



Language Technologies Institute



Multimodal Machine Learning

Lecture 1.1: Introduction Louis-Philippe Morency

> * Co-lecturer: Paul Liang. Original course co-developed with Tadas Baltrusaitis. Spring 2021 and 2022 editions taught by Yonatan Bisk

Your teaching team This Semester (11-777, Fall 2022)



Louis-Philippe Morency morency@cs.cmu.edu Course instructor



Paul Liang pliang@cs.cmu.edu Co-lecturer



溯

Catherine (Yun) Cheng <u>yuncheng@andrew.cmu.edu</u> TA



Karthik Ganesan karthikg@andrew.cmu.edu TA



Gabriel Moreira gmoreira@andrew.cmu.edu TA



Alex Wilf awilf@andrew.cmu.edu TA



Yinghuan Zhang yinghuan@andrew.cmu.edu TA

- What is Multimodal?
 - Research-oriented definition
 - Dimensions of modality heterogeneity
 - Modality connections and interactions
- Core technical and conceptual challenges
 - Representation, alignment, reasoning, generation, transference and quantification
- Course schedule

What is Multimodal?

Multimodal AI Technologies



Personal Vehicles



Ubiquitous



Online





3







Multimodal AI Technologies



wearable

What is Multimodal?



Language

- Lexicon
 - Words
- Syntax
 - Part-of-speech
 - Dependencies
- Pragmatics
 - Discourse acts

Acoustic

- Prosody
 - Intonation
 - Voice quality
- Vocal expressions
 - Laughter, moans

Visual

- Gestures
 - Head gestures
 - Eye gestures
 - Arm gestures
- Body language
 - Body posture
 - Proxemics
- Eye contact
 - Head gaze
 - Eye gaze
- Facial expressions
 - FACS action units
 - Smile, frowning

Touch

- Haptics
- Motion

Physiological

- Skin conductance
- Electrocardiogram

Mobile

- GPS location
- Accelerometer
- Light sensors

勜

Carnegie Mellon Universit

Modality

Modality refers to the way in which something expressed or perceived.



A dictionary definition...

Multimodal: with multiple modalities

A research-oriented definition...

Multimodal is the science of

heterogeneous and interconnected data

Information present in different modalities will often show diverse qualities, structures and representations.



Abstract modalities are more likely to be homogeneous

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.

1 E

Element representations: discrete, continuous, granularity

{teacup, right, laptop, clean, room}

, ,

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.

2 EI

Element distributions: density, frequency

▲ ▲ objects per image



Information present in different modalities will often show diverse qualities, structures, and representations.







Structure: temporal, spatial, hierarchical, latent, explicit

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.



Information: abstraction, entropy

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.



Noise: uncertainty, signal-to-noise ratio, missing data



teacup \rightarrow teacip right \rightarrow rihjt

Information present in different modalities will often show diverse qualities, structures, and representations.



A teacup on the right of a laptop in a clean room.



Relevance: task relevance, context dependence



→ recreational
→ living room
→ right-handed

A teacup on the right of a laptop in a clean room.

workspacestudy room

Modalities are often related and share commonality



Modality interactions

Modality elements often interact during inference



Interactions happen during inference!

"Inference" examples:

- Behavior perception
- Recognition task
- Modality translation

勜

Modalities are often related and share commonality





Modalities are often related and share commonality





Modalities are often related and share commonality





Modalities are often related and share commonality





勜

2 Modality interactions

Modality elements often interact during inference



Is this indoors?

勞

A teacup on the right of a laptop in a clean room.



Yes!

signals

inference





2 Modality interactions

Modality elements often interact during inference



Is this indoors ?

勞

A teacup on the right of a laptop in a clean room.



2 Modality interactions

Modality elements often interact during inference



Is this a living room?

A teacup on the right of a laptop in a clean room.



No, probably study room.

2 Modality interactions

Modality elements often interact during inference



A teacup on the right of a laptop in a clean room.



Is this

a

living

room?

勞

Taxonomy of Interaction Responses – A Behavioral Science View



Partan and Marler (2005). Issues in the classification of multimodal communication signals. American Naturalist, 166(2)

What are the dimensions for **digitally-represented** modalities?



- Redundancy
 - Non-redundancy
 - Dominance
 - Emergence...





- Additive
- multiplicative
- Nonlinear
- Causal,
- Logical, ...





Multimodal is the science of

heterogeneous and interconnected data 😊

Multimodal Machine Learning

Multimodal Machine Learning (ML) is the study of computer algorithms that learn and improve through the use and experience of data from multiple modalities

Multimodal Artificial Intelligence (AI) studies computer agents able to demonstrate intelligence capabilities such as understanding, reasoning and planning, through multimodal experiences, and data

Multimodal AI is a superset of Multimodal ML

Multimodal Machine Learning





Acoustic

Vision


Multimodal Machine Learning



🐞 Language Technologies Institute

What are the core multimodal technical challenges,

understudied in conventional machine learning?

Multimodal Technical Challenges – Surveys, Tutorials and Courses

2016

Multimodal Machine Learning: A Survey and Taxonomy

Tadas Baltrusaitis, Chaitanya Ahuja and Louis-Philippe Morency (Arxiv 2017, IEEE TPAMI journal, February 2019)

https://arxiv.org/abs/1705.09406

Tutorials: CVPR 2016, ACL 2016, ICMI 2016, ...

Graduate-level courses:

Multimodal Machine learning (11th edition) https://cmu-multicomp-lab.github.io/mmml-course/fall2020/

Advanced Topics in Multimodal Machine learning https://cmu-multicomp-lab.github.io/adv-mmml-course/spring2022/

2022

Fundamentals of Multimodal ML: A Taxonomy & Open Challenges

Paul Liang, Amir Zadeh and Louis-Philippe Morency

☑ 6 core challenges
☑ 50+ taxonomic classes
☑ 600+ referenced papers

Tutorials: CVPR 2022, NAACL 2022, ...

Updated graduate-level course:

Multimodal Machine learning (12th edition) Fall 2022 semester **Definition:** Learning representations that reflect cross-modal interactions between individual elements, across different modalities

> This is a core building block for most multimodal modeling problems!

Individual elements:



It can be seen as a "local" representation or representation using holistic features **Definition:** Learning representations that reflect cross-modal interactions between individual elements, across different modalities





勜

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

> Most modalities have internal structure with multiple elements

Elements with temporal structure:







Other structured examples:

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

Sub-challenges:

Connections



Explicit alignment (e.g., grounding)

Aligned Representation







Alignment + representation (aka, contextualized representation) Segmentation of individual elements

勜

Definition: Combining knowledge, usually through multiple inferential steps, exploiting multimodal alignment and problem structure



Definition: Combining knowledge, usually through multiple inferential steps, exploiting multimodal alignment and problem structure



勞

Definition: Combining knowledge, usually through multiple inferential steps, exploiting multimodal alignment and problem structure

Sub-challenges:

Structure	Intermediate	Inference	External	
Modeling	concepts	Paradigm	Knowledge	
	words or or or	$\boxed{2}$	8	

勜

Definition: Learning a generative process to produce raw modalities that reflects cross-modal interactions, structure and coherence

Sub-challenges:



勜

Definition: Transfer knowledge between modalities, usually to help the target modality which may be noisy or with limited resources



Definition: Transfer knowledge between modalities, usually to help the target modality which may be noisy or with limited resources



勜

Definition: Empirical and theoretical study to better understand heterogeneity, cross-modal interactions and the multimodal learning process

Sub-challenges:



Core Multimodal Challenges



Lecture Schedule

Classes	Tuesday Lectures	Thursday Lectures
Week 1	Course introduction	Multimodal applications and datasets
8/30 & 9/1	Multimodal core challenges	Research tasks and datasets
	Course syllabus	Team projects
Week 2	Basic concepts: neural networks	Unimodal representations
9/6 & 9/8	 Loss functions and neural networks 	 Dimensions of heterogeneity
Redu due: 9/9	 Gradient and optimization 	 Visual representations
Week 3	Unimodal representations	Multimodal representations
9/13 & 9/15	Language representations	Cross-modal interactions
Proj. Due: 9/14	 Signals, graphs and other modalities 	Multimodal fusion
Week 4	Multimodal representations	Multimodal alignment
9/20 & 9/22	Coordinated representations	Explicit alignment
Proj. aue: 9/25	Multimodal fission	 Multimodal grounding
Week 5	Project hours (Research ideas)	Aligned representations
9/27 & 9/29		Self-attention transformer models
Read due: 9/30		Masking and self-supervised learning
Week 6	Multimodal aligned representations	Multimodal Reasoning
10/4 & 10/6	 Multimodal transformers 	 Structured and hierarchical models
Proj. due: 10/9	 Video and graph representations 	Memory models

췟

Lecture Schedule

Classes	Tuesday Lectures	Thursday Lectures
Week 7 10/11 & 10/13 Read due: 10/14	 Multimodal Reasoning Reinforcement learning Discrete structure learning 	 Multimodal Reasoning Logical and causal inference External knowledge
Week 8 10/18 & 10/20	Fall Break – No lectures	
Week 9 10/25 & 10/27 Proj. due: 10/30	 Generation Translation, summarization, creation Generative models: VAEs 	GenerationGANs and diffusion modelsModel evaluation and ethics
Week 10 11/1 & 11/3	Project presentations (midterm)	Project presentations (midterm)
Week 11 11/8 & 11/10 Read due: 11/12	TransferenceModality transferMultimodal co-learning	QuantificationHeterogeneity and interactionsBiases and fairness
Week 12 11/15 & 11/17 Read due: 11/21	Project hours (Research ideas)	 New research directions Recent approaches in multimodal ML

Classes	Tuesday Lectures	Thursday Lectures
Week 13 11/22 & 11/24	Thanksgiving Week – No Class –	
Week 14 11/30 & 12/2	 Language, Vision, and Actions Motion and navigation Robots and embodied AI 	 Multimodal Applications Healthcare and affective computing Artificial social intelligence
Week 15 12/6 & 12/8 Proj. due: 12/11	Project presentations (final)	Project presentations (final)

Piazza https://piazza.com/cmu/fall2022/11777/info

ριαzza	11777 ~ Q & A <u>Resources</u> Statistics ~ Manag	e Class 🛛 🕅 Louis-Philippe Morency 💭 -
	Carnegie Mellon University - Fall 2022 11777: Multimodal Machine Le	arning
	Syllabus 🛃 🖍 📋	£
	Course Information Staff Resources	
	Description <pre> Edit </pre>	Announcements + Add
	Multimodal machine learning (MMML) is a vibrant multi-disciplinary research field which addresses some of the original goals of artificial intelligence by integrating and modeling multiple communicative modalities, including	Add an Announcement Click the Add button to add an announcement.
	visual speech recognition and more recently with language & vision projects such as image and video captioning, this research field brings some unique challenges for multimodal researchers given the heterogeneity of the data and the contingency often found between modalities. This course will teach fundamental mathematical concepts related to MMML including multimodal alignment and fusion, heterogeneous representation learning and multi- stream temporal modeling. We will also review recent papers describing state-of-the-art probabilistic models and computational algorithms for MMML and discuss the current and upcoming challenges. Recommended preparation: This is a graduate course designed primarily for PbD and research master students at LTLML D_CSD_HCII and Pi- others.	✓ Announcements
	for example (undergraduate) students of CS or from professional master programs, are advised to seek prior permission of the instructor. It is required for students to have taken an introduction machine learning course such as 10-401, 10-601, 10-701, 11-663, 11-441, 11-641 or 11-741. Prior	Question/Answers
	knowledge of deep learning is recommended. Students should have proper academic background in probability, statistic and linear algebra. Programming knowledge in Python is also strongly recommended.	Reading assignmer
	More details in the Syllabus document.	9 9
	General Information	✓ Project resources
	Time	
	Tuesdays and Thursday, 10:10am-11:30am	
	Location	

췟

Course Syllabus

Three Course Learning Paradigms



Course lecture participation (16% of your grade)



Reading assignments (12% of your grade)



Course project assignments (72% of your grade)

Course Recommendations and Requirements



Ready to read about 6 papers this semester !

- Curated list of research papers for the 6 reading assignments
- Summarize one paper and contrast it with other papers



Already taken a machine learning course

- Strongly recommended for students to have taken an introduction machine learning course
- 10-401, 10-601, 10-701, 11-663, 11-441, 11-641 or 11-741



- Motivated to produce a high-quality course project
 - Projects are designed to enhance state-of-the-art algorithms
 - Four project assignments, to help scaffold the project tasks

- Dataset should have at least two modalities:
 - Natural language and visual/images
- Teams of 3, 4 or 5 students
- The project should explore algorithmic novelty
- Possible venues for your final report:
 - ACL 2023, IJCAI 2023, ICML 2023, ICMI 2023
- We will discuss on Thursday about project ideas
- GPU resources available:
 - Amazon AWS and Google Cloud Platform

$$\begin{split} & i_t = \sigma \left(W_{ai} x_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i \right) \\ & f_t = \sigma \left(W_{af} x_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f \right) \\ & c_t = f_t c_{t-1} + i_t \tanh(W_{xc} c_t + W_{hc} h_{t-1} + b_c) \\ & o_t = \sigma \left(W_{xo} x_t + W_{ho} h_{t-1} + W_{co} c_t + b_o \right) \\ & h_t = o_t \tanh(c_t) \end{split}$$

Pre-proposal (due Wednesday Sept. 14)

Define your dataset, research task and teammates

First project assignment (due Sunday Sept. 25)

- Study related work to your selected research topic
- Second project assignment (due Sunday Oct 9)
 - Experiment with unimodal representations
- Midterm project assignment (due Sunday Oct 30)
 - Implement and evaluate state-of-the-art model(s)
- Final project assignment (due Sunday Dec. 11)
 - Implement and evaluate new research ideas

- Each team will be required to create a GitHub repository which will be accessible by TAs
- Each report should include a description of the task from each teammate
- Please let us know soon if you have concerns about the participation levels of your teammates

- Thursday 9/1: Lecture describing available multimodal datasets and research topics
- Tuesday 9/6: Let us know your dataset preferences for the course project
- Thursday 9/8: During the later part of the lecture, we will have an interactive period to help with team formation. More details to come
- Wednesday 9/14: Pre-proposals are due. You should have selected your teammates, dataset and task

- Post your project preferences:
 - List of your ranked preferred projects
 - Use alphanumeric code of each dataset
 - Detailed dataset list in the "Lecture1.2-datasets" slides
 - Previous unimodal/multimodal experience
 - Available CPU / GPU resources
- For topics or datasets not in the list:
 - Include a description with links (for other students)

Lecture Schedule

Classes	Tuesday Lectures	Thursday Lectures			
Week 1 8/30 & 9/1	 Course introduction Multimodal core challenges Course syllabus 	 Multimodal applications and datasets Research tasks and datasets Team projects 			
Week 2 9/6 & 9/8 Read due: 9/9	 Basic concepts: neural networks Loss functions and neural networks Gradient and optimization 	 Unimodal representations Dimensions of heterogeneity Visual representations Project preferences due on Tuesday 9/6 			
Week 3 9/13 & 9/15 Read due: 9/16 Proj. Due: 9/14	 Unimodal representations Language representations Signals, graphs and other modalities 	 Multimodal representations Cross-modal interactions Multimodal fusion Pre-proposals due on Wednesday 9/14			
Week 4 9/20 & 9/22 Proj. due: 9/25	 Multimodal representations Coordinated representations Multimodal fission 	 Multimodal alignment and groun Explicit alignment Multimodal grounding First assignment due on Sunday 9/25 			
Week 5 9/27 & 9/29 Read due: 9/30	Project hours (Research ideas)	 Aligned representations Self-attention transformer models Masking and self-supervised learning 			
Week 6 10/4 & 10/6 Proj. due: 10/9	 Multimodal aligned representations Multimodal transformers Video and graph representations 	 Multimodal Reasoning Structured and hierarchical models Memory models Second assignment due on Sunday 10/9 			

Lecture Schedule

Classes	Tuesday Lectures	Thursday Lectures			
Week 7Multimodal Reasoning10/11 & 10/13• Reinforcement learningRead due: 10/14• Discrete structure learning		 Multimodal Reasoning Logical and causal inference External knowledge 			
Week 8 10/18 & 10/20	Fall Break – No lectures				
Week 9 10/25 & 10/27 Proj. due: 10/30	 Generation Translation, summarization, creation Generative models: VAEs 	GenerationGANs and diffusion modelsModel evaluation and ethics	Midterm assignment due on Sunday 10/30		
Week 10 11/1 & 11/3	Project presentations (midterm)	Project presentations (midterm)			
Week 11 11/8 & 11/10 Read due: 11/12	TransferenceModality transferMultimodal co-learning	 Quantification Heterogeneity and interaction Biases and fairness 	S		
Week 12 11/15 & 11/17 Read due: 11/21	Project hours (Research ideas)	New research directionsRecent approaches in multimo	odal ML		

Classes	Tuesday Lectures Thursday Lectures			
Week 13 11/22 & 11/24	Thanksgiving Week – No Class –			
Week 14 11/30 & 12/2	 Language, Vision, and Actions Motion and navigation Robots and embodied AI 	 Multimodal Applications Healthcare and affective comp Artificial social intelligence 	outing	
Week 15Project presentations (final)Project presentations (final)Final as on S12/6 & 12/8Proj. due: 12/11				

Course Grades



$i_l =$	$\sigma \left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i \right)$
$f_t =$	$\sigma \left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f \right)$
$c_t =$	$f_t c_{t-1} + i_t \tanh \left(W_{xc} x_t + W_{hc} h_{t-1} + b_c \right)$
$o_t =$	$\sigma \left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o \right)$
$h_t =$	$o_t \tanh(c_t)$

- Lecture highlights 16%
- Reading assignments
 12%
- Project preferences/pre-proposal 2%
- First project assignment 10%
- Second project assignment 10%
- Mid-term project assignment
 - Report and presentation 20%
- Final project assignment
 - Report and presentation 30%

Lecture Highlight Form

Starting Week 2 !!

	Lecture 2.1 - Highlight Form
1	DEADLINE Submit your Lecture Highlight form by Thursday Sept 10, 2020 at 10:40am ES You have 42 hours to fill out this form, from the scheduled end time of the lecture.
	IMPORTANT: Please read the detailed instructions in Piazza's Resources section ('Lectu Highlights - Instructions.pdf', in the Instructions for Course Assignments list) before filli out this form.
1	https://piazza.com/cmu/fall2020/11777a/resources
1	Your email address (Imorency@andrew.cmu.edu) will be recorded when you submit this form. Not you? <u>Switch account</u>
	* Required
	Your answer
	(Optional) First 30 mins - Any question? Please include slide number(s)
	Your answer
	Next 20 mins . Main tales have measured (shout 15, 40 mins) *
	Next 30 mins - Main take nome message (about 15-40 mins) - 2

Similar to note-taking during lectures

For each course segment (30mins):
 2 sentences describing the main points

Help you summarizing the lecture

What is the main take-away message from the lecture Short paragraph (15-40 words)

Ask questions about the lecture

Will be answered either online or at the next lecture

Submitted same day as lecture (before 11:59pm)

Students are encouraged to attend lectures in person

	Segment 1		Segment 2		Segment 3			
10:1	0am	10:4	0am	11:1	0am	11:	:30an	า
Sche	duled					Scheo	dulec	ł
begi	nning		end					
of the lecture				0	f the I	ectu	re	

Segment 1 starts at 10:10am, even if the lecture starts slightly later.

Segment 3 ends whenever the lecture ends

Slides happening around the segment borders (+/- 5min of 10:40am and 11:10am) can be included in either neighboring segment.

- Study groups: 9-10 students per group (randomly, in Piazza)
- 3 paper options are available
 - Each student should pick one paper option!
 - Google Sheets were created to help balance the papers between group members
 - Then you will create a short summary to help others [1 point]
- Discussions with your study group
 - Read other's summaries. Ask questions!
 - Write follow-up posts comparing the papers and suggesting ideas [1 point]
 - At least one follow-up post for every paper you did not read

Four main steps for the reading assignments

- 1. Monday 8pm: Official start of the assignment
- 2. Wednesday 8pm: Select your paper
- 3. Friday 8pm: Post your summary
- 4. Monday 8pm: Post your follow-up posts

Detailed instructions posted on Piazza

https://piazza.com/cmu/fall2022/11777/resources

- Each student has 6 late submission wildcards
 - For lecture highlight forms or reading assignments
- Each project team has 2 late submission wildcards
 - For any of the project assignments
- Total number of wildcards: 8 (6 individual and 2 team-level)
- Each wildcard gives 24-hour extension
 - No partial credits for the wildcards
 - Automatically calculated (no need to contact us apriori)

See details about late submission policy in syllabus

https://piazza.com/cmu/fall2021/11777/resources
Spring 2023 Edition of the MMML Course !



Yonatan Bisk ybisk@cs.cmu.edu https://yonatanbisk.com/



Daniel Fried dfried@cs.cmu.edu

https://dpfried.github.io/

谢

Carnegie Mellon Universit