



Uncertainty-Aware Food Recognition by Deep Learning

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The Diabetes pandemy



Chronic disease statistics





What are we missing in health applications?

- Today, automatically measuring physical activity is not a problem.
- But what about food and nutrition?



Identificador	del volun	tario:		Fecha d	Fecha del examen:						
		Voluntario	Visita	Día	Mes	Año					
Visita: anotar e	Visita: anotar el número de visita										
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Comida	Hora	Alimento o preparación	I	ngredientes	Cant	idad total (gr)*					

e past year.	Never, or less	1-3 per	1 ner	2-4	5-6	1 per	2-3	4-5	6+ per	
DAIRY FOODS	per month	mo	week	week	week	day	day	day	day	C
Skim or low-fat milk (8 oz glass)	0	0	0	0	0	0	0	0	0	C
Whole milk (8 oz glass)	0	0	\odot	0	0	D	0	0	0	C
Cream, e.g. in coffee, or whipped cream (1 Tbs)	0	0	0	0	0	0	0	0	0	C
Sour cream (1 Tbs)	0	0	\odot	0	0	D	0	0	0	C
Non-dairy coffee whitener (1 tsp)	0	0	0	0	0	0	0	0	0	C
Sherbet or ice milk (1/2 cup)	0	0	0	0	0	0	0	0	0	C
Ice cream (1/2 cup)	0	0	0	0	0	0	0	0	0	C
Cottage or ricotta cheese (1/2 cup)	0	0	0	0	0	0	0	0	0	C
Cream cheese (1 oz)	0	0	0	0	0	0	0	0	0	C
Other cheese, e.g. American, cheddar, etc. plain or as part of a dish (1 slice or 1 oz serving		0	8	0	0	0	0	0	0	C
Margarine, added to food or bread (1 pat); exclude use in cooking	0	0	8	0	0	0	0	0	0	C
Butter, added to food or bread (1 pat); exclude use in cooking	0	0	8	0	0	0	0	0	0	C
Yogurt (1 cup)	0	0	\odot	0	0	0	0	0	0	C
	Never, or less	1-3 per	1 per	2-4 per	5-6 per	1 per	2-3 per	4–5 per	6+ per	
FRUITS	per month	mo	week	week	week	day	day	day	day	C
Raisins (1 oz or small pack) or grapes	0	0	(W)	0	0	0	0	0	0	C

Desayuno

Media mañana

Comida

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n, cheddar, etc. (1 slice or 1 oz serving		0	8	0	0	0	0	0	0	
r bread (1 pat);	0	0	8	0	0	0	0	0	0	ĺ
ead (1 pat);	0	0	8	0	0	D	0	0	0	ĺ
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S	Never, or less than once per month	1–3 per mo	1 per week	2–4 per week	5–6 per week	1 per day	2–3 per day	4–5 per day	6+ per day	
or grapes	0	0	(W)	0	0	0	0	0	0	ľ

What are we missing in health applications?

- But what about food and nutrition?
 - o State of the art: Nutritional health apps are based on manual food diaries.



How is today the food intake annotated?



FORMULARIO ENCUESTA ALIMENTARIA:

REGISTRO 3 DIAS

Comida	Hora	Alimento o preparación	Ingredientes	Cantidad total (gr)*
Desayuno				
Media mañana				
Comida				

24 hours dietary recall

•	* 0	▼⊿ B 3:41	@ †		
Lose It!	₹ 9	2 🗖 E	Lose It!		₹
		NEWS FEED	MY DAY		
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	20	Nutrients	Breakfast; 1	192	
CAL CAL	CRESUNDER REDEFT	Steps	5 Mill	k, Skim, v No	v/ Vitamin.
			🕴 Oat	s, Rolled,	, Old Fashid
	-		Lunch: 478		
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What we propose about it?

Automatic visual food recognition tools for dietary assessment.





What about automatic food recognition?

<mark>> NVIDIA</mark> DEVELOPER

NEWS CENTER News

Research Events

Comments A Shares

Lose It!'s New Food Recognition App Counts Calories

October 4, 2016

The diet app LoseIt! released a new deep learning feature called Snap It that lets users take photos of their food and then it automatically logs the calorie count and nutritional information.

Using the NVIDIA DIGITS deep learning training system on four TITAN X GPUs, the

company trained their network on a vast database of 230,000 food images and more than 4 billion foods logged by Lose It! users since 2008.

"The more people use this, the more it improves," said Edward W. Lowe, data scientist at Lose It. "The goal is to get the accuracy high enough in six months so it won't even need to ask you for validation."



How many food categories there are?

Today we are speaking about 200.000 food categories, 8000 basic food (Wikipedia).

Is it possible?

Why is the food recognition a challenge?



Difficulties

Huge intra-class variations

Ambiguous definition

Inter-class similarities

Mixed items

Need of huge datasets

Bad Labeled



What to do when you have a really complicate problem?

Any powerful tools for data processing of large amount of data?

Google Scholar reveals its most influential papers

Deep learning

Yann LeCun, Yoshua Bengio & Geoffrey Hinton Affiliations

Nature 521, 436–444 (28 May 2015) | doi:10.1038/nature14539 Received 25 February 2015 | Accepted 01 May 2015 | Published online 27 May 2015

- 1. <u>"Deep Residual Learning for Image Recognition"</u> (2016) Proceedings of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition 25,256 citations
- 2. "Deep learning" (2015) Nature 16,750 citations
- **3.** <u>"Going Deeper with Convolutions"</u> (2015) *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* 14,424 citations
- **4.** <u>"Fully Convolutional Networks for Semantic Segmentation"</u> (2015) Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition 10,153 citations
- 5. <u>"Prevalence of Childhood and Adult Obesity in the United States, 2011-2012"</u> (2014) JAMA 8,057 citations
- 6. <u>"Global, regional, and national prevalence of overweight and obesity in children and adults during</u> <u>1980–2013: a systematic analysis for the Global Burden of Disease Study 2013"</u> (2014) *Lancet* 7,371 citations
- 7. <u>"Observation of Gravitational Waves from a Binary Black Hole Merger"</u> (2016) *Physical Review Letters* 6,009 citations

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Deep Learning applications

DEEP LEARNING EVERYWHERE



INTERNET & CLOUD

Image Classification Speech Recognition Language Translation Language Processing Sentiment Analysis Recommendation



MEDICINE & BIOLOGY

Cancer Cell Detection Diabetic Grading Drug Discovery



MEDIA & ENTERTAINMENT

Video Captioning Video Search Real Time Translation



SECURITY & DEFENSE

Face Detection Video Surveillance Satellite Imagery



AUTONOMOUS MACHINES

Pedestrian Detection Lane Tracking Recognize Traffic Sign

Climate Change Sep 19

Amazon just pledged to hit net zero climate emissions by 2040

MIT Technology Review

Neural Networks beat humans in:

- object recognition,
- lip reading,
- high-end surveillance,
- facial recognition,
- object-based searches,
- license plate readers,
- traffic violations detection,
- breast tomosynthesis diagnosis,
- etc., etc.





Neural Style Transfer













[Gatys et al. 2015]

Neural networks (GANs) as artists



This picture made by a GAN was sold for \$432,500 and it's not even real.

Deep Learning and society expectation



Deep Learning's 'Permanent Peak' On Gartner's Hype Cycle

The Jim Cray's paradigms



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The magic triangle



The Importance of GPUs

- Nvidia Tensor Cores 2017
- Google Tensor Processing Unit (TPU) 2016
- Intel Nervana Neural Processor 2017
- GPUs in Cloud Computing (Google, 2017)





GPU cores is based on matrix multiplication

https://www.doc.ic.ac.uk/~jce317/history-machine-learning.html#top

Data

90% of all digital data were generated last 2 years.

Every minute of the day:

- 4M YouTube videos watched
- 456K tweets on Twitter
- 46K potos posted in Instagram
- 16M text messages sent
- <u>103M spam emails</u> sent

Daily:

- 300M photos get uploaded
- <u>95M photos and videos</u> are shared on Instagram
- <u>100M people</u> use the Instagram "stories"
- 15K GIFs are sent via Facebook
- 154K calls on Skype
- 4.7T photos stored in cameras



https://www.forbes.com/sites/bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/#46be238160ba

Image databases evolution

Number of objects/Database



ImageNet & Deep learning

Number of images/Database



Deep Learning Datasets







Places2: 10M images



Food datasets

Food256: 25.600 images (100 images/class) Classes: 256



Food101 – 101.000 images (1000 images/class) Classes: 101

Food101+FoodCAT: 146.392 (101.000+45.392) Classes: 231

Food DB 150.000 images 231 categories ImageNet

1.400.000 images 1000 categories Future Food DB

????? images 200.000 categories

FoodImageNet soon to come!

How many images should

contain the real FoodDB?













What is a Neural Network?





LeCun, Chief AI Scientist for **Facebook** AI Research (FAIR), and a Silver Professor at New York University



A.Krijevksi et.al. 2012, Google Brain & Waymo.

Analysis of CNNs



Millions of parameters!!!

The process of training a CNN consists of training all hyperparameters: convolutional matrices and weights of the fully connected layers.

What makes DNN so popular?

It has the three advantages:

• 1. Self-learned high-level features representations



• 2. Modularity



• 3. Transfer Learning



Use Transfer Learning

Henry Roth is a man afraid of commitment up until he meets the beautiful Lucy.

They hit it off and Henry think he's finally found the girl of his dreams,

until he discovers **she has short-term memory loss and forgets him the next day.**





Transfer Learning



Transfer learning (TL)









Food Recognition as MTL



Cuisine: French. Categories: Meat.

Ingredients: salt, oil, onion, garlic, black pepper, tomato, cloves, parsley, thyme, bay, white wine, clove, duck, fat, mutton.

Dish: Confit de canard.

Multi-Task Learning (MTL)

- Learning multiple objectives from a shared representation
 - *Efficiency* and prediction *accuracy*.

- Crucial importance in systems where long computation run-time is prohibitive
 - Combining all tasks *reduces computation*.
- Inductive knowledge transfer

- <u>Generalization</u> by sharing the domain information between complimentary tasks.

Food Recognition as a MTL



 $L_{total} = \sum \omega_i L_i$

How to define the importance of each task?

- Weighted uniformly the losses.
- Manually tuned the losses.
- Dynamic weighted of the losses.
 - The main task is fixed and weights are learned for each side-task ([1]).
 - Weight the tasks according to the homoscedastic uncertainty ([2]).

[1] X. Yin and X. Liu. Multi-task convolutional neural network for face recognition.

[2] A. Kendall, Y. Gal, and R. Cipolla. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics.

Let's talk about uncertainty

But many unanswered questions...

- Why doesn't my model work?
- -> Why does my model work?
 - Why does my model work?
 - What does my model know?
 - Why does my model predict this and not that?

Our models are black boxes and not interpretable...

• Physicians and others need to understand why a model predicts an output.





Model uncertainty

1. Given a model trained with several pictures of fruits, a user asks the model to decide what is the object using a photo of a chocolate cake.





Who is the guilty for this?



Model uncertainty

2. We have different types of images to classify fruits, where one of the category comes with a lot of clutter/noise/occlusions.



Model uncertainty

3. What is the best model parameters that best explain a given dataset? What model structure should we use?



Gal (2016)

Types of uncertainty in Bayesian modeling

Aleatoric – captures the noise inherent in the observations

- heteroscedastic data-dependent
- homoscedastic constant for different data points,
 - but can be task-dependent.
- **Epistemic** model uncertainty
 - Can be explained away given enough data
 - Uncertainty about the model parameters
 - Uncertainty about the model structure





Food Recognition as a MTL

Aleatoric uncertainty – How to model it?





How to determine the total loss of the MTF?

- Expensive to learn & Affects the performance and the efficiency.

Use aleatoric uncertainty modeling to make the model more clever! 09:42 •

Our FoodImageNet

Our FoodImageNet

- Food 450 dishes, 11 categories, 11 cuisines
- Ingredients 65
- Drinks 40
- Labeled images
- Segmented images
- Recipes

In total: more than 550.000 images



Eduardo Aguilar, Marc Bolaños, Petia Radeva: **Regularized uncertainty-based multi-task learning model for food analysis.** J. Visual Communication and Image Representation 60: 360-370 (2019) 09:42

Food ingredients recognition



Dish: prime rib

Prediction: 'olive oil', 'kosher salt', 'minced garlic', 'thyme', 'peppercorns', 'rosemary', 'ribeye roast',

GT: 'olive oil', 'kosher salt', 'minced garlic', 'thyme', 'peppercorns', 'rosemary', 'ribeye roast',



Dish: caesar salad

Prediction: 'salt', 'extra-virgin olive oil', 'dijon mustard', 'freshly ground black pepper', 'red wine vinegar', 'dried mixed herbs', 'toasted pine nuts', 'beets', 'gorgonzola', 'baby spinach',

GT: 'salt', 'garlic', 'pepper', 'dijon mustard', 'worcestershire sauce', 'lemon juice', 'romaine lettuce', 'croutons', 'plain greek yogurt' 'parmesan cheese', anchovy paste',

Dish: chicken curry

Prediction: 'salt', 'sugar', 'vegetable oil', 'ground black pepper', 'yellow onion', 'corn starch', 'garlic cloves', 'fresh ginger', 'frozen peas', 'chopped fresh cilantro', 'boneless skinless chicken breasts', 'low sodium chicken broth', 'greek yogurt', 'curry powder',

GT: 'salt', 'sugar', 'vegetable oil', 'ground black pepper', 'yellow onion', 'corn starch', 'garlic cloves', 'fresh ginger', 'frozen peas', 'chopped fresh cilantro', 'boneless skinless chicken breasts', 'low sodium chicken broth', 'greek yogurt', 'curry powder',



Dessert		
Meat		

Beet Salad

Dish



Try with example

Chosen Image









Food category and class recognition



Food Recognition





	Dish	Cuisine		Categories			Ingredients		
	Acc	Acc	F_1	Pre	Rec	F_1	Pre	Rec	MTA
Single-task	0.8334	0.8649	0.8709	0.8944	0.8485	0.8992	0.9143	0.8846	0.6713
MTL	0.8303	0.8958	0.8811	0.9042	0.8592	0.8780	0.8972	0.8596	0.6927
RMTL	0.8351	0.8917	0.8834	0.8789	0.8880	0.8809	0.8613	0.9014	0.7061
UMTL	0.8221	0.8944	0.8925	0.9067	0.8788	0.8943	0.9095	0.8795	0.7478
RUMTL	0.8358	0.8934	0.8944	0.9041	0.8848	0.8988	0.9084	0.8893	0.7600

Food Recognition

R 🖨 🗊 Figure 1

green_beans bread beef_burger_meat



bread



beef_burger_meat

green_beans





B

Understanding the cooking process



Conclusions

- Food image world brings us huge amount of data and Computer Vision questions
- It makes us redefine which are :
 - Datasets
 - Problems, Q&A
 - Methodologies & Technologies
- Transfer learning and its subproblems as multi-task learning open huge amount of opportunities
- Uncertainty modeling is a hot topic with many open questions and challenges!
 - Epistemic uncertainty
 - Aleatoric uncertainty
- A huge impact of food analysis is expected from point of view of:
 - Science, but also
 - Real world applications, specially important for the society.

