Recipe Recognition with Large Multimodal Food Dataset

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Outline

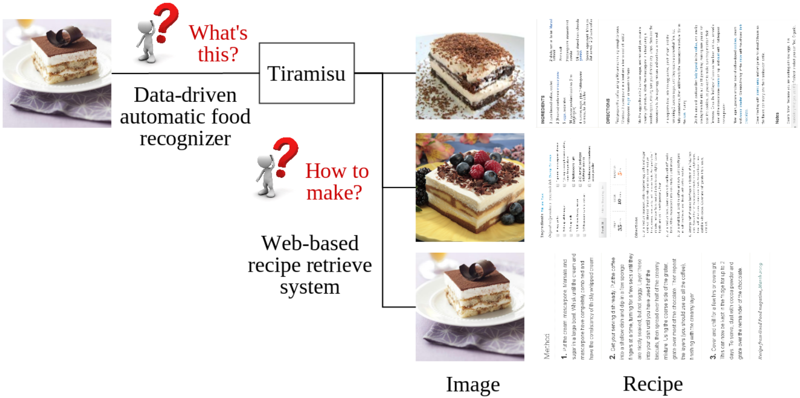
1. Context
2. New Dataset: UPMC Food-101
3. Experiments
4. Conclusions & Perspectives

Outline

Problem

Problem

Recipe recognition: food description $\Rightarrow$ food recipe



Problem

Core Problem

Food category classification: key technology for many food-related applications such as:

1. monitoring healthy diet[a] [b]
2. recording eating activities[c]
3. food recommendation system[d]

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[a] Aizawa, K., Maruyama, Y., Li, H., and Morikawa, C. (2013). Food balance estimation by using personal dietary tendencies in a multimedia food log. IEEE Transactions on Multimedia,

[b] Khanna, N. and et al. (2010). An overview of the technology assisted dietary assessment project at purdue university.

[c] Aizawa, K. and et al. (2014). Comparative Study of the Routine Daily Usability of FoodLog: A Smartphone-based Food Recording Tool Assisted by Image Retrieval. Journal of diabetes science and technology.

[d] Takuma Maruyama Yoshiyuki Kawano Keiji Yanai, Real-time Mobile Recipe Recommendation System Using Food Ingredient Recognition, IMMPD'12

Motivation

Motivation 1

1. Needs of large scale dataset:
   - Pittsburgh Food Image Dataset (PFID): 4556 images
   - UNICT-FD889 dataset: 889 images
   - UEC-Food100 (without extension): 100 categories, 100 images / category
2. Needs of **multi-modal** food dataset

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2. Needs of **multi-modal** food dataset

Motivation

Motivation 1: Large scale multi-modal dataset

Training a generic multi-modal supervised automated recipe recognition system needs:

1. Large number of food categories
2. Large number of food examples
3. Food image + text

Motivation 2: Twin datasets

Same categories, different data sources:

- ETHZ Food-101 [ECCV 2014]: Collected from only gourmet sites
- UPMC Food-101: Collected from Google Images Search engine

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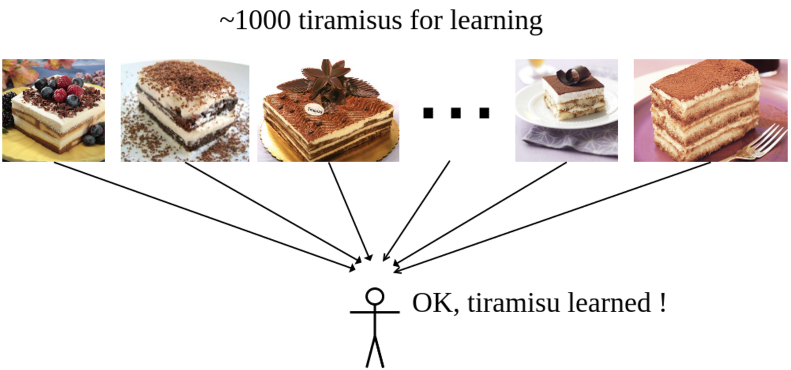
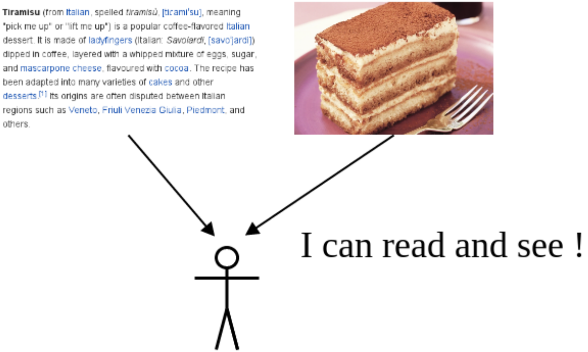
Properties

1. Large scale: large number ($\sim 101,000$) of training images



Properties

1. Large scale
2. Multimodal dataset: visual information + textual information



Properties

1. Large scale
2. Multimodal dataset
3. Web-based source: Building UPMC Food-101 from web

Dataset acquisition protocol

Dataset acquisition protocol

1. Same category names as ETHZ Food-101
2. Suffix *recipe* after each category name
3. First 1000 results of Google Image search engine
4. Data cleaning

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100 category examples of UPMC Food-101 dataset

Class wise performance: Best 5

Spaghetti Carbonara 73 %

Deviled Eggs 65 %

Grilled cheese sandwich 59 %

Prime Rib 57 %

Chicken Wings 52 %

Class wise performance: Worst 5

Ravioli
8.5 %

Gnocchi
~12.5 %

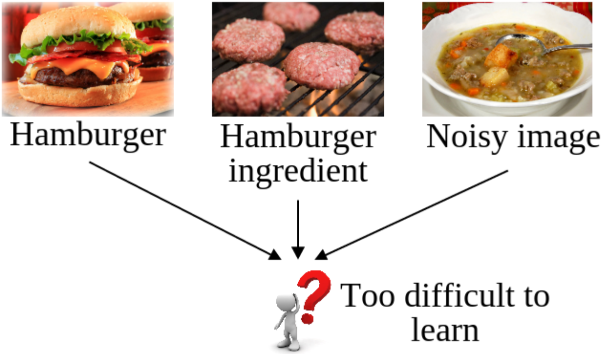
Hamburger
~12.5 %

Ice-cream
~12.5 %

Dumplings
13 %

Difficulties of dataset

- Food deformation
- Noisy image

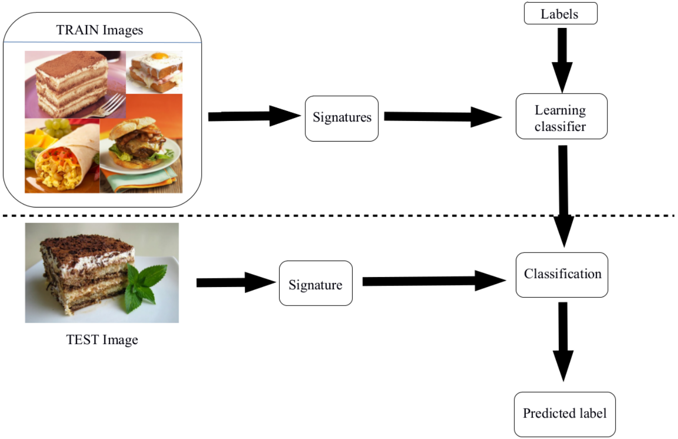


Outline

Supervised food category classification

Goal

Predict food category by using the data (image / text)



Visual features (1)

Traditional visual features: Dense-SIFT + BoW Presentation

1. Dense-SIFT: Bag-of-Words histogram with a spatial pyramid
2. BossaNova[a]: Pooling by considering distance between a word and a given center of a cluster

[a] Avila, S., and Thome, N., Cord M., Valle E., Araujo A. Pooling in image representation: The visual codeword point of view. CVIU 2013

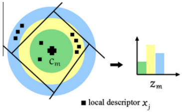


Figure: BossaNova pooling

BoW	BossaNova
23.96%	28.59%

Table: Avg. accuracy of BoW and BossaNova

Visual features (2)

Deep visual features

1. Deep CNN[a]: *fast network*, 9 layers CNN, 4096 dimensions.
2. Very Deep CNN[b]: 19 layers CNN, 4096 dimensions.

[a] Sermanet, P., Eigen, D., Zhang, X., and LeCun, Y. . Overfeat: Integrated recognition, localization and detection using convolutional networks, ICLR 2014.

[b] Simonyan, K. and Zisserman, A. Very deep convolutional networks for large-scale image recognition, ICLR 2015.

Deep	Very Deep
33.91%	40.21%

Table: Avg. accuracy of deep and very deep features.

Textual features

Textual Features

1. TF-IDF : Term frequency - Inverse Document Frequency
2. Word2vec[a] : Embedded vector representations of words

[a] Mikolov, T., Sutskever, I., and Chen, K.. Distributed representations of words and phrases and their compositionality, NIPS 2013.

TF-IDF	word2vec
85.10%	67.21%

Table: Avg. accuracy of TF-IDF and word2vec

Features and Performances

Late fusion

Fusion score:

$$s_f = \alpha s_i + (1 - \alpha) s_t,$$

α: Fusion parameter, in the range $[0, 1]$
s_i: Classification score of the image classifier
s_t: Classification score of the text classifier

Visual				Textual		Fusion
BoW	BossaNova	Deep	**Very Deep**	**TF-IDF**	word2vec	**TF-IDF + Very Deep**
23.96%	28.59%	33.91%	40.21%	82.06%	67.21%	85.10%

Table: Classification results (avg. accuracy %) on UPMC Food-101 for visual, textual features and fusion.

Comparing UPMC Food-101 and ETHZ Food-101

train / test	UPMC	ETHZ
UPMC (600 examples)	40.56%	25.63%
ETHZ (600 examples)	25.28%	42.54%
UPMC (all examples)	-	24.06%
ETHZ (all examples)	24.92%	-

Table: Avg. accuracy of transfer learning (very deep features) between UPMC Food-101 and ETHZ Food-101.

Analysis

1. Systematic loss: $\sim 15\%$ when training on one dataset and testing on the other dataset.
2. Increasing training images does not achieve better results.

Different data sources

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Different data sources

Word2vec: a powerful semantic tool

Word2vec evaluation

rice	japan	rice japan
calros 0.59	osaka 0.70	**koshihikari 0.64**
basmati 0.59	tokyo 0.62	awabi 0.61
vermicelli 0.58	kyoto 0.62	japanes 0.61
stirfri 0.58	chugoku 0.61	nishiki 0.59
veget 0.58	gunma 0.60	chahan 0.57

Table: Short phrase **rice japan**, represented as the average of **rice** and **japan**, is closest to **koshihikari**, which is neither among the 101 categories, nor among the neighbors of **rice** or **japan**.

Outline

Recognizer based on UPMC Food-101

Demo (ongoing work)

Figure: Results for a pizza image

Recognizer based on UPMC Food-101

Demo (ongoing work)

Figure: Results for a pizza image

Conclusion & Perspective

Conclusions

1. UPMC Food-101: a large scale multimodal food recipe dataset
2. Detailed classification experiments
3. Semantic vectorial text representation tool word2vec
4. Recipe retrieval system prototype

Perspectives

- Active learning to improve the retrival system based on user interaction
- Levaraging twin datasets to achieve better results

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Thank you for your attention! Questions?

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Dataset available on demand

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