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REDS
MÉTHODOLOGIE RECHERCHE

Présentation des sujets

Wednesday 9th December, 2020

Laure Soulier

LIP6

MLIA Machine Learning & Deep Learning for Information Access

Objectifs Méthodologie Recherche

Objectifs

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Comprendre, proposer, évaluer des modèles

- Réaliser un état de l'art
- Proposer un nouveau modèle
- Proposer un protocole d'évaluation adapté

Pas si simple que ça...

- On reste dans la réflexion et l'organisation
  $\rightarrow$ Pas d'implémentation !!!

Thématiques de recherche

Traitement automatique du langage

Extraction d'entités nommées (1/2)

In fact, the Chinese NORP market has the three CARDINAL most influential names of the retail and tech space – Alibaba GPE , Baidu ORG , and Tencent PERSON (collectively touted as BAT ORG), and is betting big in the global AI GPE in retail industry space . The three CARDINAL giants which are claimed to have a cut-throat competition with the U.S. GPE (in terms of resources and capital) are positioning themselves to become the 'future AI PERSON platforms'. The trio is also expanding in other Asian NORP countries and investing heavily in the U.S. GPE based AI GPE startups to leverage the power of AI GPE . Backed by such powerful initiatives and presence of these conglomerates, the market in APAC AI is forecast to be the fastest-growing one CARDINAL , with an anticipated CAGR PERSON of 45% PERCENT over 2018 - 2024 DATE .

To further elaborate on the geographical trends, North America LOC has procured more than 50% PERCENT of the global share in 2017 DATE and has been leading the regional landscape of AI GPE in the retail market. The U.S. GPE has a significant credit in the regional trends with over 65% PERCENT of investments (including M&As, private equity, and venture capital) in artificial intelligence technology. Additionally, the region is a huge hub for startups in tandem with the presence of tech titans, such as Google ORG , IBM ORG , and Microsoft ORG .

- Les catégories de modèles
  - Linguistiques (patrons, POS, ...)
  - Classifieur CRF
  - Neuronales (CNN, BiLSTM-CRF)
- Les exemples d'application
  - Traitement de documents (articles, contrats, compte-rendus médicaux...)

Extraction d'entités nommées (2/2)

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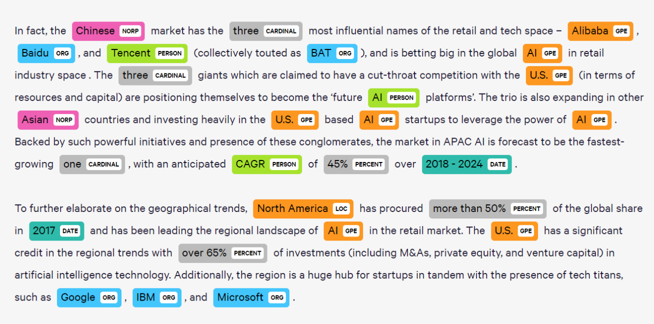
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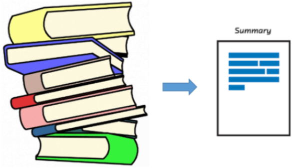
- Papiers
  - (Huang 2015) Bidirectional LSTM-CRF Models for Sequence Tagging. arxiv
  - (Lample 2016) Neural architectures for Named-Entity Recognition. NAACL 2016
  - (Devlin 2019) BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL 2019

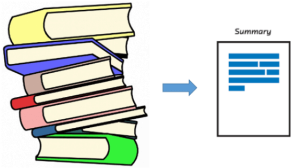
Résumé automatique (1/2)



Summarization systems aim at generating relevant and informative summaries given a variable-length text as input.

- Les catégories de modèles
  - Extractive summarization : Select and extract the relevant parts from the input text
  - Abstractive summarization : Generate in natural language (i.e. in a human manner)
- Les exemples d'application
  - presse / news
  - meeting de réunion en entreprise
  - contrats juridiques

Résumé automatique (2/2)



- Papiers
  - Mihalcea. (2004). Graph-based ranking algorithms for sentence extraction, applied to text summarization. ACL
  - Gehrmann et al. (2018). Bottom-up abstractive summarization. arXiv preprint arXiv:1808.10792.
  - Dong et al. (2019). Unified Language Model Pre-training for Natural Language Understanding and Generation. arXiv preprint arXiv:1905.03197

Système Questions-Réponses

Extraction d'informations dans un texte ou un corpus de textes :

where is the world s largest ice sheet located today? →

The Antarctic ice sheet is the largest single mass of ice on Earth. It covers an
Earth's ice mass is in Antarctica,[3] which, if melted, would cause sea levels to
Antarctica is positive and significant at >0.05 °C/decade since 1957.[5]

- Utilisation : afficher directement une réponse sur un moteur de recherche
- Modèles avec des graphes de connaissances
- Modèles type RNN / CNN / Transformers pour calculer des représentations jointes de la question et du contexte
- Papiers
  - (Bordes et al. 2014) Question Answering with Subgraph Embeddings
  - (Lu et al. 2019) Answering Complex Questions by Joining Multi-Document Evidence with Quasi Knowledge Graph
  - (Seo et al. 2016) Bidirectional Attention Flow for Machine Comprehension
  - (Yu et al. 2018) QANet: Combining Local Convolution with Global Self-Attention for Reading Comprehension

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- Quelques jeux de données :
  - (Kwiatkowski et al. 2019) Natural Questions [...]
  - (Choi et al. 2018) QuAC : Question Answering in Context
  - (Reddy et al. 2018) CoQA: A Conversational Question Answering Challenge
  - et beaucoup (beaucoup) d'autres

Data-to-text (1/2)

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(John_E_Blaha birthDate 1942_08_26)
(John_E_Blaha birthPlace San_Antonio)
(John_E_Blaha occupation Fighter_pilot)

→

John E Blaha, born in San Antonio on 1942-08-26, worked as a fighter pilot

TEAM	H/V	WIN	LOSS	PTS	REB	AST	FG_PCT	FG3_PCT	...
KNICKS	H	16	19	104	46	26	45	46	...
BUCKS	V	18	16	105	42	20	47	32	...

PLAYER	H/V	PTS	REB	AST	BLK	STL	MIN	CITY	...
CARMELO ANTHONY	H	30	11	7	0	2	37	NEW YORK	...
DERRICK ROSE	H	15	3	4	0	1	33	NEW YORK	...
COURTNEY LEE	H	11	2	3	1	1	38	NEW YORK	...
GIANNIS ANTETOKOUNMPO	V	27	13	4	3	1	39	MILWAUKEE	...
GREG MONROE	V	18	9	4	1	3	31	MILWAUKEE	...
JABARI PARKER	V	15	4	3	0	1	37	MILWAUKEE	...
MALCOLM BROGDON	V	12	6	8	0	0	38	MILWAUKEE	...
MIRZA TELETOVIC	V	13	1	0	0	0	21	MILWAUKEE	...
JOHN HENSON	V	2	2	0	0	0	14	MILWAUKEE	...
...	...	...	...	...	...	...	...		

(a) Box score: Top contingency table shows number of wins and losses and summary of each game. Bottom table shows statistics of each player such as points scored (PLAYER's PTS), and total rebounds (PLAYER's REB).

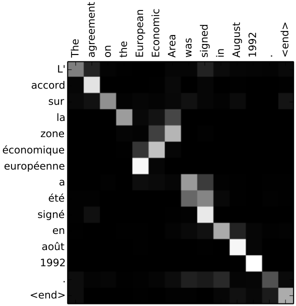
The **Milwaukee Bucks** defeated the **New York Knicks**, **105-104**, at Madison Square Garden on Wednesday. The **Knicks** (**16-19**) checked in to Wednesday's contest looking to snap a five-game losing streak and heading into the fourth quarter, they looked like they were well on their way to that goal. . . . **Antetokounmpo** led the Bucks with **27** points, **13** rebounds, **four** assists, a steal and **three** blocks, his second consecutive double-double. **Greg Monroe** actually checked in as the second-leading scorer and did so in his customary bench role, posting **18** points, along with **nine** boards, **four** assists, **three** steals and a block. **Jabari Parker** contributed **15** points, **four** rebounds, **three** assists and a steal. **Malcolm Brogdon** went for **12** points, **eight** assists and **six** rebounds. **Mirza Teletovic** was productive in a reserve role as well, generating **13** points and a rebound. . . . **Courtney Lee** checked in with **11** points, **three** assists, **two** rebounds, a steal and a block. . . . The Bucks and Knicks face off once again in the second game of the home-and-home series, with the meeting taking place Friday night in Milwaukee.

(b) NBA basketball game summary: Each summary consists of game victory or defeat of the game and highlights of valuable players.

Data-to-text (2/2)

- Les catégories de modèles
  - Template based
  - Encoder-Decoder
- Les exemples d'application
  - Weather Forecast
  - Sport Broadcasting
  - Journalism
- Papiers
  - Reiter et al. - 2005 - Choosing words in computer-generated weather forecasts
  - Wiseman et al. - 2017 - Challenges in Data-to-Document Generation
  - Liu et al. - 2019 - Hierarchical Encoder with Auxiliary Supervision for Neural Table-to-Text Generation: Learning Better Representation for Tables
  - Kale - 2020 - Text-to-Text Pre-Training for Data-to-Text Tasks

Traduction



Années 2010s : Passage de modèles basés sur les statistiques de *"phrases"* à des modèles neuronaux (LSTM, Attention, Transformers. . .)

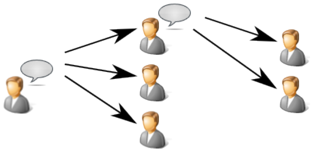
- **Supervisé** Corpus parallèle, l'entrainement se fait sur des paires de phrases avec le même sens.
- **Non supervisé** L'entrainement se fait sur deux ensembles de phrases sans qu'il n'existe nécessairement une correspondance 1-à-1.

- Cho et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." EMNLP 2014
- Bahdanau, Cho and Bengio "Neural machine translation by jointly learning to align and translate." ICLR 2015
- Vaswani et al. "Attention is all you need." NeurIPS 2017
- Lample et al. "Unsupervised Machine Translation Using Monolingual Corpora Only." EMNLP 2018

Interactions utilisateurs

Diffusion dans les réseaux

- Extraction des dynamiques dans les réseaux (sociaux) à partir d'évènements d'infection
- Les catégories de modèles:
  - Modèles Macro : statistiques globales de diffusion
  - Modèles Micro : analyse des influences
    - Linear Threshold models (centrés recepteur)
    - Cascade models (centrés émetteurs)
- Les exemples d'application
  - Prédiction du futur d'une diffusion
  - Détection de la source d'une diffusion
  - Identification de relations d'influence



- Quelques papiers
  - (Saito et al. 2008) Independent Cascade
  - (Saito et al. 2009) Continous-Time Independent Cascade
  - (Bourigault et al. 2016) Embedded Cascade Model
  - (Lamprier 2019) Recurrent Neural Cascade Model

Systèmes de dialogues (1/2)

- Les catégories de modèles
  - Patrons : "slot filling"
  - Réseaux Recurrent Hiérarchique
  - Apprentissage par renforcement, supervisé et non supervisé
- Les exemples d'application
  - Assister des personnes aveugles
  - Planification de tâche complexes (voyage, déménagement, ...)
  - Interfaces Homme Machine plus accessible

Systèmes de dialogues (2/2)

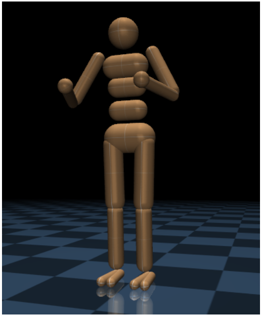
- Papiers
  - Learning end-to-end goal-oriented dialog, Bordes et al.
  - Towards end-to-end reinforcement learning of dialogue agents for information access, Dhingra et al.
  - A Survey on Dialogue Systems: Recent Advances and New Frontiers, Chen et al.

Apprentissage par Renforcement pour les jeux

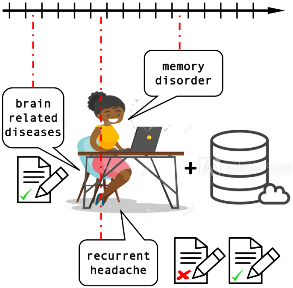
- Les catégories de modèles
  - Apprentissage de Politique
  - Curiosité
  - Monte Carlo Tree Search
- Les exemples d'application
  - Starcraft, Capture the Flag, ...
  - Jeux de plateau (Go, Echec, Shogi, Dame, ...)
  - Jeux de carte complexe (Hanabi)
- Papiers
  - Mastering the game of Go without human knowledge, Nature
  - Human-level performance in first-person multiplayer games with population-based deep reinforcement learning

Contrôle de squelettes

- Les catégories de modèles
  - Apprentissage de Politique
  - Curiosité
- Les exemples d'application
  - Simulation d'humanoide (ou autre)
  - Simulation de bras robotisé
- Papiers
  - Artificial Intelligence for Prosthetics — challenge solutions, NeurIPS 2018
  - Hierarchical Deep Reinforcement Learning: Integrating Temporal Abstraction and Intrinsic Motivation



Génération de requêtes avec contexte



Contexte : requêtes précédentes, clics, documents, ...

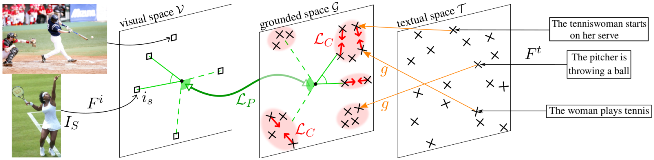
- Applications:
  - Suggestion de requêtes
  - Modélisation utilisateur
  - Ranking de documents
  - Segmentation de sessions, découpage de tâche en sous tâches
- Types de modèles:
  - Naive Markovian methods : compte des cooccurrence des requêtes dans les logs [Huang, Chien, and Oyang 2003; Jain, Ozertem, and Velipasaoglu 2011]
  - RNN based models: avec attention, avec mécanisme de copie [Dehghani et al. 2017], avec hiérarchie [Sordoni et al. 2015]
  - Transformer based models [Garg, Dhillon, and Yu 2019; Mustar, Lamprier, and Piwowarski 2020]

Images - Vidéos

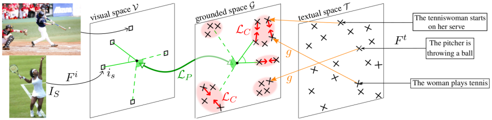
Multi-modal embeddings (1/2)

Word	*Teraword*	*Knext*
Spoke	11,577,917	372,042
Laughed	3,904,519	179,395
Murdered	2,843,529	16,890
Inhaled	984,613	5,617
Breathed	725,034	41,215

Word	*Teraword*	*Knext*
Hugged	610,040	11,453
Blinked	390,692	21,973
Was late	368,922	31,168
Exhaled	168,985	4,052
Was on time	23,997	14



Multi-modal embeddings (2/2)



- Les catégories de modèles
  - Sequential (learn embedding then add visual info)
  - Joint models
  - visual info: high/low level, avec/sans contexte, ...
- Papiers
  - Collell et al.. 2017. Imagined visual representations as multimodal embeddings. In AAAI 2017.
  - Lazaridou et al. 2015. Combining language and vision with a multimodal skip-gram model. In NAACL.
  - Kiela et al. 2017.Learning Visually Grounded Sentence Representations.

Zero-shot learning (1/2)

- "I saw a cute, hairy *wampimuk* sleeping behind a tree"
- "Don't you think that the *wampimuk*'s head looks like a rhino's?"

Zero-shot learning (2/2)

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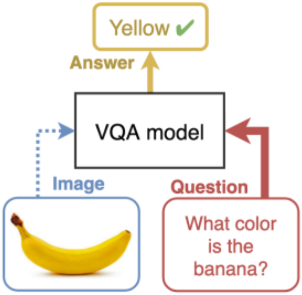
- Les catégories de modèles
  - Cross-modal mapping avec l'espace d'embedding sémantique (texte)
  - Caractéristiques intrinsèques de l'objet
  - Avec/sans contexte de l'objet
  - Avec/sans bases de connaissances
- Papiers
  - Frome, A. et al. Devise: A deep visual-semantic embedding model.NIPS 2013
  - Verma et al. Generalized Zero-Shot Learning via Synthesized Examples
  - Zablocki et al. Context-Aware Zero-Shot Learning for Object Recognition. ICML 2019

Visual Question Answering



- Les catégories de modèles
  - Attention (SAN)
  - Fusions bilinéaires (MCB, MuREL)
  - Object-based features (Up-Down)
  - Symbolic / Neural Module Network
  - Transformers (VilBERT, LXMERT)
- Les exemples d'application
  - Assistances de personnes aveugles (VizWiz)
  - Communication avec un robot
- Papiers
  - VQA: Visual Question Answering, ICCV 2015
  - Stacked Attention Networks for Image Question Answering, CVPR 2016
  - Bottom-up and top-down attention for image captioning and visual question answering, CVPR 2018

Image Style Transfert

- Les catégories de modèles
  - Gram matrix based
  - Pixel space alignement
  - Style/Content disentanglement
- Les exemples d'application
  - Edition d'Image
  - Assistant pour Concept Artist (doodle -> photo)
  - Deep Fakes

- Image Style Transfer Using Convolutional Neural Network [Gatys, Ecker, and Bethge 2016]
- A learned representation for Artistic Style [Dumoulin, Shlens, and Kudlur 2016]
- FaderNetworks [Lample et al. 2017]
- MUNIT [Huang et al. 2018]
- Pix2Pix [Isola et al. 2017], Cycle-GAN [Zhu et al. 2017], GauGAN [Park et al. 2019]

Video prediction

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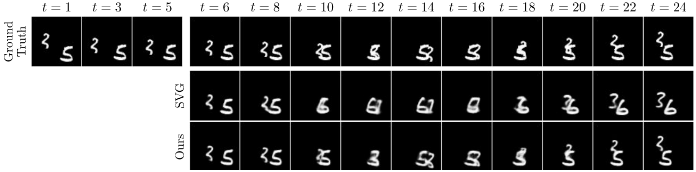
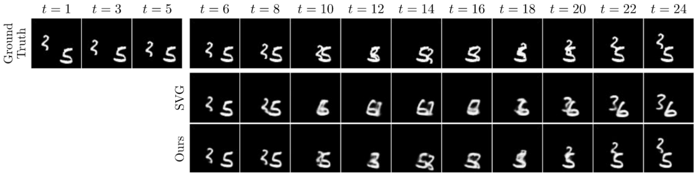


- Les catégories de modèles
  - Modèles temporels :
    - réseaux récurrents dans l'espace latent
    - flots optiques, transformations dans l'espace des pixels
  - Entraînement :
    - régression
    - coût adversaire
    - autoencodeurs variationels
    - maximisation de vraisemblances (modèles autorégressifs, flots)

Video prediction



- Les exemples d'application :
  - aide à la robotique, utilisé dans l'apprentissage par renforcement, apprentissage de représentations
  - compréhension du monde, prévention des risques
- Références:
  - Mathieu, Couprie, and LeCun 2016; Lee et al. 2018: ajout d'un coût adversaire pour améliorer la qualité visuelle
  - Kalchbrenner et al. 2017; Weissenborn, Täckström, and Uszkoreit 2020: génération par maximisation de vraisemblance
  - Denton and Fergus 2018; Franceschi et al. 2020: prédictions latentes stochastiques

Reconstruction/*inpainting* des images et vidéos

- Catégories d'approches:
  - Approches avec supervision sur la vérité terrain : régression ; approches adversaires avec GANs, à l'aide des informations des textures, du contexte, ou des mouvements pour les vidéos.
  - Approches non supervisées : Deep Image Prior, Noise2Noise ; approches adversaires : AmbientGAN, UNIR (Pajot et al., 2019), MisGAN.
- Exemples d'application
  - Débruitage des images (enlèvement des artefacts, super-résolution).
  - Enlèvement des objets.
  - Complétion des données satellite obstruées par les nuages.

Reconstruction/*inpainting* des images et vidéos

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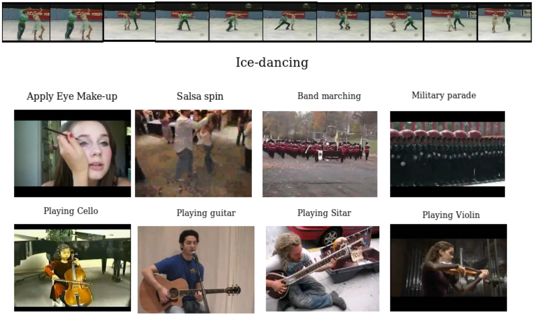
- L'état de l'art:
  - Generative Image Inpainting with Contextual Attention (Yu et al., 2018, *inpaining* des images supervisé)
  - Deep Video Inpainting (Kim et al., 2019, *inpaining* des vidéos supervisé)
  - Noise2Noise: Learning Image Restoration without Clean Data (Lehtinen et al., 2018, reconstruction des images non supervisée)
  - Unsupervised Adversarial Image Reconstruction (Pajot et al., 2019, reconstruction des images non supervisée)

Action Recognition in Videos 1/7



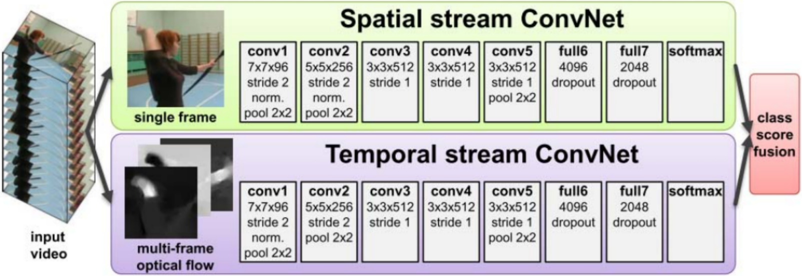
UCF-101 dataset (trimmed videos)

Les catégories d'action (classes/labels)

UCF101 : A Dataset of 101 Human Action Classes From Videos in The Wild. CRCV-TR-12-01, November, 2012
The Kinetics Human Action Video Dataset. CVPR, 2017
NTU RGB+D 120 : A Large-Scale Benchmark for 3D Human Activity Understanding. TPAMI, 2019

Two-person Interaction Detection Using Body-Pose Features and Multiple Instance Learning. CVPRW, 2012

Action Recognition in Videos 2/7

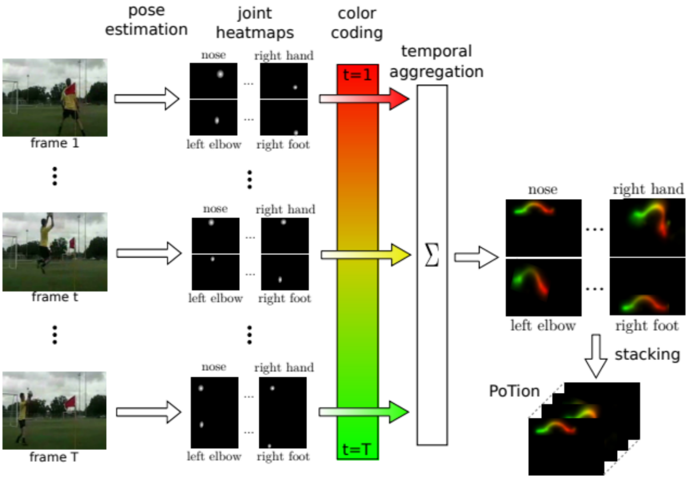


Two-Stream Convolutional Networks for Action Recognition in Videos. NIPS, 2014
Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset. CVPR, 2017

Action Recognition in Videos 3/7

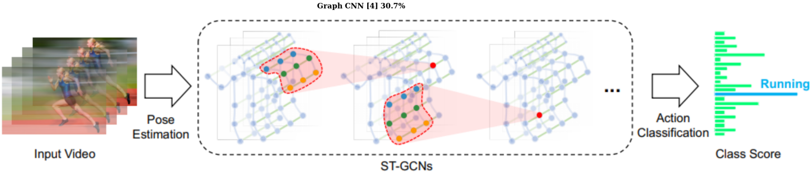
Pose Estimation : Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. CVPR, 2017

Action Recognition in Videos 4/7



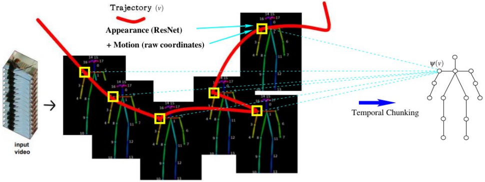
Motion Representation : PoTion, Pose MoTion Representation for Action Recognition. CVPR, 2018
FlowNet 2.0: Evolution of Optical Flow Estimation with Deep Networks. CVPR, 2017

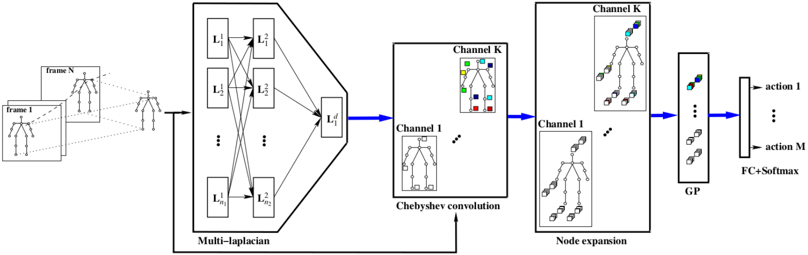
Action Recognition in Videos 5/7



Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition. AAAI, 2018

Action Recognition in Videos 6/7





MLGCN : Multi-Laplacian Graph Convolutional Neural Network for Human Action Recognition. BMVC, 2019

Action Recognition in Videos 7/7

Type de modèles :

- CNNs Euclidiens : 2D/3D
- CNNs Non-Euclidiens (Graphes) : méthodes spatiales/spectrales (GCNs)

Les entrées des modèles :

1. **CNNs 2D/3D**
   - **Branche d'apparence : Frames RGB**
   - **Branche du mouvement : Flux optique ou les cartes thermiques (heatmaps)**
2. **GCNs:**
   - **Branche d'apparence : coordonnées spatiales + features ResNet**
   - **Branche du mouvement : squelettes 2D/3D, les cartes thermiques (heatmaps)**

Domaines d'application :
Scene understanding, video captioning, video surveillance, video annotation and retrieval, human computer interaction and robotics.

Audio

Machine learning pour l'audio

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- Les catégories de modèles
  - Réseaux convolutionnels
  - Weakly supervised, noisy labels
  - Augmentation de données
- Les exemples d'application
  - Environnement sonore d'une voiture autonomes
  - Assistants domestiques
  - Détection d'évènements anormaux
- Integrating the Data Augmentation Scheme with Various Classifiers for Acoustic Scene Modeling, Chen et al.
- Acoustic Scene Classification and Audio Tagging with Receptive-Field-Regularized CNNs, Koutini et al.
- Weakly Labelled AudioSet Tagging with Attention Neural Networks, Kong et al

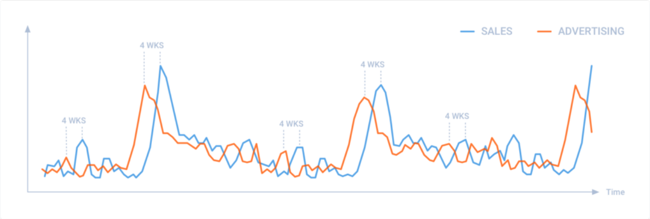
Machine learning avancé

Signaux EEG

SCIENCES SORBONNE UNIVERSITÉ

- Les catégories de modèles
  - Réseaux convolutionnels
  - Géométrie riemmaniennes
  - SVM, LDA, k-NN sur la variété riemannienne
- Les exemples d'application
  - Interface cerveau-machine
  - Médical
  - Signaux temporels mono- et multi-variés
- Multiclass Brain–Computer Interface Classification by Riemannian Geometry, Barachant et al.
- Fast and Accurate Multiclass Inference for MI-BCIs Using Large Multiscale Temporal and Spectral Features, Hersche et al.
- EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces, Lawhern et al.

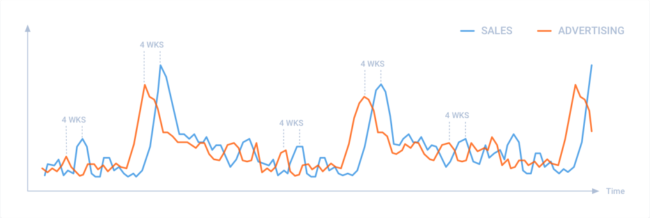
Time series (1/2)



- Les catégories de modèles
  - Smoothing, Interpolation, Spline Methods
  - AR, MA, ARMA, ARIMA
  - Variational Inference, Gaussian Process
  - ODE, PDE, Stochastic ODE/PDE
  - CNN, RNN, GAN
- Les exemples d'application
  - Forecasting
  - Data Imputation
  - Classification

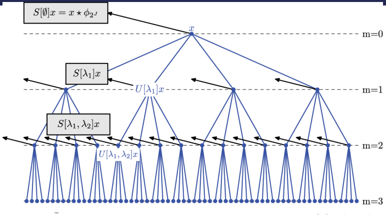
Time series (2/2)

SCIENCES SORBONNE UNIVERSITÉ



- Time Series Classification with HIVE-COTE: The Hierarchical Vote Collective of Transformation-Based Ensembles
- GAIN: Missing Data Imputation using Generative Adversarial Nets
- Data driven governing equations approximation using deep neural networks

Transformée en Scattering



- Les catégories de modèles
  - Pas d'apprentissage et générique.
  - Bonnes propriétés statistiques (e.g., invariance)
  - Constitué principalement d'ondelettes.
- Les exemples d'application
  - Reconstruction, classification d'images naturelles, textures...
  - Classification de sons, de séries temporelles
  - Chimie quantique (estimation d'un potentiel à partir de la géométrie de la mollécule)
- Papiers
  - Invariant Scattering Convolution Networks, TPAMI 2012
  - Deep Roto-Translation Scattering for Object Classification

Continual Learning

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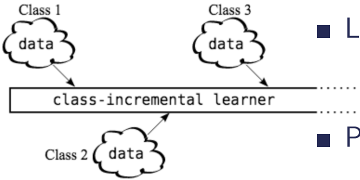
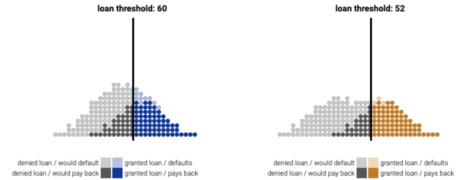
Apprentissage incrémental de classes sans oubli catastrophique.



- Les catégories de modèles
  - **Constraints** between f^{t-1} and f^t (EWC, LwF, GEM, PODNet)
  - **Reharsal** learning (iCaRL, Mnemonic Training)
  - **Adaptive** architectures (DEN, PathNet)
- Les examples d'application
  - Robot apprenant in-the-wild tout au long de sa vie
- Papiers:
  - iCaRL (Rebuffi et al. 2017)
  - Elastic Weight Consolidation EWC (Kirkpatrick et al. 2017)
  - Dynamically Expendable Network DEN (Yoon et al. 2018)

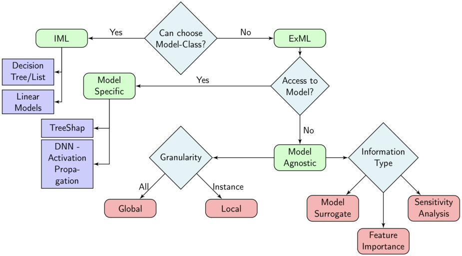
Fairness

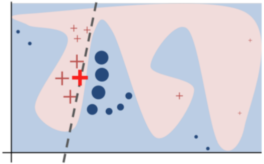
→



- Les catégories de modèles:
  - Pre-Processing: Transformer les données d'entraînement en une représentation équitable
  - In-Processing: Modification de l'entraînement de l'algorithme en gardant les données biaisées.
  - Post-Processing: L'entraînement est déjà réalisée, modification des prédictions biaisées en sortie pour réduire la discrimination.
- Les exemples d'application
  - Prédictions de récidive criminelle aux Etats-Unis - Compass
- Quelques papiers
  - (MJ Kusner et al. 2017) Counterfactual Fairness
  - (BH Zhang et al. 2018) Mitigating Unwanted Biases
  - (M Hardt et al. 2016) Equality of Opportunity in Supervised L.

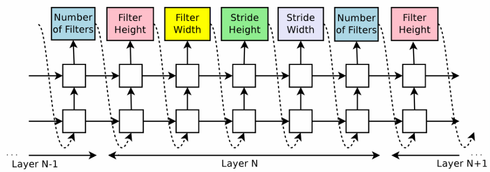
Interpretabilité





- Les exemples d'application
  - Acquérir des connaissances sur des processus ou phénomènes
  - Loi et l'éthique (GDPR, régulateurs,...)
  - Confiance dans l'utilisation des modèles ML (Améliorer l'acceptation ML...)
  - Améliorer la qualité des modèles (Expliquer les sous-espaces,...)
- Quelques papiers
  - (M Ribeiro et al. 2016) Why should i trust you?
  - (S Lundberg et al. 2017) A unified approach to interpreting model predictions

Neural Architecture Search



- Les catégories de modèles
  - Algorithmes de recherche classiques (grille & aléatoire)
  - Apprentissage par renforcement
  - Algorithmes évolutionnistes
- Les exemples d'application
  - Automatiser le travail des experts (AutoML).
  - Trouver des architectures respectant des contraintes spécifiques au problème (systèmes embarqués, assistants virtuels, ...)
- Evolving Neural Networks Through Augmenting Topologie [Stanley and Miikkulainen 2002]
- NAS with Reinforcement Learning [Zoph and Le 2016]
- DARTS: Differentiable Architecture Search [Liu, Simonyan, and Yang 2018]

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