Feedback on the conference

France is AI

Anastasia Lieva
Data-Humanist
@lievAnastazia

France is AI

Mission

Support and promote
Artificial Intelligence ecosystem in France

France is AI

Format

Two day conference :

1st day focused on Tech and Research

2nd day on Business and Applications

In between : meetups meetings!

France is AI

Conferences

AI for GOOD

Love Machine

What future of AI would be like for you?

AI for GOOD

Love Machine

What future of AI would like for you?

90% of Terminator story

10% Entertainment story

CREDIT : Alexandre Cadain

Social side

AI for GOOD

CREDIT : Alexandre Cadain

Social side

AI for GOOD

OrCam

CREDIT : Alexandre Cadain

Social side

AI for GOOD

CREDIT : Alexandre Cadain

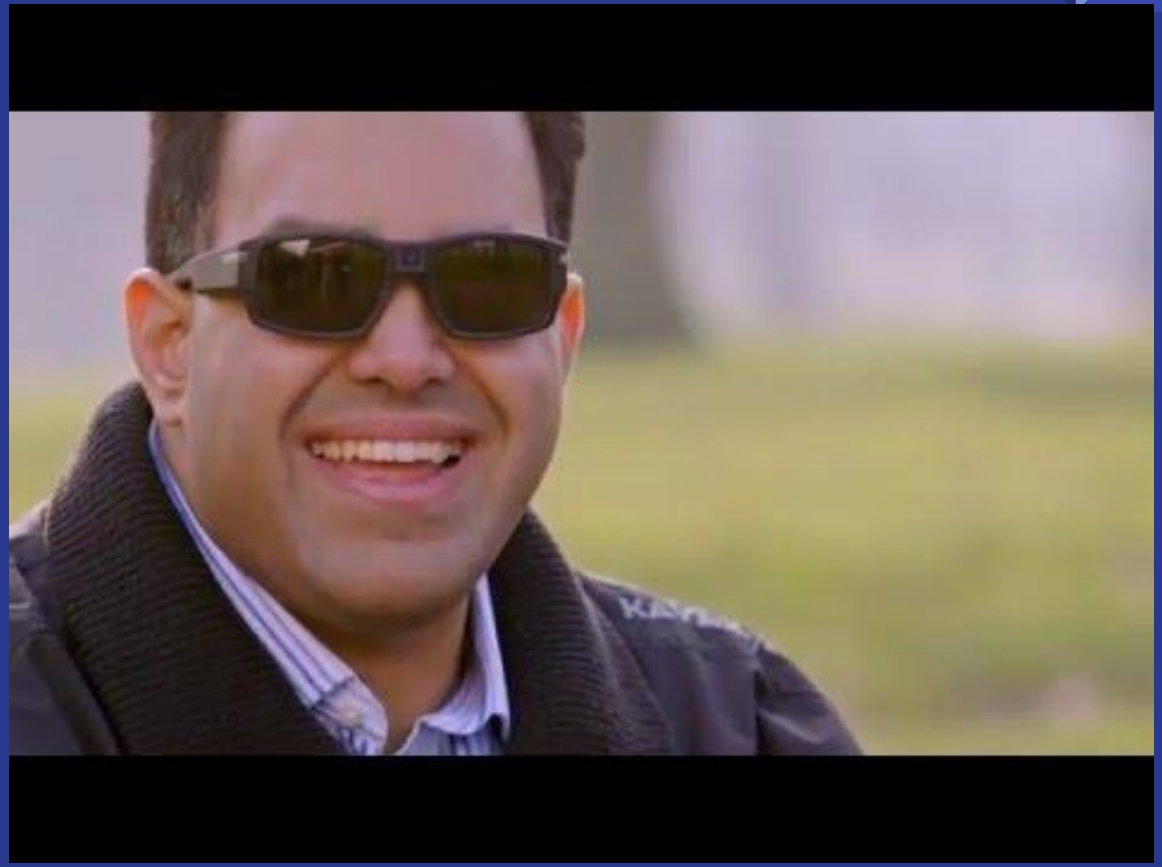
Social side

AI for GOOD

CREDIT : Alexandre Cadain

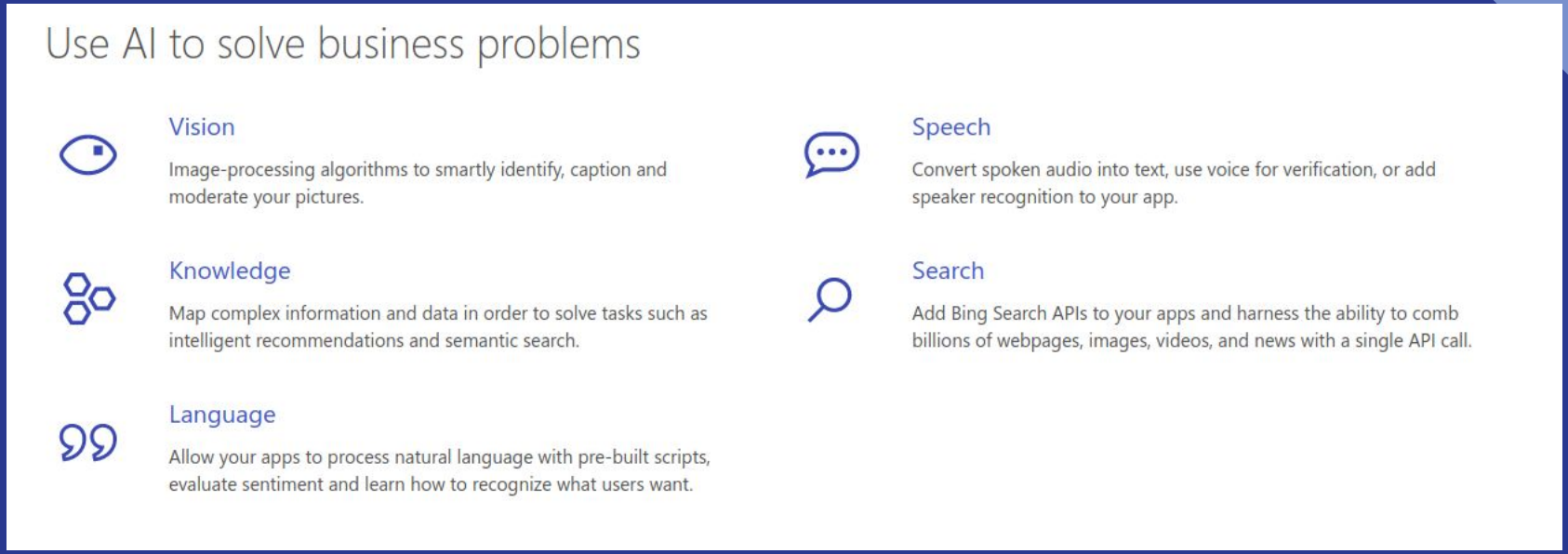
Business and Applications

Democratizing AI



Business and Applications

Democratizing AI



https://github.com/Microsoft/CNTK

MICROSOFT

Data scarcity

Directions

Transfer learning

Learn from rich simulations

Learn generative models

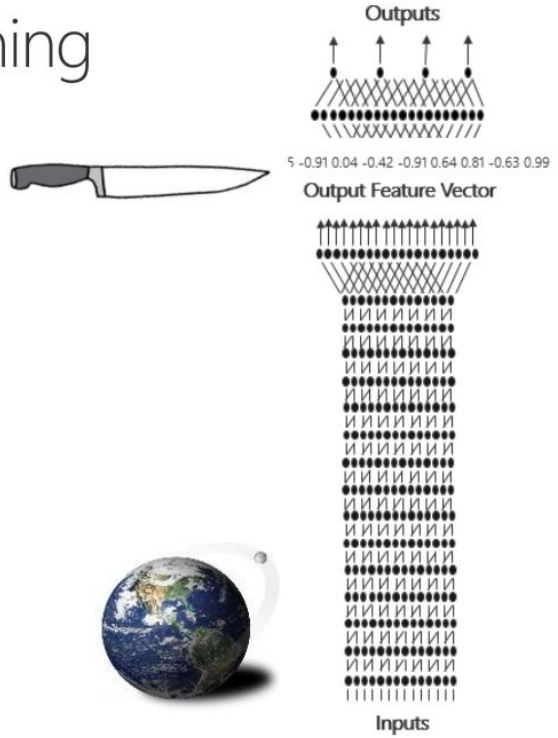
MICROSOFT

Embedded deep transfer learning

Less data with better features

ImageNet 1000, 1M photos

Cut off top layer



M. Gabel, R. Caruana, M. Philipose, O. Dekel

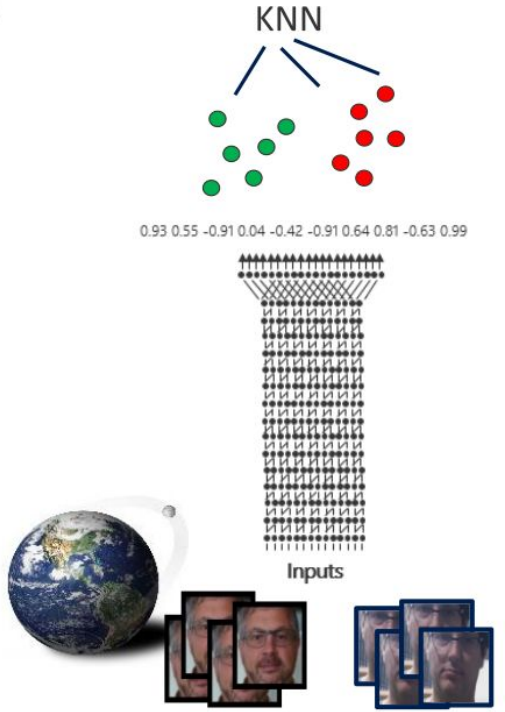
MICROSOFT

Embedded deep transfer learning

Less data with better features

ImageNet 1000, 1M photos

Cut off top layer



M. Gabel, R. Caruana, M. Philipose, O. Dekel

Business and Applications

Generating customer responses with GANs

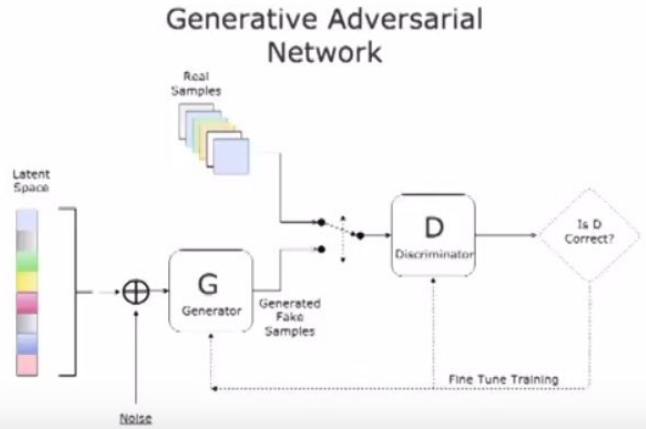
- Personal Assistant and Bot Acceleration
  - VoiceBot, MailBot,ChatBot, ... (what we call xBot at xBrain)
  - Labelled data and Classification through user (or customer) is really hard !
- Real Life hurts :
  - How to bootstrap a bot with little ~~efforts~~ (data labeled) ?
  - How to manage the improvement without ~~effort~~ (data labelisation) ?
- From Unstructured Data to Structured Data
  - How to discover the hidden structured in the data ?
  - Clustering Algo (like K-means) or Generative models (GANs)

CREDIT : X-BRAIN

Business and Applications

Generating customer responses with GANs

Generative adversarial networks (GANs) are a class of artificial intelligence algorithms used in unsupervised machine learning, implemented by a system of two neural networks contesting with each other in a zero-sum game framework.



Toward Controlled Generation of Text

Zhiting Hu [1 2] Zichao Yang [1] Xiaodan Liang [1 2] Ruslan Salakhutdinov [1] Eric P. Xing [1 2]

CREDIT : X-BRAIN

Business and Applications

Bots Overview and AI Rethinking Media : JAM

Business and Applications

Bots Overview and AI Rethinking Media : JAM

- **Context is a king**
- **Readers come to be inspired**
- **From content to action :**

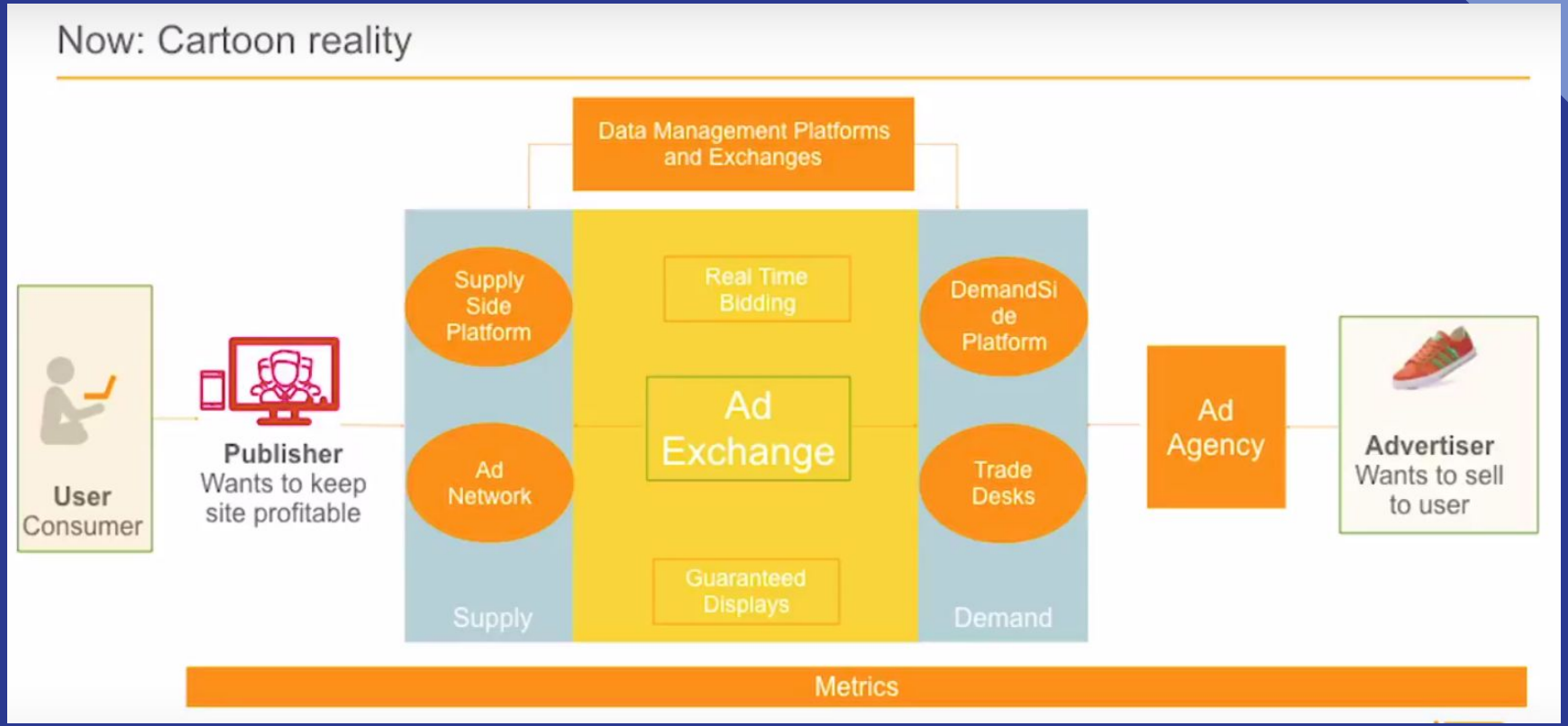
  reminder, reservation, payment, sharing

CREDIT : Marjolaine Grondin

Evolution of Computational Advertising

Vice President Of Research Criteo

Evolution of Computational Advertising by Criteo



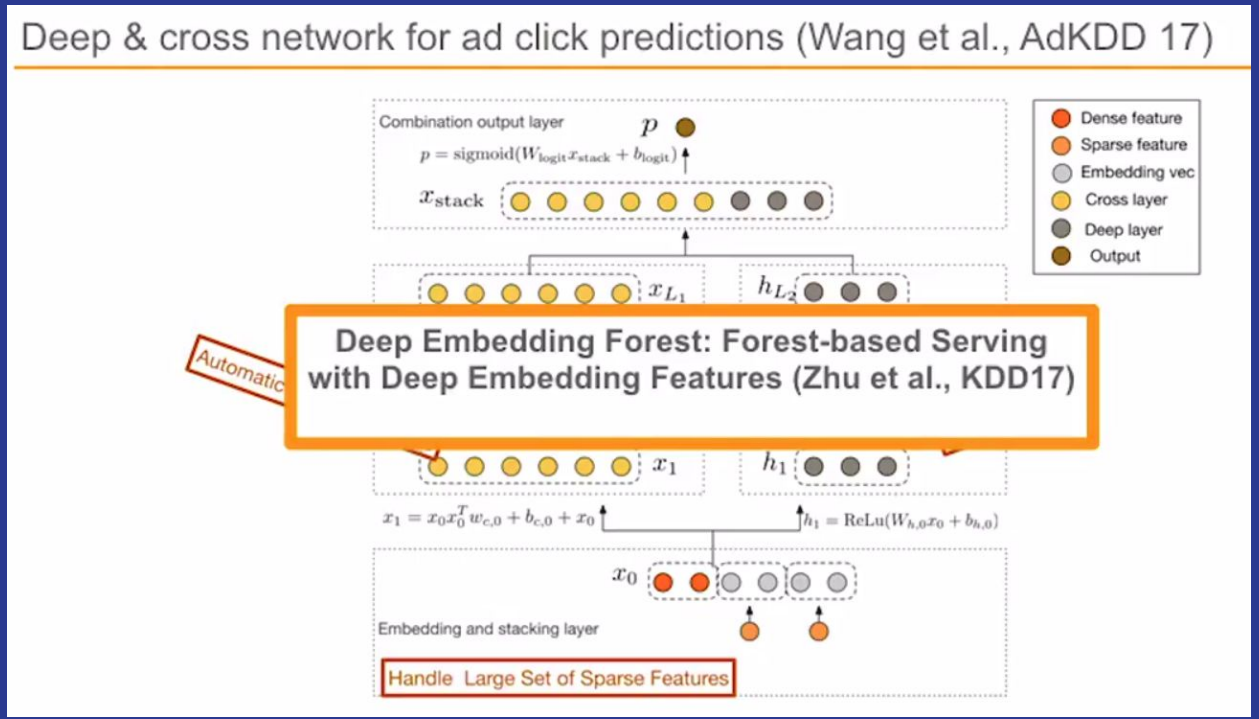
CREDIT : CRITEO RESEARCH 2016

Evolution of Computational Advertising by Criteo

- Model CTR prediction as a logistic regression problem
  - $p_t = \sigma(w_t . x_t)$ where $\sigma(x) = (1 + \exp(-x))^{-1}$ is the sigmoid function
  - Given true label y_t, we want to minimize the logistic loss $l_t(w_t) = -y_t \log p_t - (1 - y_t)\log(1 - p_t) + \lambda \| w \|^2$
- Features of x_t can be based on publisher, user & context of interaction

CREDIT : CRITEO RESEARCH 2016

Evolution of Computational Advertising by Criteo



CREDIT : CRITEO RESEARCH 2016

Attributes Extraction in e-Commerce at Racuten

The Problem: low quality catalog

Low quality catalog:

- unstructured catalog
- missing or incorrect attributes
- poor or outdated reference values

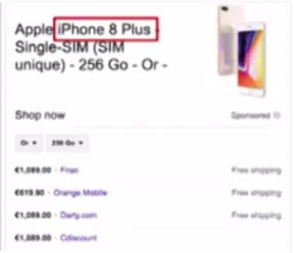
id	url	type	color	
0001	x.jpg	shoe		← green
0002	y.jpg	shoe	multicolor	← orange

no attributes!

values in catalog
for attribute *Phone Model*

Phone Models

…
iPhone 6 (2014 - 2016)
iPhone 6 Plus (2014 - 2016)
iPhone 6S (2015 - .)
iPhone 6S Plus (2015 - .)
iPhone SE (2016 - .)
iPhone 7 (2016 - .)
iPhone 7 Plus (2016 - .)
iPhone 8 (2017 - .)
?

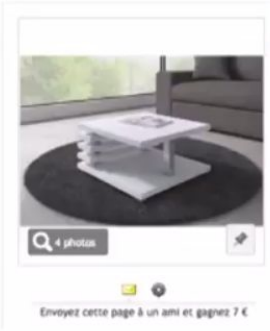


Rakuten

CREDIT : RACUTEN

Attributes Extraction in e-Commerce at Racuten

Possible solution: information extraction from text and picture



Descriptif

- Fabricant : E-Com

Table Basse Oslo 60x60cm Blanc Mat Longueur : 60 cn

Descriptif

Fabricant	E-Com
Matière Dominante	Bois plaquage
Couleur	Blanc

Popular search keywords
Leroy Merlin
Ikea
…

Reference lists

Manifacturer	Material	Color
Ikea	Glass	Black
Castorama	Wood	Brown
Leroy Merlin	Metal	White
…	…	…

Learn to identify attribute values in product **descriptions**

- belonging to a reference list
- new and pertinent

Learn to identify attribute values in product **pictures**

- belonging to a reference list
- visual

CREDIT : RACUTEN

Attributes Extraction in e-Commerce at Racuten

Learn words semantics

Named Entity Recognition (NER) problem

LOCATION COLOR TYPE
A jewel in the [living room], this [golden-yellow] [armchair]
SHAPE
is very confortable and has a [rectangular] storage pocket…
not related to product

Approaches:

- CRF*
  - ✓ models dependencies between words
  - ✓ handcrafted features:

word-level
sub-word

word embedding
word2vec GloVe
trained on generic data
task-specific

CREDIT : RACUTEN

Attributes Extraction in e-Commerce at Racuten

Learn words semantics

Named Entity Recognition (NER) problem

LOCATION COLOR TYPE
A jewel in the [living room], this [golden-yellow] [armchair]
SHAPE
is very confortable and has a [rectangular] storage pocket…
not related to product

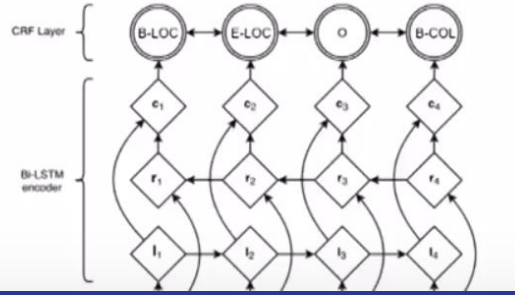
Approaches:

- CRF
  - ✓ models dependencies between words
  - ✓ handcrafted features:

word-level
sub-word

word embedding
word2vec GloVe
trained on generic data
task-specific

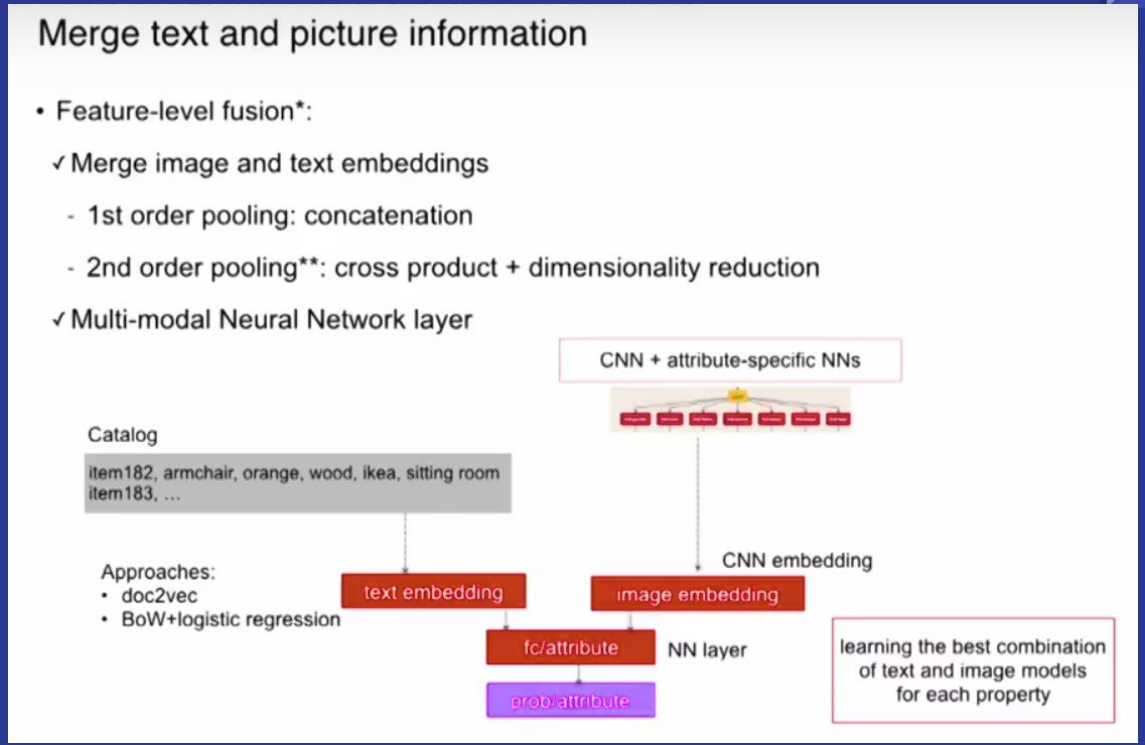
- Bidirectional LSTM-CRF*
  - ✓ no feature engineering
  - ✓ character-based word representation



CREDIT : RACUTEN

Business and Applications

Attributes Extraction in e-Commerce at Racuten



MUTAN: Multimodal Tucker Fusion for Visual Question Answering

CREDIT : RACUTEN

VISUAL QUESTION ANSWERING

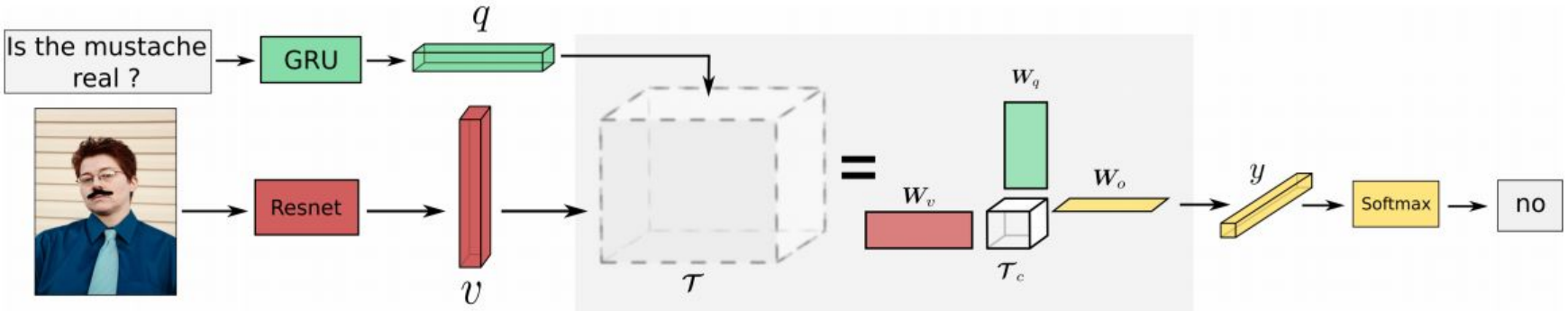


Figure 2: MUTAN fusion scheme for global Visual QA. The prediction is modeled as a bilinear interaction between visual and linguistic features, parametrized by the tensor $\mathcal{T}$. In MUTAN, we factorise the tensor $\mathcal{T}$ using a Tucker decomposition, resulting in an architecture with three intra-modal matrices $\boldsymbol{W}_q$, $\boldsymbol{W}_v$ and $\boldsymbol{W}_o$, and a smaller tensor $\mathcal{T}_c$. The complexity of $\mathcal{T}_c$ is controlled *via* a structured sparsity constraint on the slice matrices of the tensor.

MUTAN: Multimodal Tucker Fusion for Visual Question Answering

Business and Applications

On recent advances in machine listening and ambient sound detection

Machine perception

- Computer Vision
- Speech recognition
- Music understanding

Challenge

what about an "everyday" ambiant sound?

- smart house for isolated elderly people
- sounds surrounding a self-driving car

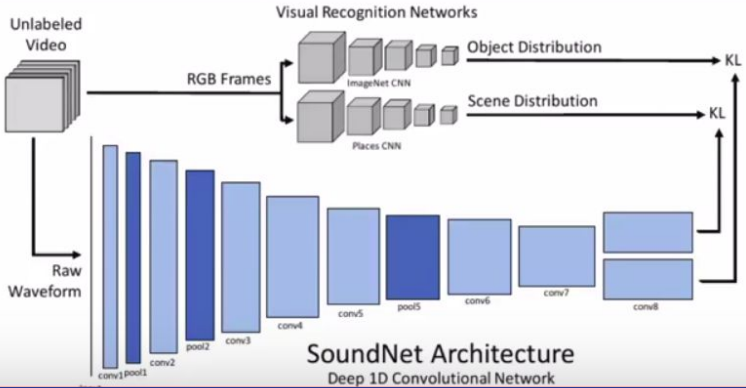
CREDIT : Alain Rakotomamonjy

On recent advances in machine listening and ambient sound detection

Vision-guided learning of audio features

SoundNet [Aytar et al, NIPS16]

- Leverages unlabelled video and SOA visual recognition networks for learning audio features
- principal idea : sound/video synchronization ; train audio model using visual supervision
- match posterior probabilities of classes



CREDIT : Alain Rakotomamonjy

AI at scala @Twitter : Ranking The Timelines

- Billions of positive user engagements per day — TRAINING
- 6M tweets to score per second (at peak) — SERVING
- 1 second —> total time budget to serve the timelines — LATENCY

CREDIT : TWITTER

AI at scala @Twitter : Ranking The Timelines

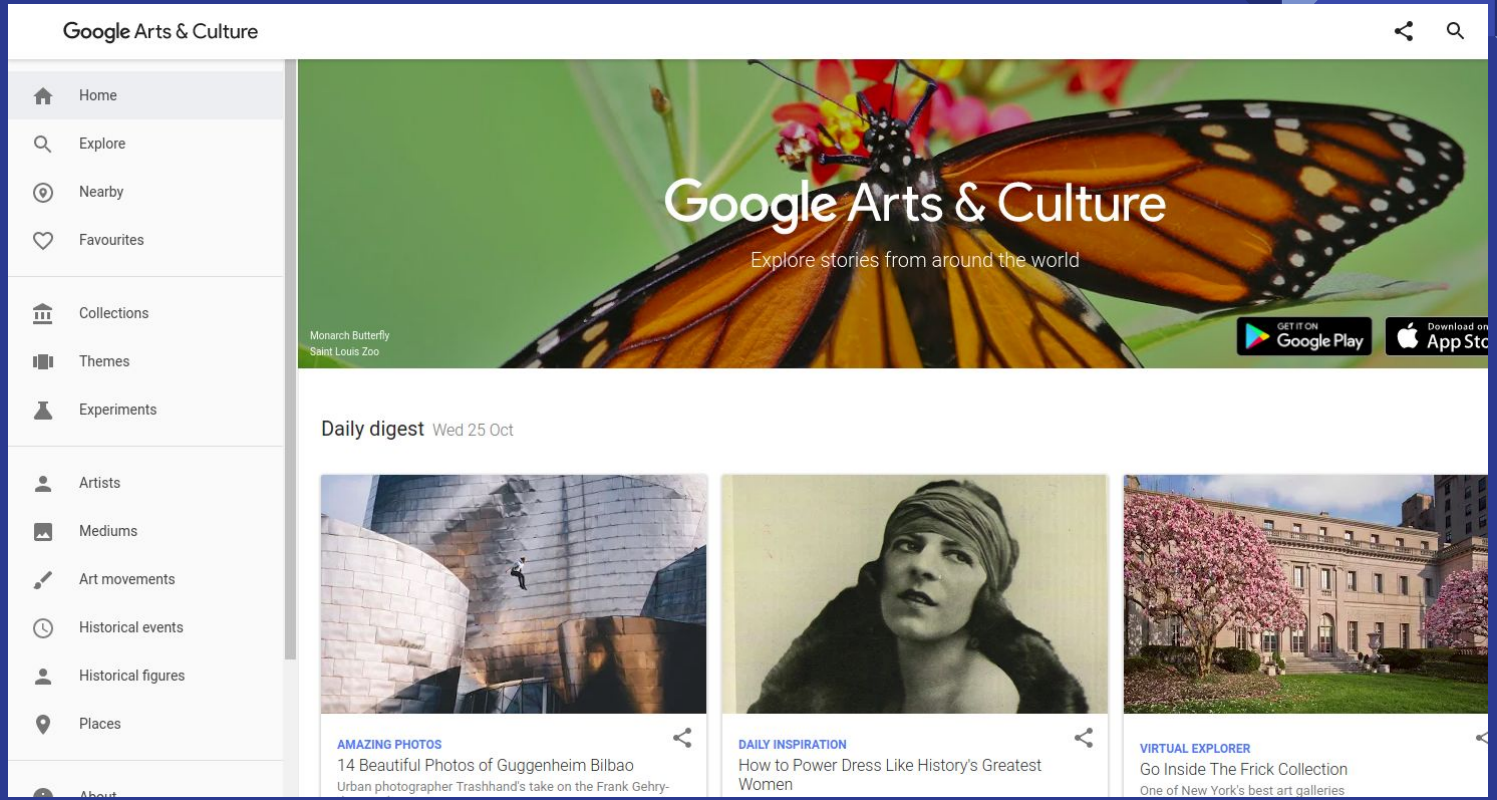
The Impact of Recommendation System

- User happiness: +4.5M DAU, +500M UAM
- Engagements: +140M Fav, +35M RT, +9M replies
- Creation: +18M Tweets composed
- Ads spend: +10%

CREDIT : TWITTER

Business and Applications

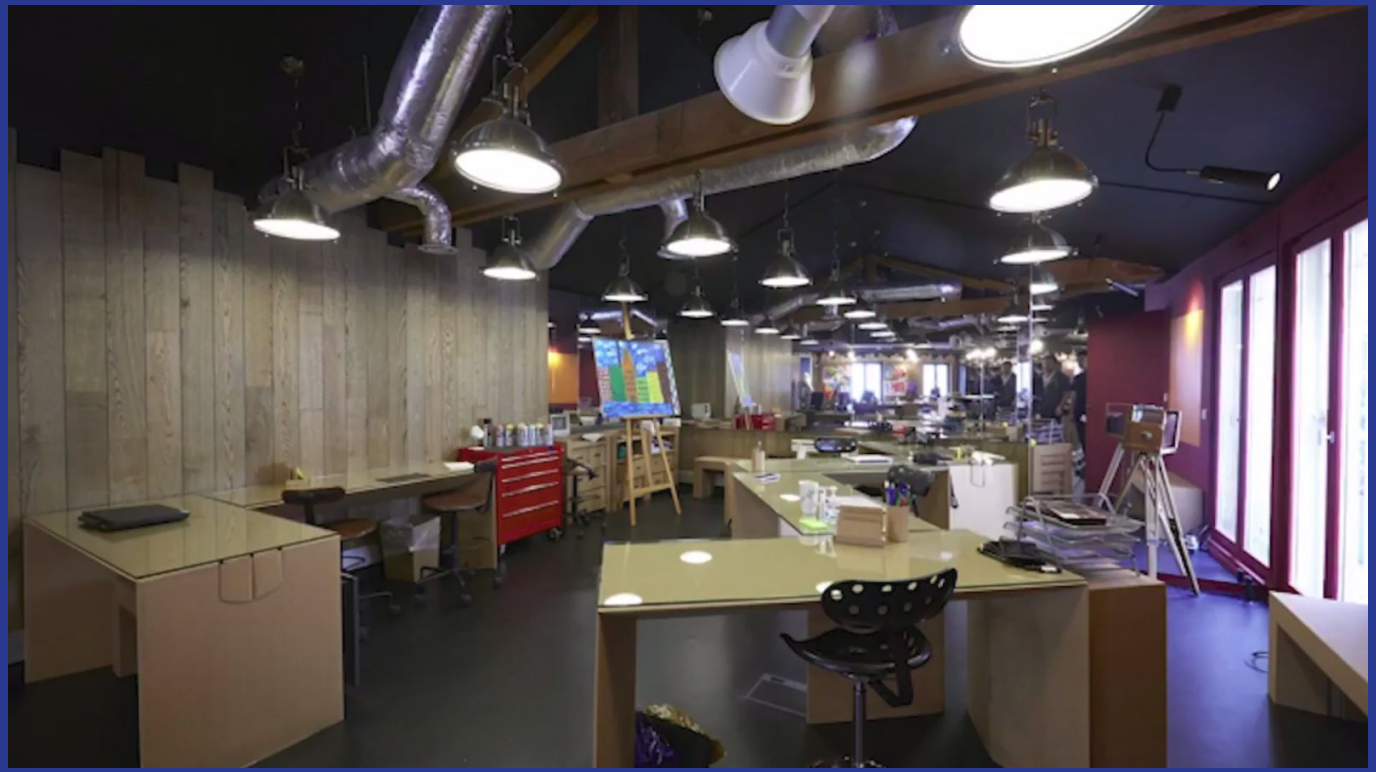
GOOGLE RESEARCH in PARIS



CREDIT : Damien Henry

Business and Applications

Google Arts & Culture Lab



CREDIT : Damien Henry

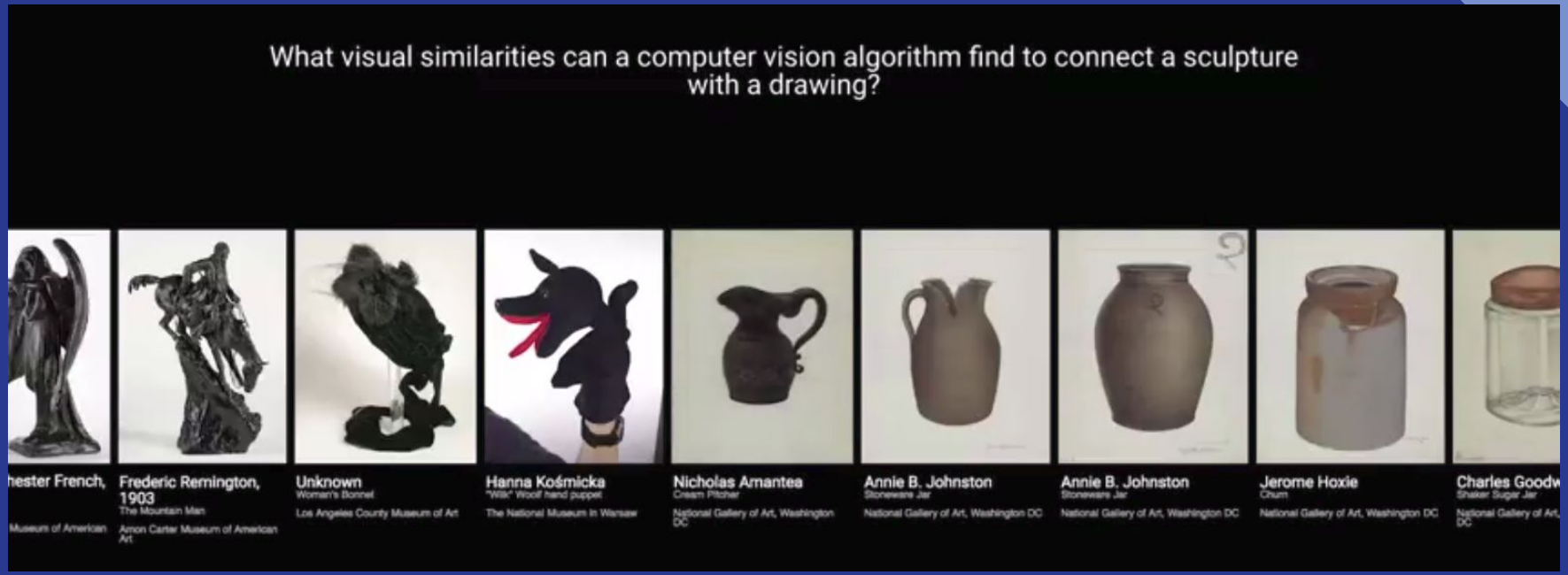
Business and Applications

GOOGLE RESEARCH in PARIS

400 000 paintings and drawings
6 000 000 pictures

Business and Applications

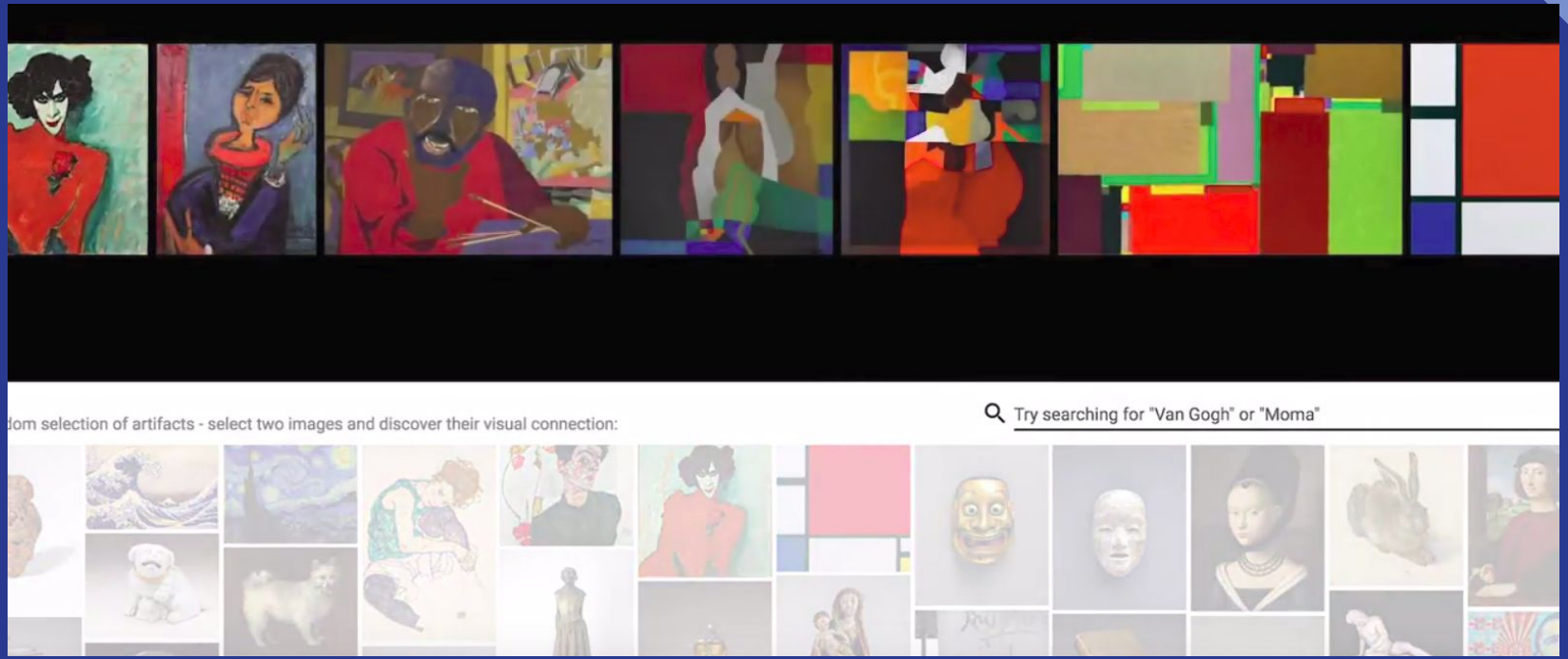
Google Arts & Culture Lab



CREDIT : Damien Henry

Business and Applications

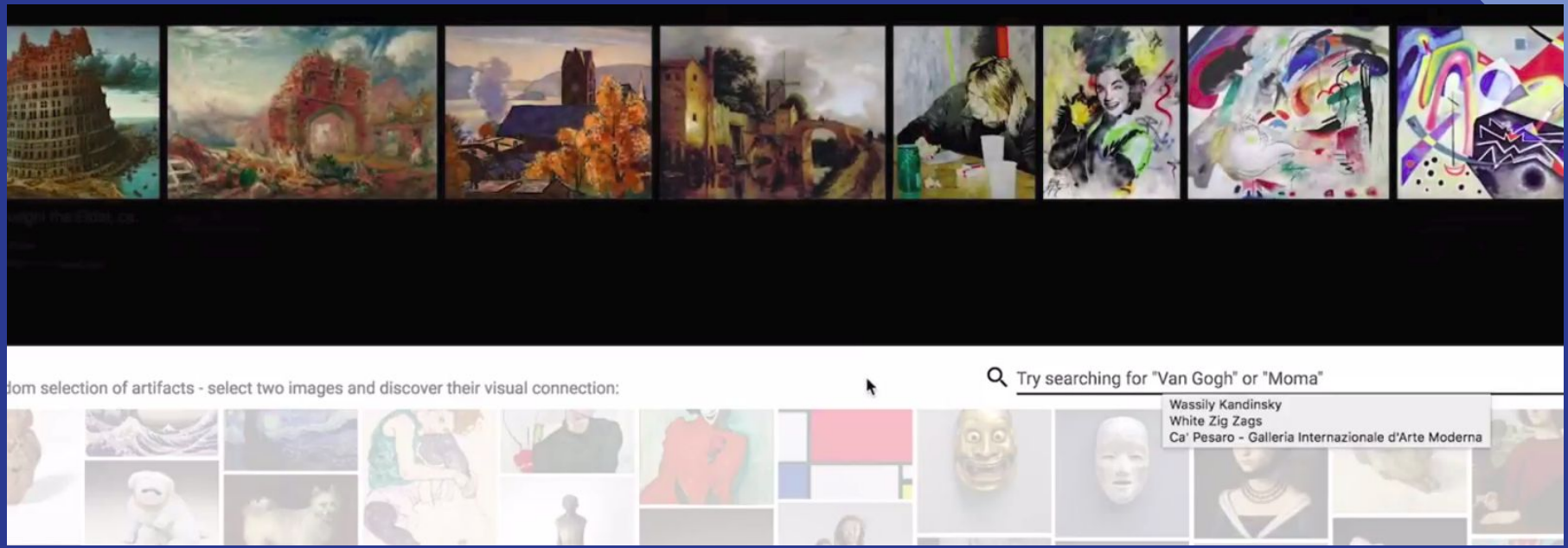
Google Arts & Culture Lab



CREDIT : Damien Henry

Business and Applications

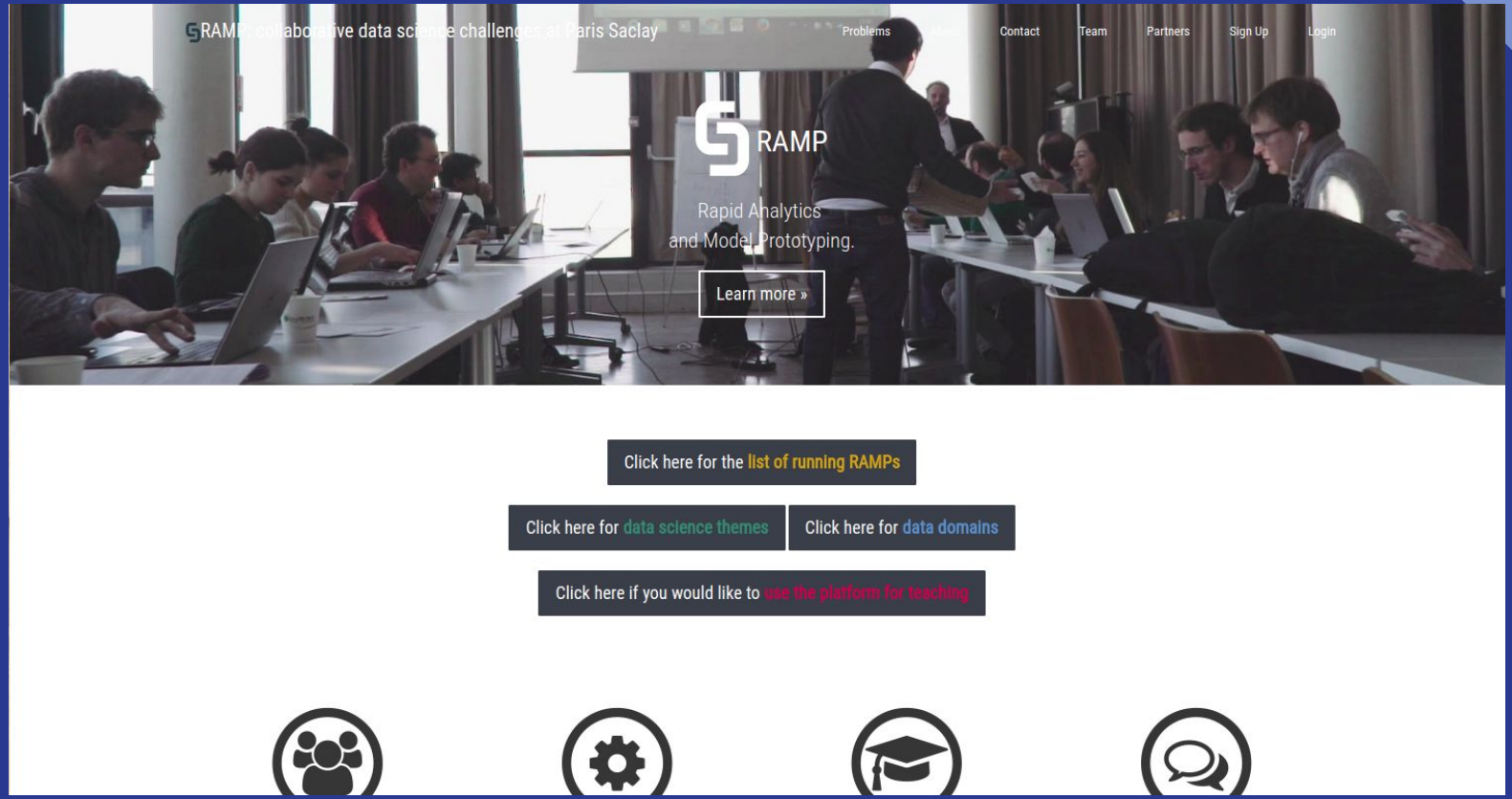
Google Arts & Culture Lab



CREDIT : Damien Henry

Business and Applications

French Kaggle!



Social side

Community

Social side

Mission Cedric Villani

Social side

Mission Cedric Villani

1. Directive approach?
2. GDPR
3. Crucial role of education
4. Are there enough specialists in France?
5. What is the goal of Cedric Villani’s mission?

Social side

Mission Cedric Villani

1. Make France a big AI player

2. Don’t reserve it to profit of few

What is the goal of Cedric Villani’s mission?

Social side

Meetup cooperation

1. Soutien de l’association France is AI
2. Slack Intelligence Artificielle Francaise
3. Échange d'expériences et de speakers
4. Meta Meetup dans le sud de la France ?
5. Avez-vous des suggestions ?

Ressources

1. Deep Embedding Forest: Forest-based Serving with Deep Embedding Features

Jie Zhu, Ying Shan, JC Mao, Dong Yu, Holakou Rahmanian, Yi Zhang

https://arxiv.org/abs/1703.05291

2. Generative Adversarial Networks

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair

https://arxiv.org/abs/1406.2661

3. MUTAN: Multimodal Tucker Fusion for Visual Question Answering

Hedi Ben-younes, Rémi Cadene, Matthieu Cord, Nicolas Thome

https://arxiv.org/abs/1705.06676

4. SoundNet: Learning Sound Representations from Unlabeled Video

Yousuf Aytar, Carl Vondrick, Antonio Torralba

http://papers.nips.cc/paper/6146-soundnet-learning-sound-representations-from-unlabeled-video

5. FRANCE IS AI PLAY LIST https://www.youtube.com/channel/UCsG0yqQg3_r8VikxC8He3lQ/videos