Deep Learning for Multi-Modal Systems

DS3 Data Science Summer School

Dr Christian Arnold (Cardiff University)

August 4, 2022

Logistics

- The repo with all material is at `https://github.com/chrisguarnold/ds3_mmdl`
- Please do ask questions in the chat: Huy and Olga will handle them.

My Background

This is the most exciting time

to be a social scientist.

Ever.

My Background

Academic Background

- Senior Lecturer at Cardiff University
- PhD, University of Mannheim
- Research interests using DL, e.g.
  - **Voting Fraud Detection:** Multimodal data (satellite and micro data) to detect voting irregularities in remote areas.
  - **Private Synthetic Data:** Generative Adversarial Networks for differentially private synthetic micro data.

Industry Background

- Data Scientist with KIANA and KPMG
- Scientific advisory committee for the GSS, Office for National Statistics
- Alan Turning Institute Networking Grant for AI in Public Policy

What I Assume About Your Background

General Background

- Background mostly in Social Sciences
- At the moment: postgraduate academic qualification
- You know R or Python
- You know machine learning

Experience with Deep Neural Networks

Basic exposure ——[xxxxxxxxxx]————— Expert data scientist

Today's Agenda

1. Introduction
2. Foundation
3. Basic Multimodal Learning
4. Extensions

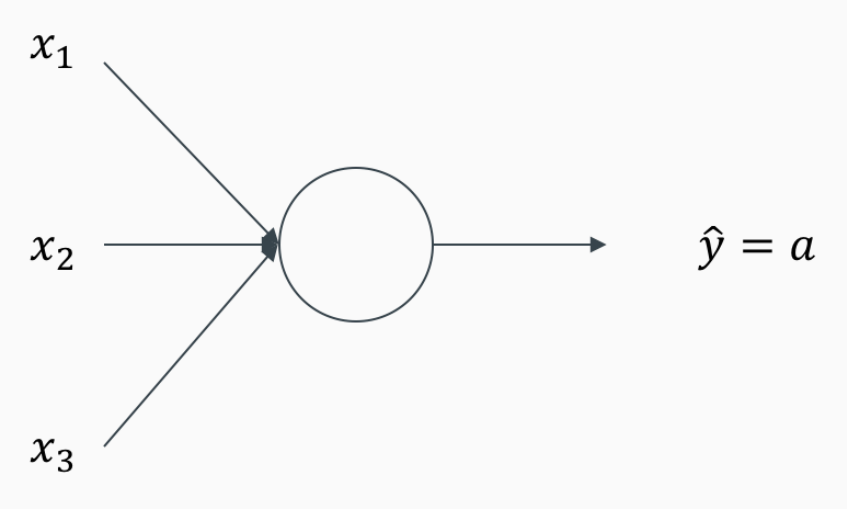
Today's Learnings

Topic	Knowledge	Experience	Skill
Introduction	X	X	
Foundation	X		
Basic MML	X	X	X
Extensions	X	X	

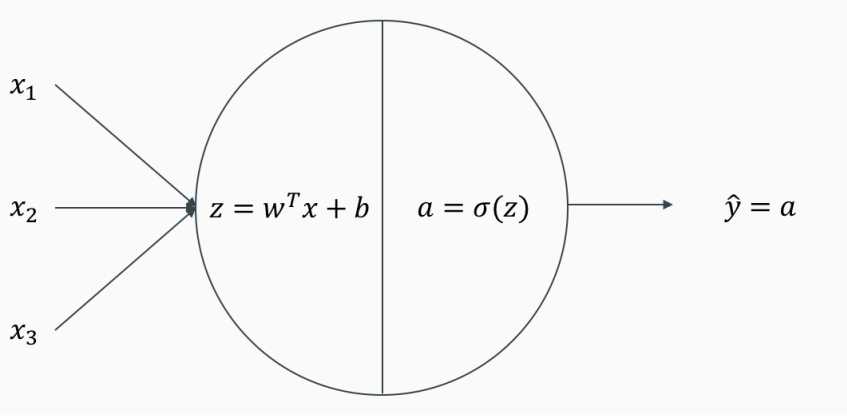
Foundation

Deep Learning

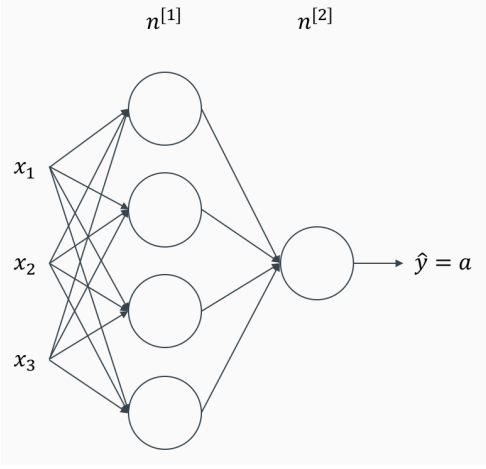
Logistic Regression



One Neuron



(Shallow) Neural Net



The Different Layers

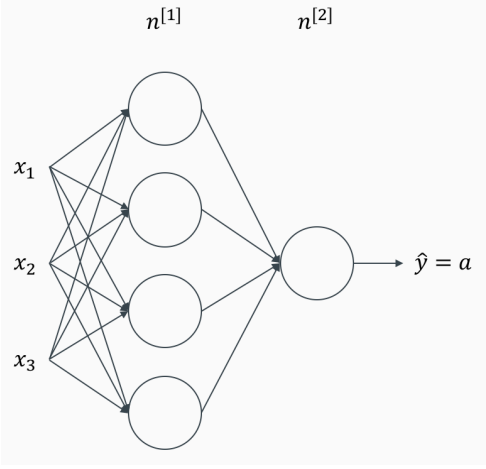
- Input layer
- Hidden layer
- Output layer

How to Train Neural Nets?

The Mantra

- Predict
- Calculate how wrong the prediction is
- Propagate the information back
- Update weights

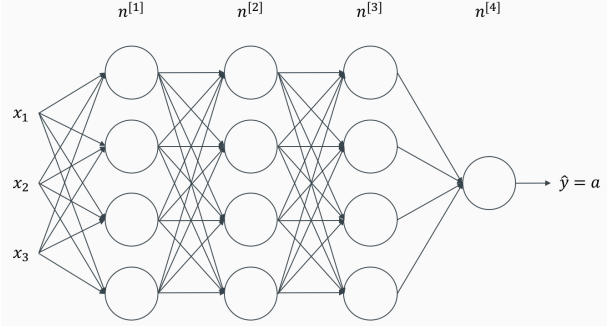
(Shallow) Neural Net



Four Steps to Repeat

- Predict
- Calculate how wrong the prediction is
- Propagate the information back
- Update weights

Deep Neural Net



The Different Layers

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A Geometric Interpretation of a DNN

$$a = g(wx + b)$$

A Simple RNN

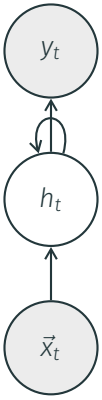

Figure 1: A simple RNN loops the output of h_t as an additional input to h_{t+1}.

Unrolling the RNN

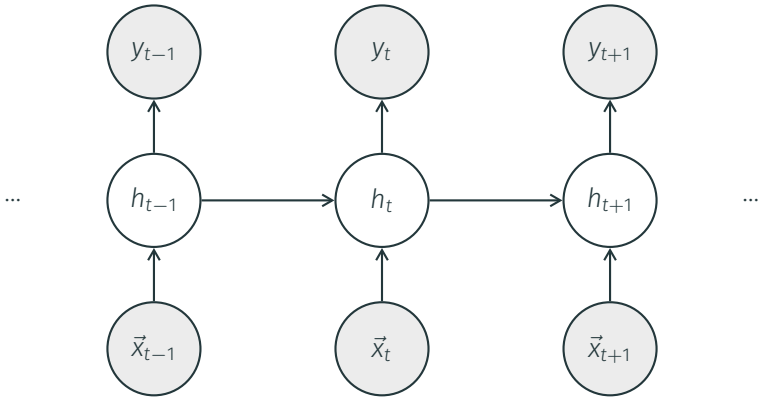

Figure 2: Unrolling the loop shows what happens in the RNN.

Visual Data Analysis with Convolutional Neural Nets (CNN)

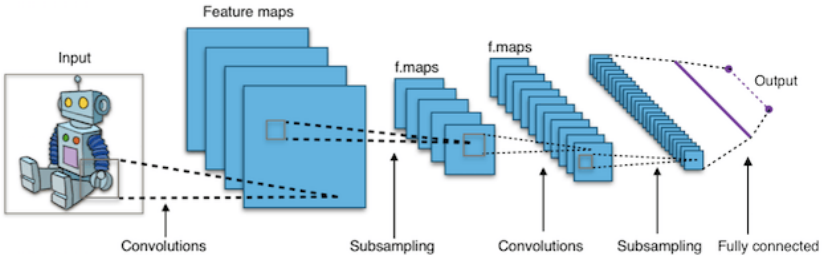

Figure 3: Typical CNN Architecture. Source: Keras Tutorial

In Sum: A Look at Different NN architectures

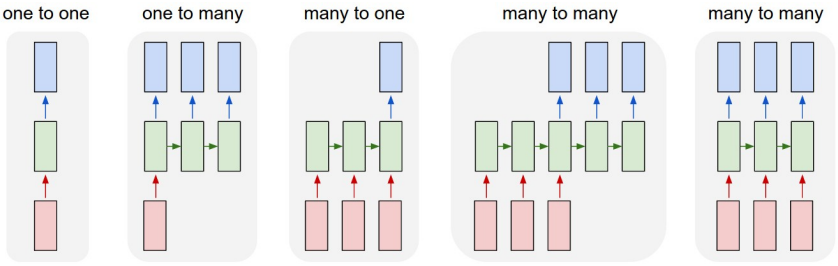

Figure 4: Different NN architectures. Source: Andrej Karpathy

Foundation

Multi Modal Learning

Multi Modal Learning & Social Sciences

Development of Data Sources

- Structured data $\rightarrow$ unstructured data
- Text data: documents, speeches
- But is a text really all?

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Social Media Over Time

- Twitter/Facebook
- Instagram/Snapchat
- TikTok/Instagram/YouTube Shorts

The McGurk Effect (1976)

https://www.youtube.com/watch?v=PWGeUztTkRA

Examples for Multimodal Signals

Humans

- Language: Words, syntax, speech acts
- Acoustic: Intonation, voice quality, vocal expressions
- Visual: gestures, body language, facial expressions
- Touch
- Any body signal: MRI, ECG,

Society

- Surveys
- Governmental statistics

Technology

- Mobile phones
- Internet
- GPS
- Remote sensing

Modalities

Modality

"A modality refers to the way in which something happens or is experienced." (Baltrušaitis et al. 2017)

Spectrum: Closeness to Sensors

- Audio, image or video data
- Language, entity and object detection
- Sentiment intensity, object categories

Multimodality

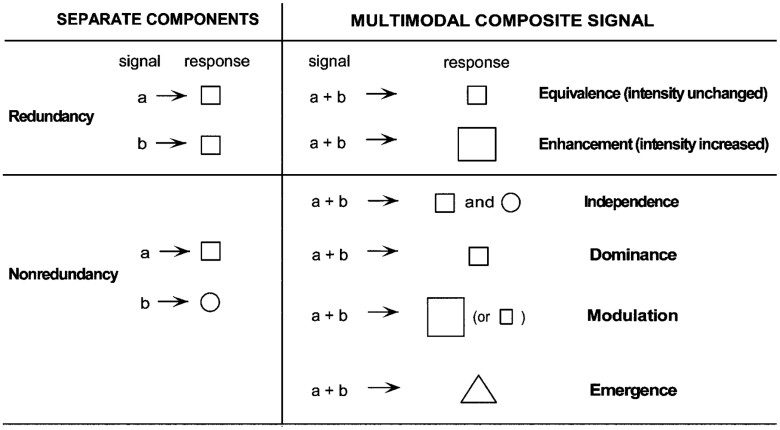
Multi Modal Learning

- Involves multiple modalities
- Data is heterogenous and interconnected

Spectrum: Homogenous and Heterogenous Modalities

- Same picture from different angles
- Text in two different langauges
- Image and its description
- Image and socio economic data

Cross Modal Interactions



Source: Partan and Marler (2005)

Examples for Multi Modal Learning in Political Sciences

Rittman, Ringwald and Nyhuis

- Are legislators more likely to deliver emphatic speeches if district preferences on a bill align with their vote choice?
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Dietrich and Ko (2022)

- During COVID 19 TV coverage: Is Fauci on the programme and does his presence change the content of the news coverage?
- Image data and text transcripts.

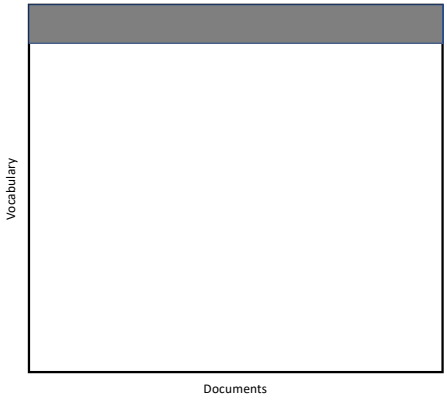
Basic Multimodal Learning

Representation

Representation in Language

Term Document Matrix

- Corpus with documents and vocabulary
- Count each word in each document
- Loss of word order and grammar
- Static



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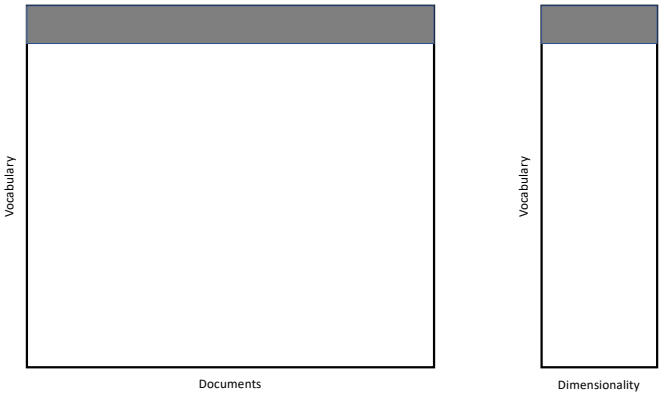
- I dined off bread and chees and this excellent bardiwac.
- The drinks were delicious: blood-red bardiwac as well as light, sweet Rhenish.

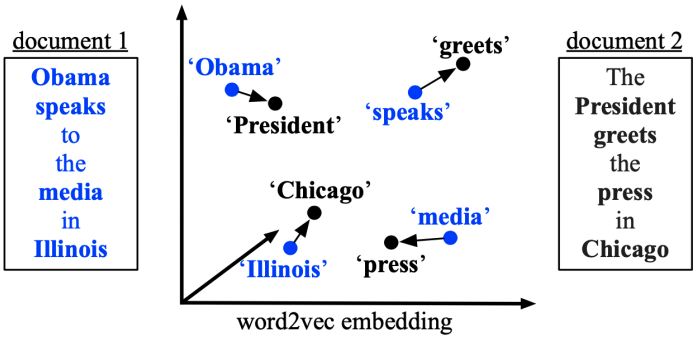
Word Embeddings

Evolution of Models

- Word2Vec
- GloVe
- BERT
- RoBERTa
- and of course BART, CamemBERT, RetriBERT, HerBERT, HUBERT . . .

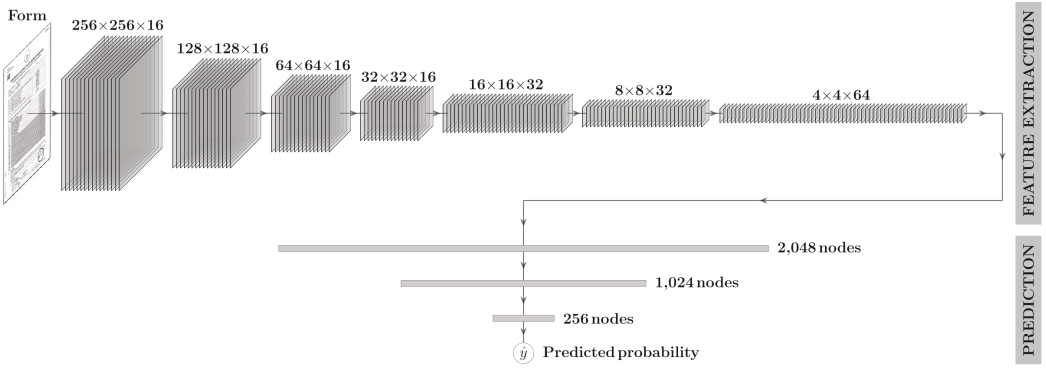


Doing Things with Wordembeddings

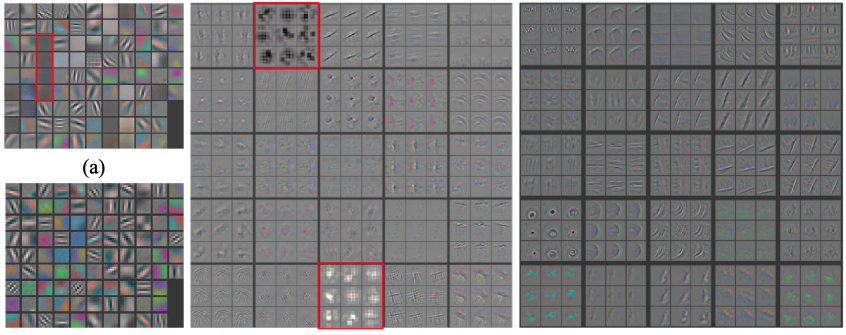


Source: Kusner et al. (2015)

Visual Embeddings

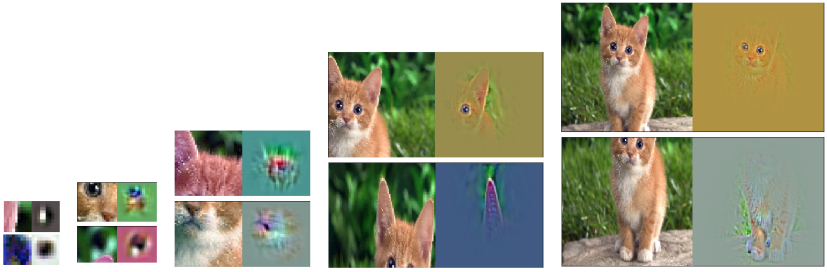


Filters



Source: Qin et al. (2018)

Features



Source: Qin et al. (2018)

Basic Multimodal Learning

Fusion

Fusion

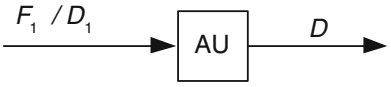
Multimodal Fusion

Process of joining information from modalities for prediction

Examples

- Audio-visual speech recognition
- Audio-visual emotion recognition
- Speaker identification
- ...

Building Blocks: Analysis Unit

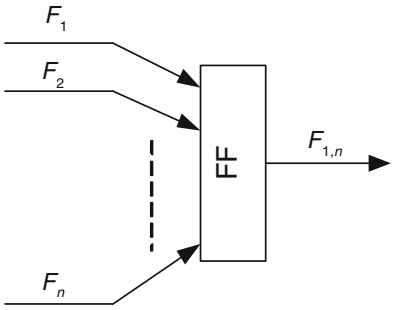


with

- F: Features
- D: Decisions

Source: Atrey et al. (2010)

Building Blocks: Feature Fusion Unit

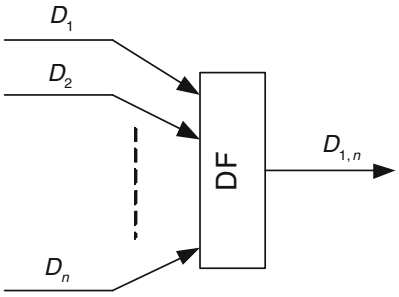


with

- F: Features

Source: Atrey et al. (2010)

Building Blocks: Decision Fusion Unit



with

- D: Decisions

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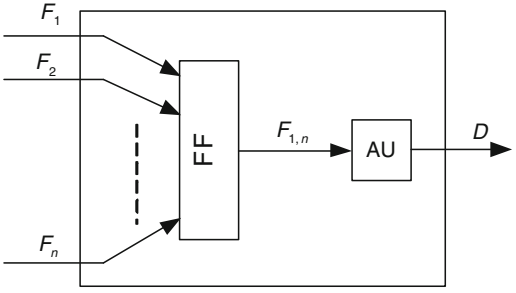
Early Fusion/Feature Level MML

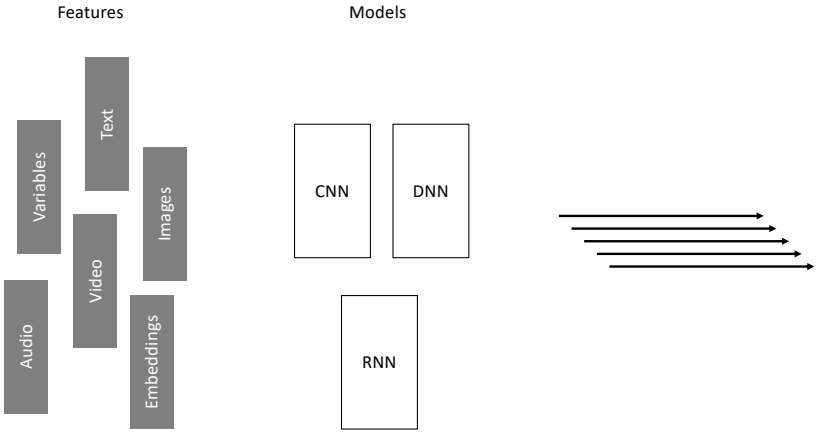


Source: Atrey et al. (2010)

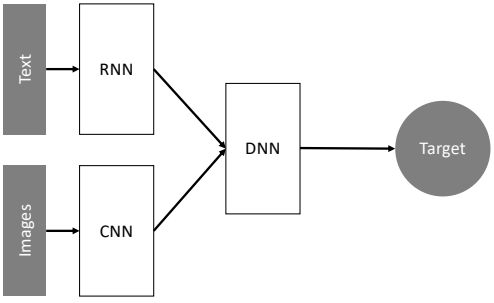
with

- F: Features
- D: Decisions
- Concatenate features
- Uses Correlations between features
- One learning phase
- May be high dimensional
- But: What if different granularities between modalities?

Quick Recap: What Do We Have to Play With?



Early Fusion with Neural Networks



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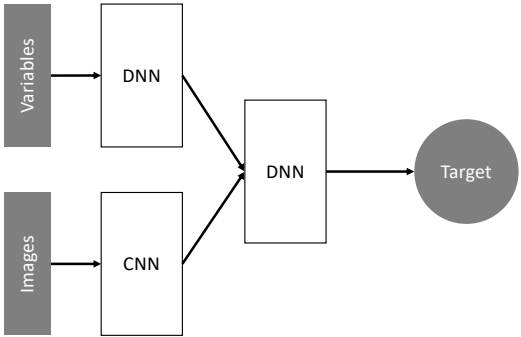

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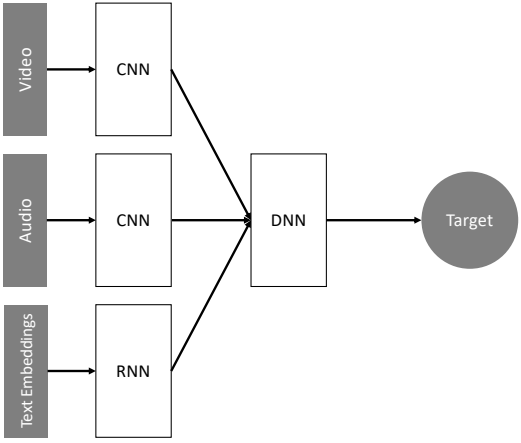
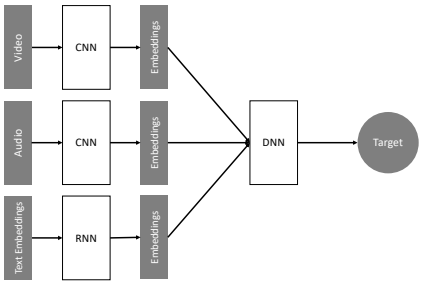


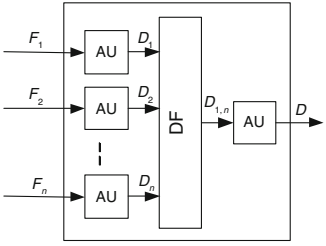
Early Fusion with Neural Networks

How does the data look like?

- Raw data?
- Features?
- Embeddings?



Late Fusion/Decision Level MML

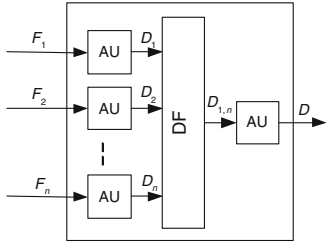


with

- F: Features
- D: Decisions

Source: Atrey et al. (2010)

Late Fusion/Decision Level MML



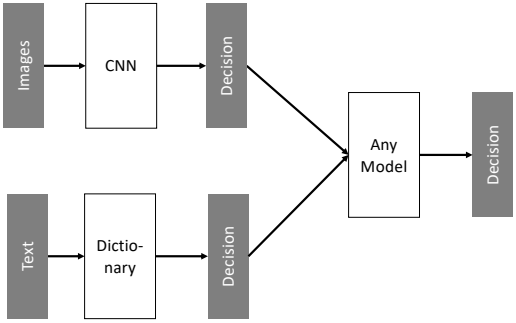
with

- F: Features
- D: Decisions

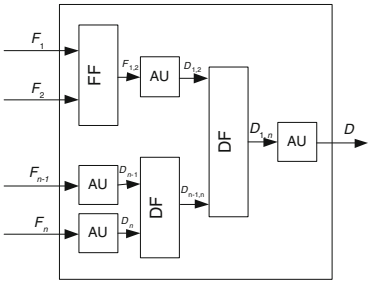
Source: Atrey et al. (2010)

- Multiple training stages: customize each prediction model with domain knowledge
- Fusion mechanisms: voting, weighted sums, or machine learning
- Granularity of features does not need to be the same: decisions syncronise
- No low level interactions between modalities
- Is this ensemble learning?

Late Fusion with Neural Networks



Hybrid Fusion/Hybrid MML



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Source: Atrey et al. (2010)

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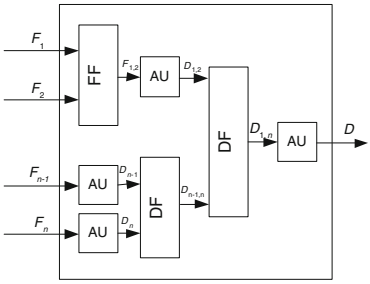


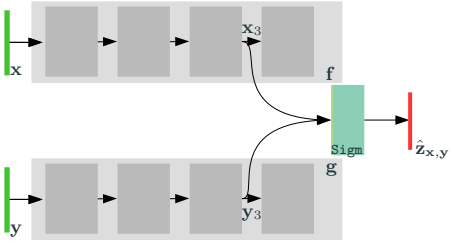
with

- F: Features
- D: Decisions

Source: Atrey et al. (2010)

- Can have advantages of early and late fusion, e.g. interactions at lower and higher levels
- But may compound disadvantages, e.g. re training and complexity

Hybrid Fusion with Neural Networks



Source: Pérez-Rúa et al. (2019)

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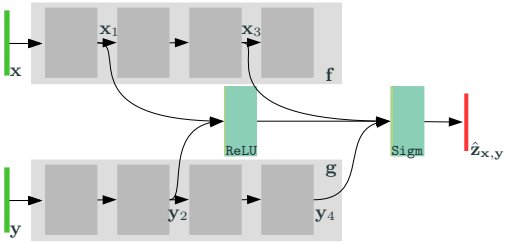
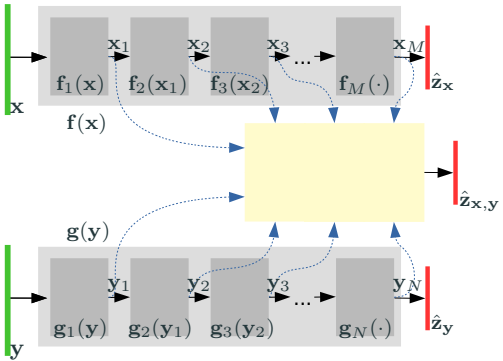


Source: Pérez-Rúa et al. (2019)

Hybrid Fusion with Neural Networks: Fusion Layer Unit



Source: Pérez-Rúa et al. (2019)

Code

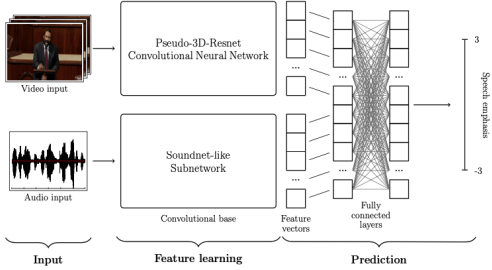
How to Build a Multi Modal Model with Keras

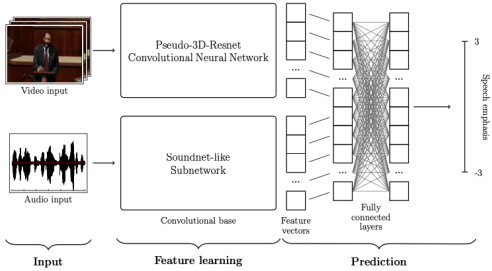
- Sequential and Functional API
- Model Fusion
- Google Collab: `https://colab.research.google.com/drive/1ZKqndxBsSZ2Yuu-kgafJnAgvnYDfHDjm?usp=sharing`

Basic Multimodal Learning

Examples from Political Science Revisited

Rittman, Ringwald and Nyhuis: *Public Opinion and Emphatic Legislative Speech*

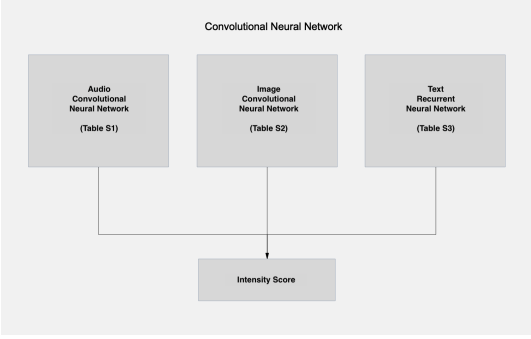


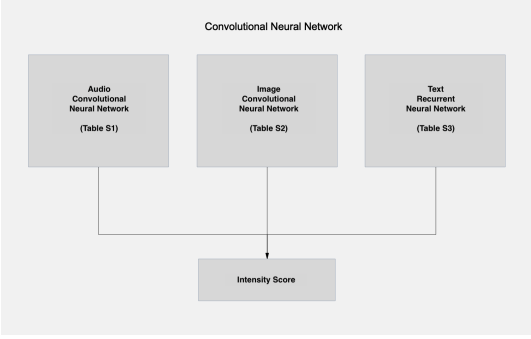


Modelling

- Syncronised video input and audio input
- Early fusion
- Fusion mechanism: concatenation
- Training: Adam with low learning rate

Dietrich, Mondak and Williams: *Assessing Affective Polarization*

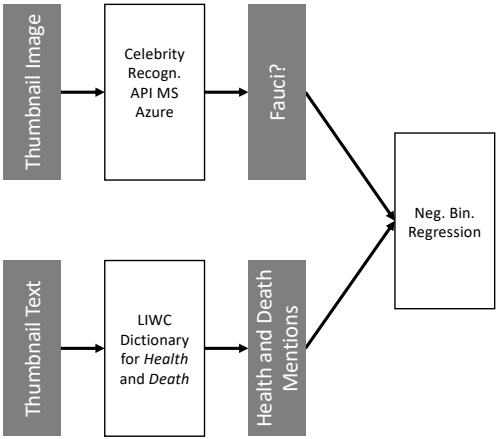




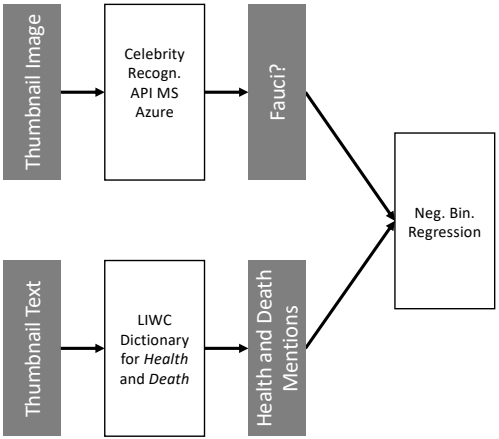
Modelling

- Syncronised video, audio and text input at word level with KALDI (Ochshorn and Hawkins 2016)
- Early fusion
- Fusion mechanism: concatenation

Dietrich and Ko (2022): *Finding Fauci*



Dietrich and Ko (2022): *Finding Fauci*



Modelling

- Internet archive: 2020 programming from CNN, Fox News, and MSNBC with search terms Covid and coronavirus
- One minute segments with closed-captioning and thumbnails
- Late fusion
- Low level models: proprietary “AI” and dictionaries
- High level model: Negative Binomial regression
- Fusion mechanism: decision level
- Syncronisation: decisions on one minute segments

Code

Predicting House Prizes

- Predict the prize of a house on the basis of its images and characteristics
- Regression
- Google Collab: `https://colab.research.google.com/drive/1HVb5yBkN1TSiCo_1Nf4RW6RQ6aZgJO8w?usp=sharing`

Basic Multimodal Learning

Learning and Optimization

Learning and Optimization

Challenge

- Data is from different sources.
- Different subgraphs

Example: Sentiment with Images and Captions

- CNN require high decaying learning rate
- RNN like adaptive methods and SGD
- DNN like adaptive methods

Learning and Optimization

Solution: Pre-training

- Train each modality separately
- Assemble and fine-tune
- Adaptive methods (e.g. Adam) are not good for fine tuning because of their high initial momentum

Example: Sentiment with Images and Captions

1. Train CNN & RNN separately on sentiment
2. Generate visual and verbal representations
3. Train DNN with representations on sentiment
4. Fine tune all on sentiment

Solution: Transfer Learning

- VGG for CNN
- Language models for RNN
- Train DNN layer-by-layer

Extensions

Representation Fusion

A Closer Look at Fusion

Definition

Learn a joint representation that models cross-modal interactions between individual elements of different modalities.

Fusing Modalities is a Continuum

- Homogenous modalities, e.g. two different camera angles
- Heterogenous modalities, e.g. a picture and text

A Closer Look at Fusion

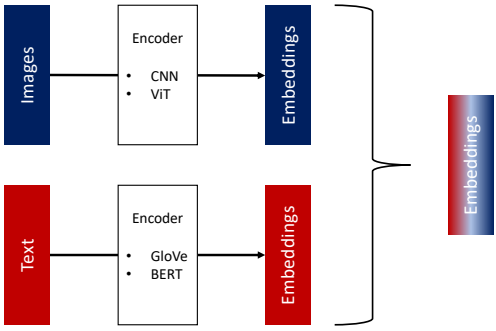
Definition

Learn a joint representation that models cross-modal interactions between individual elements of different modalities.

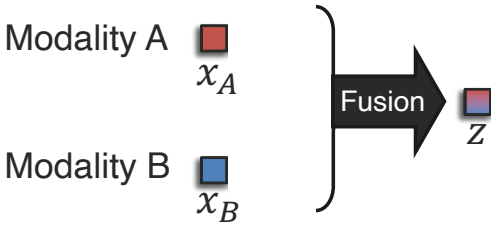
Fusing Modalities is a Continuum

- Homogenous modalities, e.g. two different camera angles
- Heterogenous modalities, e.g. a picture and text

Challenge: How to Fuse Heterogenous Modalities?



Unimodal Univariate Case



Additive Interaction

$$z = w_1 x_1 + w_2 x_2 + \epsilon$$

Multiplicative Interaction

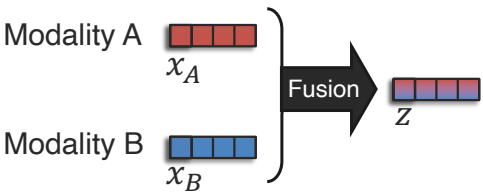
$$z = w_3 (x_1 x_2) + \epsilon$$

Additive and Multiplicative Interaction

$$z = w_1 x_1 + w_2 x_2 + w_3 (x_1 x_2) + \epsilon$$

Source: Morency et al. (2022)

Unimodal Multivariate Case



Additive Interaction

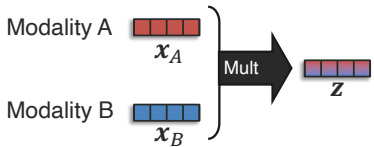
$$z = w_1 x_1 + w_2 x_2 = W \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Source: Morency et al. (2022)

Unimodal Multivariate Case

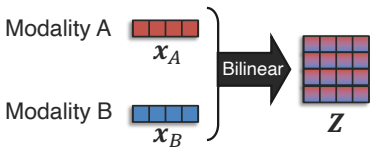
Multiplicative Fusion

$$z = w(x_1 \times w_2)$$



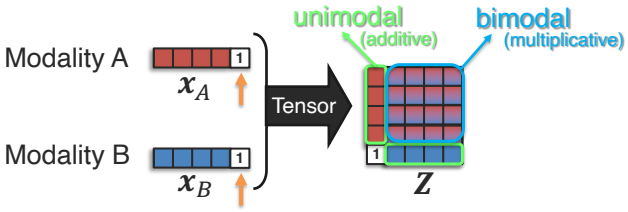
Billinear Fusion

$$Z = w(x_1^T \times w_2)$$



Source: Morency et al. (2022)

Unimodal Multivariate Case



Tensor Fusion

$$Z = w([x_1 1]^T \times [x_2 1])$$

Source: Morency et al. (2022), Zadeh et al. (2017)

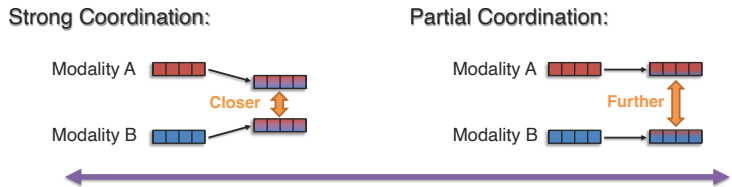
Extensions

Representation Coordination

Representation Coordination

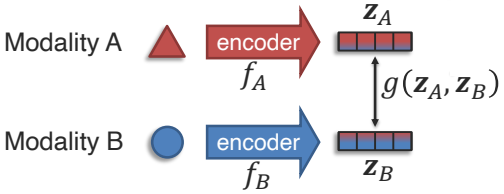
Definition

Learn multimodally-contextualized representations that are coordinated through their cross-modal interactions.

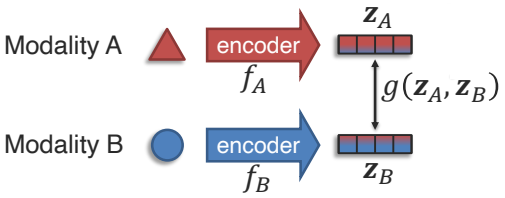


Source: Morency et al. (2022)

Examples for Coordination Functions $g()$:



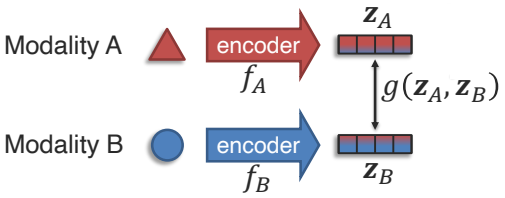
Examples for Coordination Functions $g()$:



Cosine Similarity

$$g(z_A, z_B) = \frac{k(z_A, z_B)}{\|z_A\| \|z_B\|}$$

Examples for Coordination Functions $g()$:



Source: Morency et al. (2022)

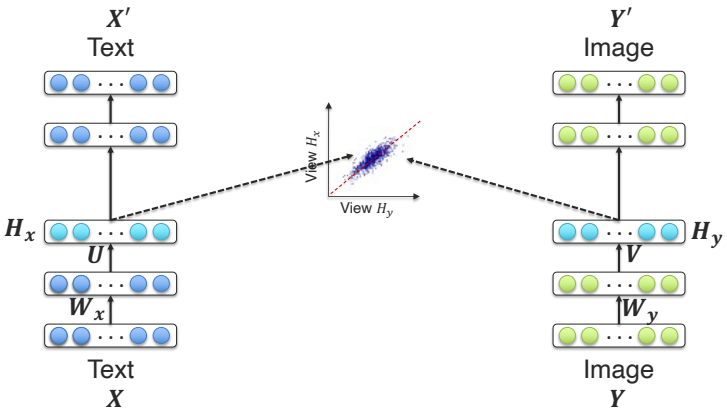
Cosine Similarity

$$g(z_A, z_B) = \frac{k(z_A, z_B)}{\|z_A\| \|z_B\|}$$

Canonical Correlation Analysis (CCA)

$$\underset{V,U,f_A,f_B}{\operatorname{argmax}} \operatorname{corr}(z_A, z_B)$$

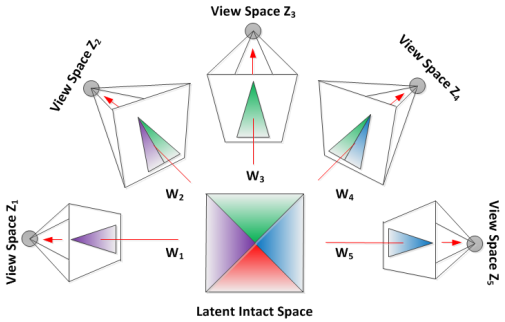
Deep Canonically Correlated Autoencoders (DCCAE)



- Cost function?
- How to train?

Source: Morency et al. (2022), Wang et al. (2015)

Intuition: Why is a Coordinated Embedding Space Useful?

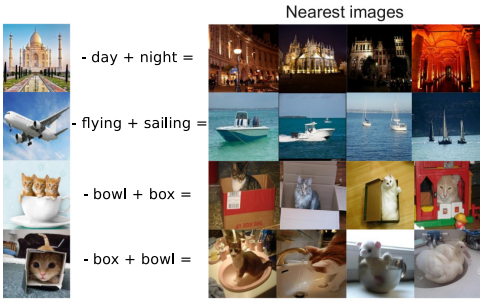


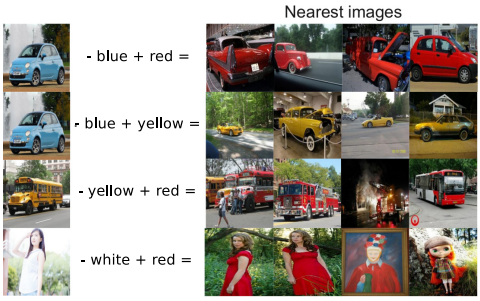
Source: Xu and Tao (2015)

Multiple Views from the Same Object

- Intact representation that is complete and not damaged
- Individual views z_i are partial representations of the intact representation

Intuition: Why is a Coordinated Embedding Space Useful?





Source: Kiros et al. (2014)

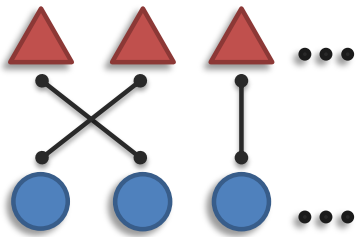
Extensions

Alignment

Multimodal Alignment

Definition

Identifying and modeling cross-modal connections between all elements of multiple modalities, building from the data structure.



Source: Morrency et al. (2022)

Connection Types

- Equivalence: No extra information
- Correspondence: Enhanced information
- Dependencies: Complementary information

Multimodal Alignment

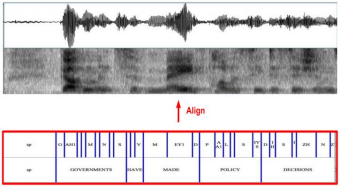
Two Ways of Alignment

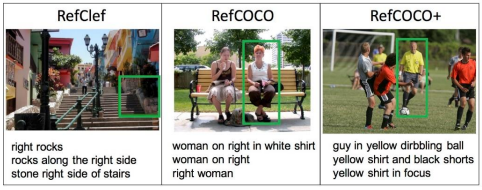
- Explicit aligment:
  - Alignment is the task itself.
  - $\rightarrow$ Alignment is the loss function.
- Implicit alignment:
  - Alignment is an intermediate step that is built into the model
  - Goal of the task is something else.
  - If the model aligns well, the model performance will be higher.

Explicit Multimodal Alignment

Examples

- Images and captions
- Speech signal to transcript
- Co-referring expressions





Source: Morency (2020)

Dynamic Time Warping: Unimodal

Two unaligned unimodal temporal signals

$$X = [x_1, x_2, \ldots, x_{n_x}]$$

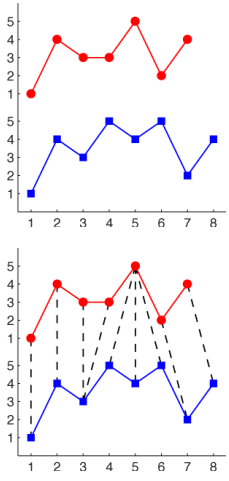
$$Y = [y_1, y_2, \ldots, y_{n_y}]$$

Find set of indices to minimize alignment difference

$$L(p^x, p^y) = \sum_{t=1}^{l} \left\| x_{p_t^x} - y_{p_t^y} \right\|_2^2$$

$\rightarrow$ Dynamic Time Warping is designed to find the vectors p^x and p^y

Source: Morency (2020)

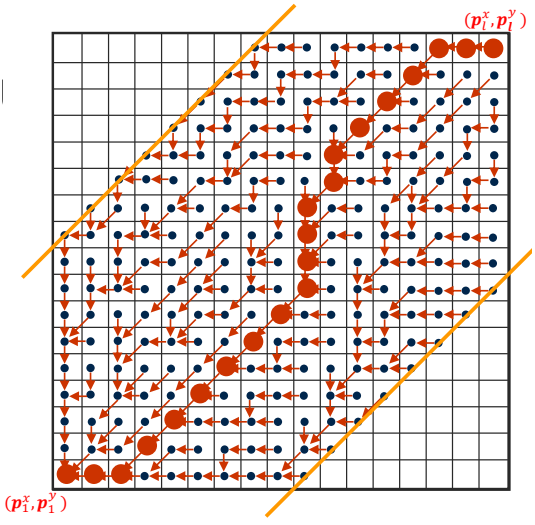


Dynamic Time Warping

Solve: Lowest Cost Path in Cost Matrix

- Monotonicity: no going back
- Continuity: no gaps
- Boundary conditions: start and end at same points
- Warping window: don't get too far from diagonal
- Slope constraint: Do not insert or skip too much

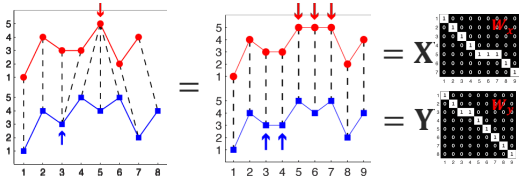
Source: Morency (2020)



Dynamic Time Warping: Alternative Formulation

Objective So Far

$$L(p^x, p^y) = \sum_{t=1}^{l} \left\| x_{p_t^x} - y_{p_t^y} \right\|_2^2$$



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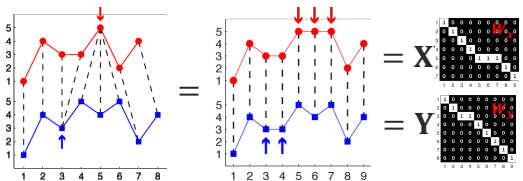


Source: Morency (2020)

Alternative Objective

$$L(W_x, W_y) = \|XW_x - YW_y\|_F^2$$

with

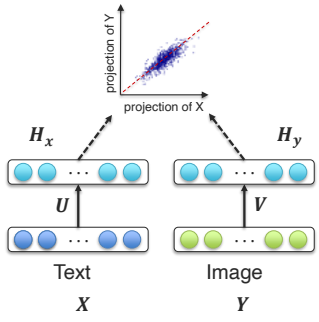
- X, Y original signals
- W_x, W_y alignment matrices to find

But: Computationally complex, sensitive to outliers, unimodal

Dynamic Time Warping + Canonical Correlation Analysis = Canonical Time Warping

Canonical Correlation Analysis

$$L(U, V) = \left\| U^T X - V^T Y \right\|_F^2$$



Dynamic Time Warping + Canonical Correlation Analysis = Canonical Time Warping

Canonical Correlation Analysis

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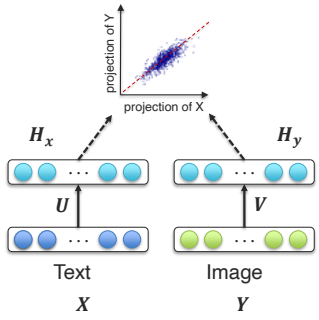


Canonical Time Warping

$$L(U, V, W_x, W_y) = \left\| U^T X W_x - V^T Y W_y \right\|_F^2$$

- Allows to align multi modal and multi view
- W_x, W_y for temporal alignment
- U, V for cross-modal alignment

Source: Morrency (2020), Zhou and De la Torre (2009)

Canonical Time Warping + NN = Deep Canonical Time Warping

Canonical Time Warping

$$L(U, V, W_x, W_y) = \left\| U^T X W_x - V^T Y W_y \right\|_F^2$$

- W_x, W_y for temporal alignment
- U, V for cross-modal alignment

Deep Canonical Time Warping

$$L(\theta_1, \theta_2, W_x, W_y) = \left\| f_{\theta_1}(X) X W_x - f_{\theta_2}(Y) Y W_y \right\|_F^2$$

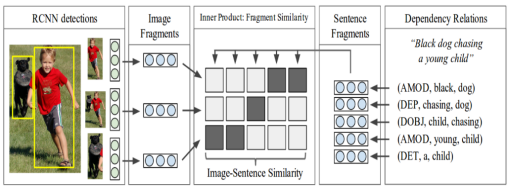
- Addresses non-linearities in alignment

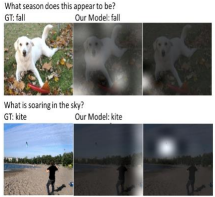
Source: Zhou and De la Torre (2009), Trigeorgis et al. (2016)

Implicit Alignment

Examples

- Machine translation
- Visual question answering
- Cross-modal retrieval



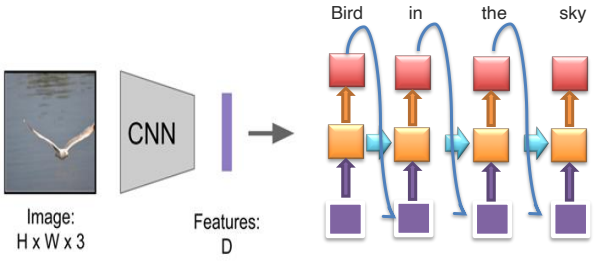


Source: Morency (2020)

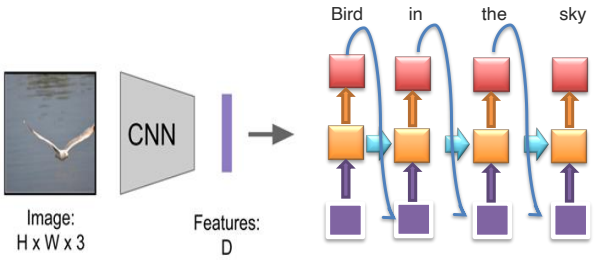
Visual Captioning with Soft Attention

Source: Xu et al. (2015)

Recap: Initialise RNN for Generating Captions



Recap: Initialise RNN for Generating Captions

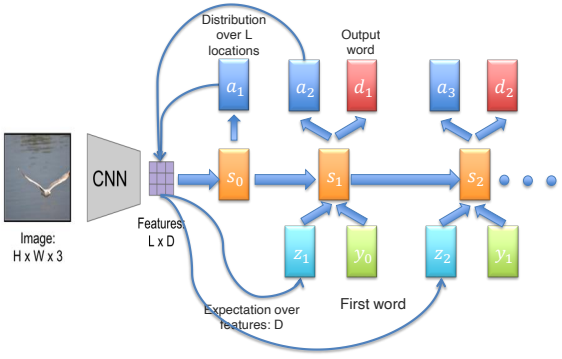


Why is it not a good idea to use the final layer of the CNN?

- Will the information of the image reach the end of the sentence?

Source: Morency (2020)

Soft Attention to Look at More Fine Grained Features



Source: Morency (2020)

Attention

- Output from response maps to the convolution (e.g. 4x4x64)
- Where to focus on the image
- For each location in the image (1x64)

Im Sum

- Allows for latent data alignment
- Allows us to get an idea of what the network “sees”
- Can be optimized using back propagation

Code

Multimodal Entailment: Does a Social Media Post Contradict or Imply Each Other?

- Recognizing Multimodal Entailment tutorial was held virtually at ACL-IJCNLP 2021 on August 1st.
- Event: `https://multimodal-entailment.github.io/`
- Baseline model: `https://keras.io/examples/nlp/multimodal_entailment`

Sources

Readings

- Atrey, Pradeep K., M. Anwar Hossain, Abdulmotaleb El Saddik and Mohan S. Kankanhalli. “Multimodal Fusion for Multimedia Analysis: A Survey.” *Multimedia Systems* (2010) 16: 345–379.
- Baltrušaitis, Tadas, Chaitanya Ahuja, and Louis-Philippe Morency. “Multimodal Machine Learning: A Survey and Taxonomy.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 41.2 (2018): 423-443.”
- Bengio, Yoshua, Aaron Courville, and Pascal Vincent. “Representation learning: A Review and New Perspectives.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 35.8 (2013): 1798-1828.
- Goodfellow, Ian and Yoshua Bengio and Aaron Courville. 2016. *Deep Learning*. MIT Press.

Sources

Internet Resources

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Working with Deep Learning? Get in touch!

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