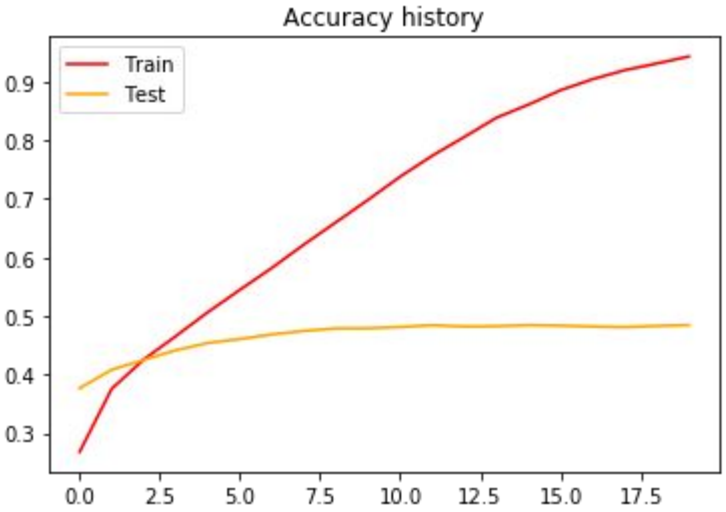
- ★ LinearSVC : 0.8730
- ★ Réseau de neurones avec 5 couches : 0.7734
- ★ Réseau de neurones plus simple : 0.8319

```python
# Using simple network gives better results ...

class myNet2(nn.Module):
    def __init__(self, input_size, num_classes):
        super(myNet2, self).__init__()
        self.classifier = nn.Sequential(
            nn.Linear(input_size, 1024),
            nn.Dropout(0.3),
            nn.Linear(1024, num_classes),
        )

    def forward(self, x):
        x = self.classifier(x)
        return x
```

Problème d'entraînement d’image

★ Overfitting ...





Améliorations

★ Preprocess bien les images
- ○ Resize
- ○ Data augmentation
  - ■ RandomResizedCrop
  - ■ RandomHorizontalFlip

```
data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(299),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(312),
        transforms.CenterCrop(299),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}
```

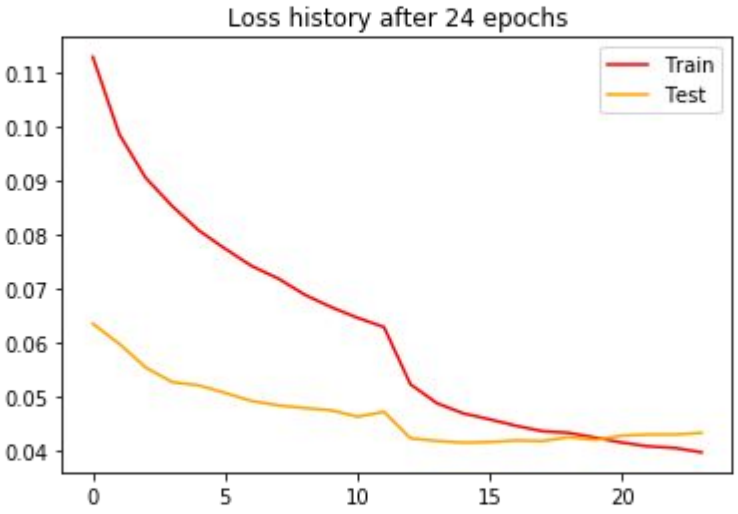
➜ **grands improvements :**

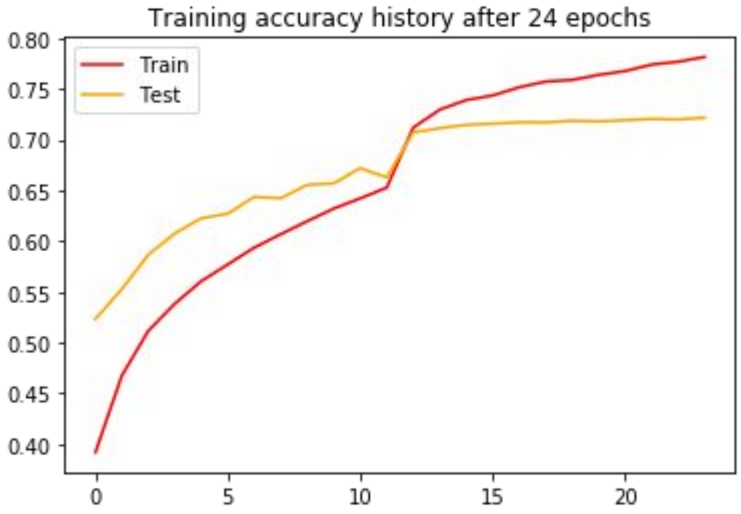
	sans data augmentation	avec data augmentation
VGG	0.4842	**0.5242**
Resnet	0.4524	**0.6667**
Inception	0.5578	**0.7217**

Améliorations

★ Preprocess bien les images

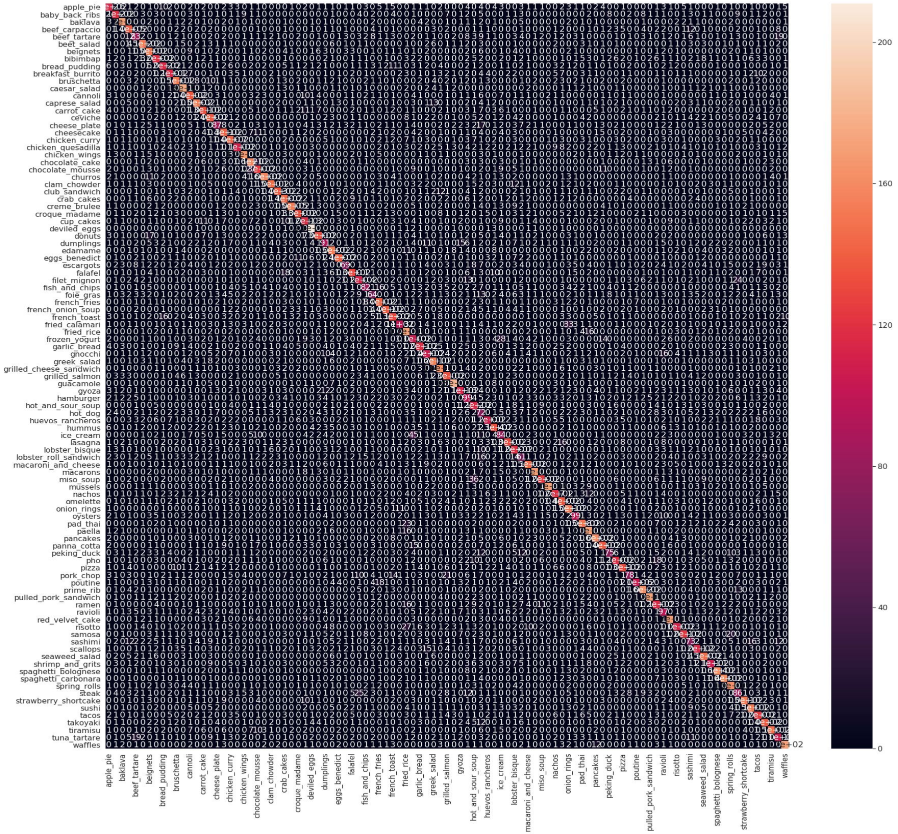
➜ **eviter overfitting :**





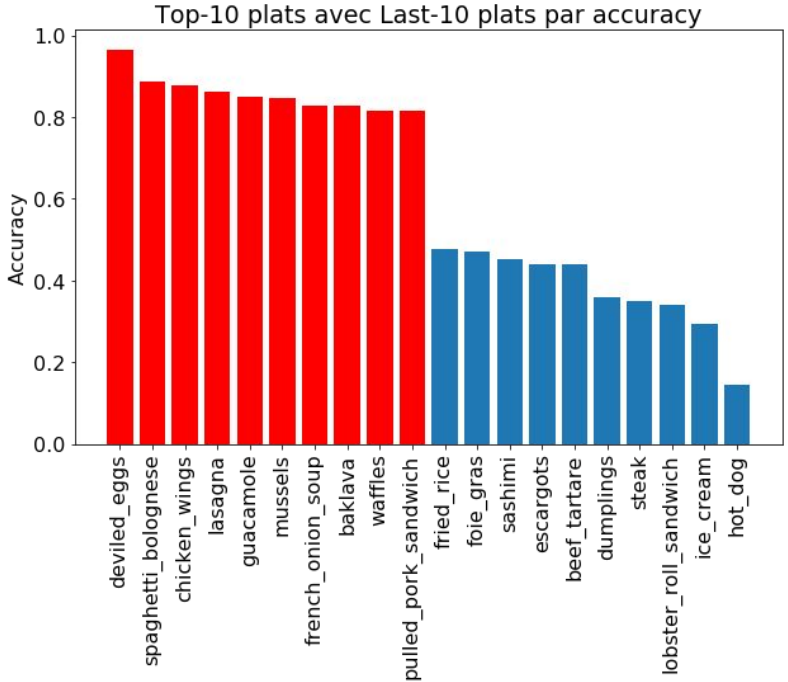
Analyse approfondie sur les données

★ Matrix de confusion



Analyse approfondie sur les données

★ Classer les classes par la précision



Analyse approfondie sur les données

★ Classer les classes par la précision

seulement 75/701 images sont les vraies ...

Analyse approfondie sur les données

★ Les plats confondus ...

```
ice_cream -> frozen_yogurt : 49.0
dumplings -> gyoza : 27.0
frozen_yogurt -> ice_cream : 26.0
french_toast -> bread_pudding : 24.0
filet_mignon -> steak : 22.0
chocolate_mousse -> chocolate_cake : 21.0
hot_dog -> lobster_roll_sandwich : 18.0
chocolate_cake -> chocolate_mousse : 18.0
gyoza -> dumplings : 17.0
bread_pudding -> french_toast : 14.0
donuts -> beignets : 13.0
paella -> fried_rice : 12.0
sashimi -> sushi : 12.0
crab_cakes -> falafel : 12.0
carrot_cake -> cup_cakes : 12.0
scallops -> gnocchi : 12.0
miso_soup -> hot_and_sour_soup : 12.0
onion_rings -> fried_calamari : 11.0
risotto -> fried_rice : 11.0
```

Analyse approfondie sur les données

★ Les plats confondus ...

frozen_yogurt

ice_cream

Analyse approfondie sur les données

- On reçoit quelques recettes des plats en prenant les mots dominants de chaque classe :
  - **apple_pie**: streusel, dutch, peel, fill, core, lattic, cinnamon, crust, pie, appl
  - **foie_gras:** torchon, luxuri, sear, terrin, goos, duck, lobe, liver, gra, foie
  - **ice_cream:** heavi, oreo, churn, freezer, vanilla, maker, freez, cream, icecream, ice
  - **pizza:** calzon, base, margherita, stone, prebak, pepperoni, mozzarella, dough, crust, pizza

Autre tentative d'amélioration

- ❖ Créer un réseau de neurones permettant de classifier Food/Non-Food
- ❖ Utiliser le model pour supprimer les mauvaises images dans les données
- ❖ Equilibrer les tailles de données par un WeightedRandomSample
- ❖ Entraîner sur les nouveaux données avec le model entraînée

➜ Le résultat n’est pas meilleur ...

Fusion de textes et images

- ★ Entraîner le réseau pour les textes et le modèle classifier de VGG
- ★ Combiner les deux 101-dimensional outputs avec un taux r variable :

output = r*ouput_text + (1-r)*output_VGG

➥ **TF-IDF deep + VGG : 0.8836**

UPMC data & EZTH data

★ **InceptionV3 model**

	Validate on UPMC	Validate on EZTH
Train on UPMC	**0.7217**	0.6170
Train on EZTH	0.5868	**0.8379**


STORCK
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