



Language  
Technologies  
Institute

Carnegie  
Mellon  
University

# Advanced Multimodal Machine Learning

## Lecture 1.2: Challenges and applications

Louis-Philippe Morency

\* Original version co-developed with Tadas Baltrusaitis

## Lecture Objectives

---

- Identify tasks/applications of multimodal machine learning
- Knowledge of available datasets to tackle the challenges
- Appreciation of current state-of-the-art

# Process for Selecting your Course Project

---

- Thursday 8/30: Lecture describing available multimodal datasets and research topics
- Monday 9/3: Submit a short paragraph listing your top 3 choices
- Tuesday 9/4: During the later part of the lecture, we will have a discussion period to help with team formation
- **Wednesday 9/12**: Pre-proposals are due. You should have selected your teammates, dataset and task
- Following week: meeting with TAs to discuss project

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

# Course Project

---

- Pre-proposal (in 2 weeks)
  - Define your dataset, research task and teammates
- First project assignment (in 5 weeks)
  - Experiment with unimodal representations
  - Explore/discuss simple baseline model(s)
- Midterm project assignment (in 10 weeks)
  - Implement and evaluate state-of-the-art model(s)
  - Discuss new multimodal model(s)
- Final project assignment (in 14 weeks)
  - Implement and evaluate new multimodal model(s)
  - Discuss results and possible future directions

# Research tasks and datasets

---

# Real world tasks tackled by MMML

- Affect recognition
  - Emotion
  - Personality traits
  - Sentiment
- Media description
  - Image captioning
  - Video captioning
  - Visual Question Answering
- Event recognition
  - Action recognition
  - Segmentation
- Multimedia information retrieval
  - Content based/Cross-media



# Affect recognition

---

- Emotion recognition
  - Categorical emotions – happiness, sadness, etc.
  - Dimensional labels – arousal, valence
- Personality/trait recognition
  - Not strictly affect but human behavior
  - Big 5 personality
- Sentiment analysis
  - Opinions



# Affect recognition dataset 1 (A1)

---

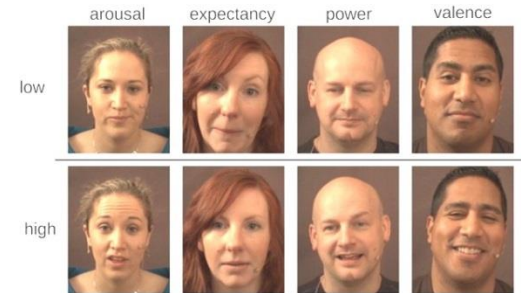
- [AFEW](#) – Acted Facial Expressions in the Wild (part of EmotiW Challenge)
- Audio-Visual emotion labels – acted emotion clips from movies
  - 1400 video sequences of about 330 subjects
- Labelled for six basic emotions + neutral
- Movies are known, can extract the subtitles/script of the scenes
- Part of [EmotiW](#) challenge





# Affect recognition dataset 2 (A2)

- Three AVEC challenge datasets 2011/2012, 2013/2014, 2015, 2016, 2017, 2018
- Audio-Visual emotion recognition
- Labeled for dimensional emotion (per frame)
- 2011/2012 has transcripts
- 2013/2014/2016 also includes depression labels per subject
- 2013/2014 reading specific text in a subset of videos
- 2015/2016 includes physiological data
- 2017/2018 includes depression/bipolar



[AVEC 2011/2012](#)



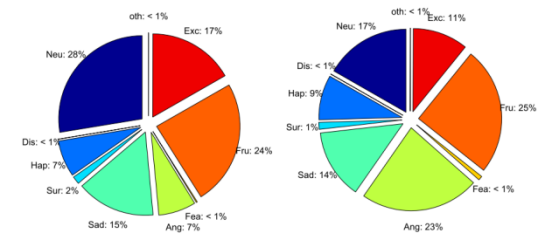
[AVEC 2013/2014](#)



[AVEC 2015/2016](#)

# Affect recognition dataset 3 (A3)

- The Interactive Emotional Dyadic Motion Capture ([IEMOCAP](#))
- 12 hours of data, but only 10 participants
- Video, speech, motion capture of face, text transcriptions
- Dyadic sessions where actors perform improvisations or scripted scenarios
- Categorical labels (6 basic emotions plus excitement, frustration) as well as dimensional labels (valence, activation and dominance)
- Focus is on speech



# Affect recognition dataset 4 (A4)

---

- Persuasive Opinion Multimedia (POM)
- 1,000 online movie review videos
- A number of speaker traits/attributes labeled – confidence, credibility, passion, persuasion, big 5...
- Video, audio and text
- Good quality audio and video recordings



**Positive opinions  
(5-star ratings)**



**Negative opinions  
(1- or 2-star ratings)**

# Affect recognition dataset 5 (A5)

---

- Multimodal Corpus of Sentiment Intensity and Subjectivity Analysis in Online Opinion Videos ([MOSI](#))
- 89 speakers with 2199 opinion segments
- Audio-visual data with transcriptions
- Labels for sentiment/opinion
  - Subjective vs objective
  - Positive vs negative



# Affect Recognition: CMU-MOSEI (A6)

- Multimodal sentiment and emotion recognition
- CMU-MOSEI : 23,453 annotated video segments from 1,000 distinct speakers and 250 topics

*And he I don't think he got mad when hah  
I don't know maybe.*

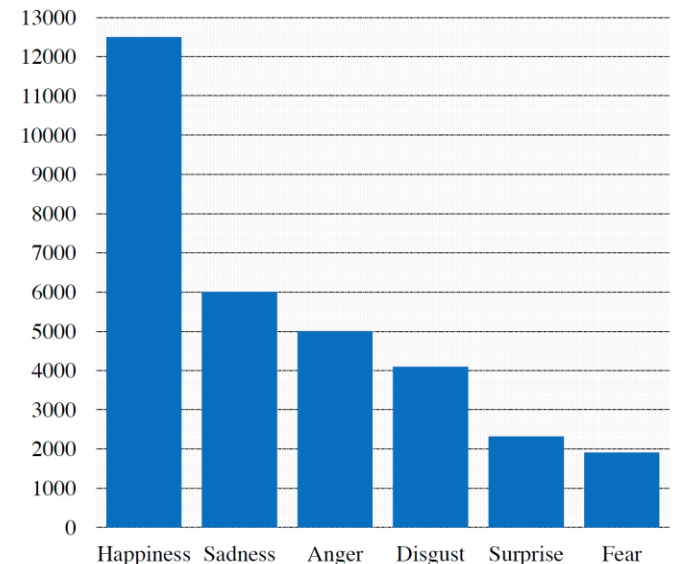
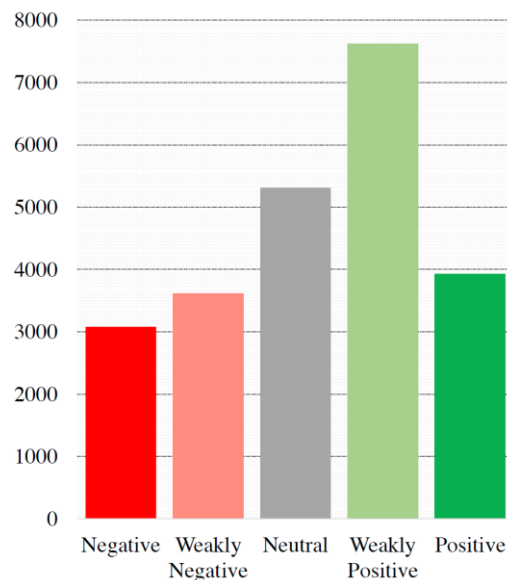


Gaze aversion  
(frustrated voice)

*All I can say is he's a pretty average guy.*



Contradictory smile  
(disappointed voice)



# Tumblr Dataset: Sentiment and Emotion Analysis (A7)

---

- [Tumblr Dataset](#) – Tumblr posts with images and emotion word tags.
- 256,897 posts with images.
- Labels obtained from 15 categories of emotion word tags.
- Dataset not directly available but code for collecting the dataset is provided.



Figure 1: Optimistic: “This reminds me that it doesn’t matter how bad or sad do you feel, always the sun will come out.” Source: travelingpilot [42]



Figure 2: Happy: “Just relax with this amazing view (at McWay Falls)” Source: fordosjulius [37]

# AMHUSE Dataset: Multimodal Humor Sensing (A8)

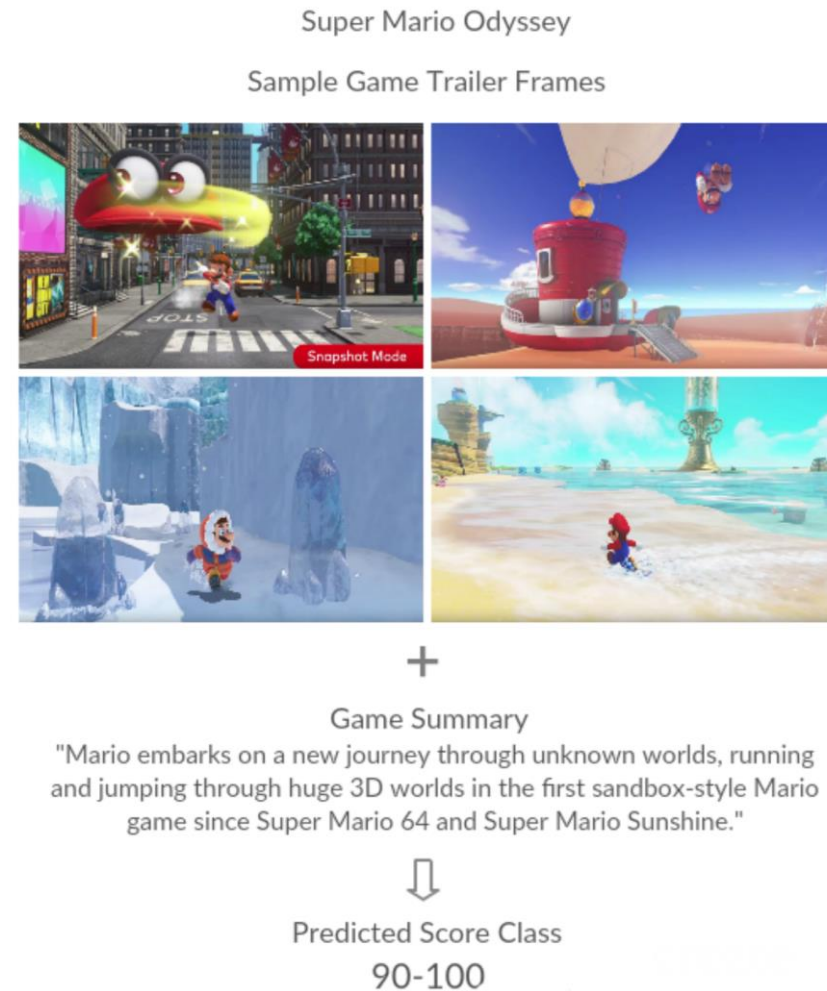
---

- AMHUSE – Multimodal humor sensing.
- Include various modalities:
  - Video from RGB-d camera, **but no audio/language**
  - Sensory data: blood volume pulse, electrodermal activity, etc.
- Time series of 36 recipients during 4 different stimuli.
- Continuous annotations of arousal, dominance throughout each time series. Case-level annotation of level of pleasure is also available.



# Video Game Dataset: Multimodal Game Rating (A9)

- [VGD](#) – Video Game Dataset, game rating based on text and trailer screenshots.
- 1,950 game trailers.
- Labelled for score ranges of the game, based on online critics.





## Other Affect Datasets (A10)

---

- MMDB: Multimodal Dyadic Behaviour Database



# Affect recognition technical challenges

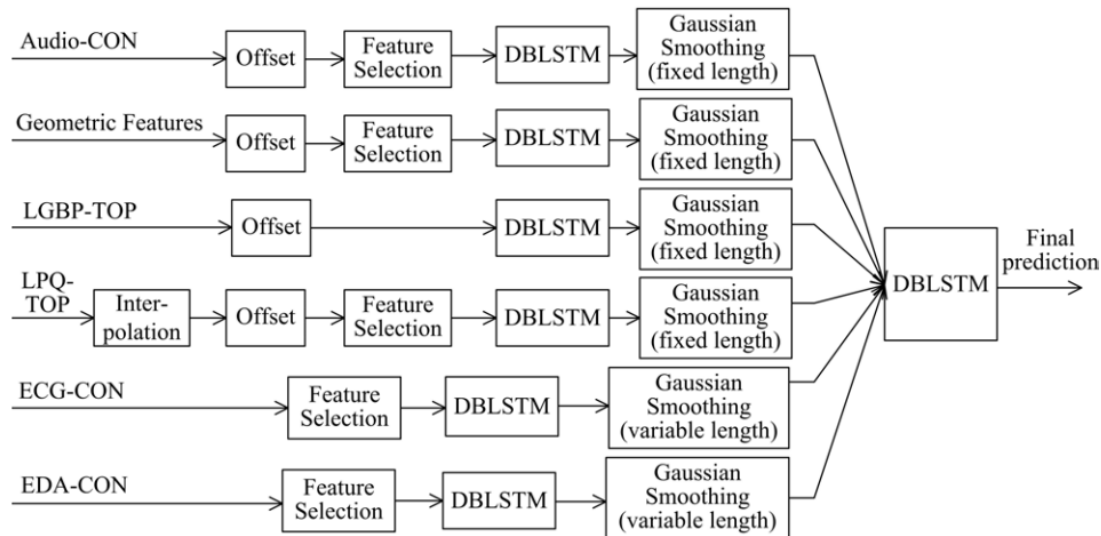
---

- What technical problems could be addressed?
  - Fusion
  - Representation
  - Translation
  - Co-training/transfer learning
  - Alignment (after misaligning)

# Affect recognition Challenges

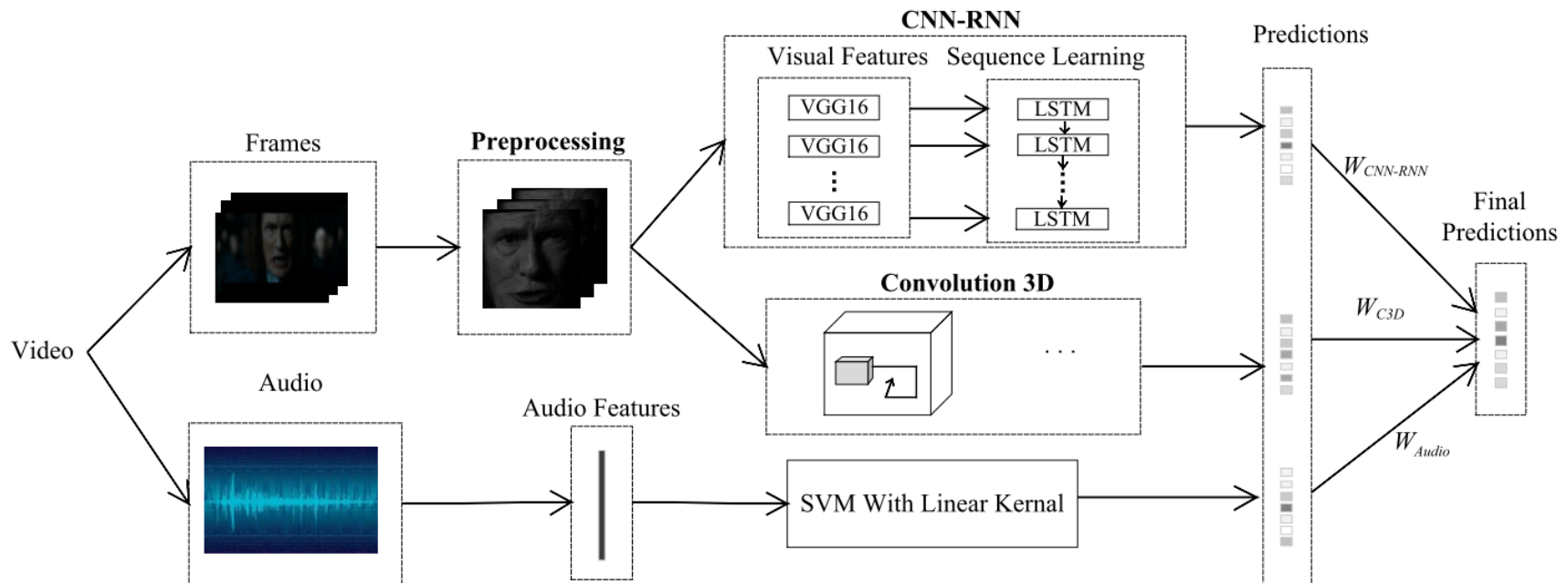
---

- AVEC 2015 challenge winner:
  - Multimodal Affective Dimension Prediction Using Deep Bidirectional Long Short-Term Memory Recurrent Neural Networks
- Will learn more about such models in week 4



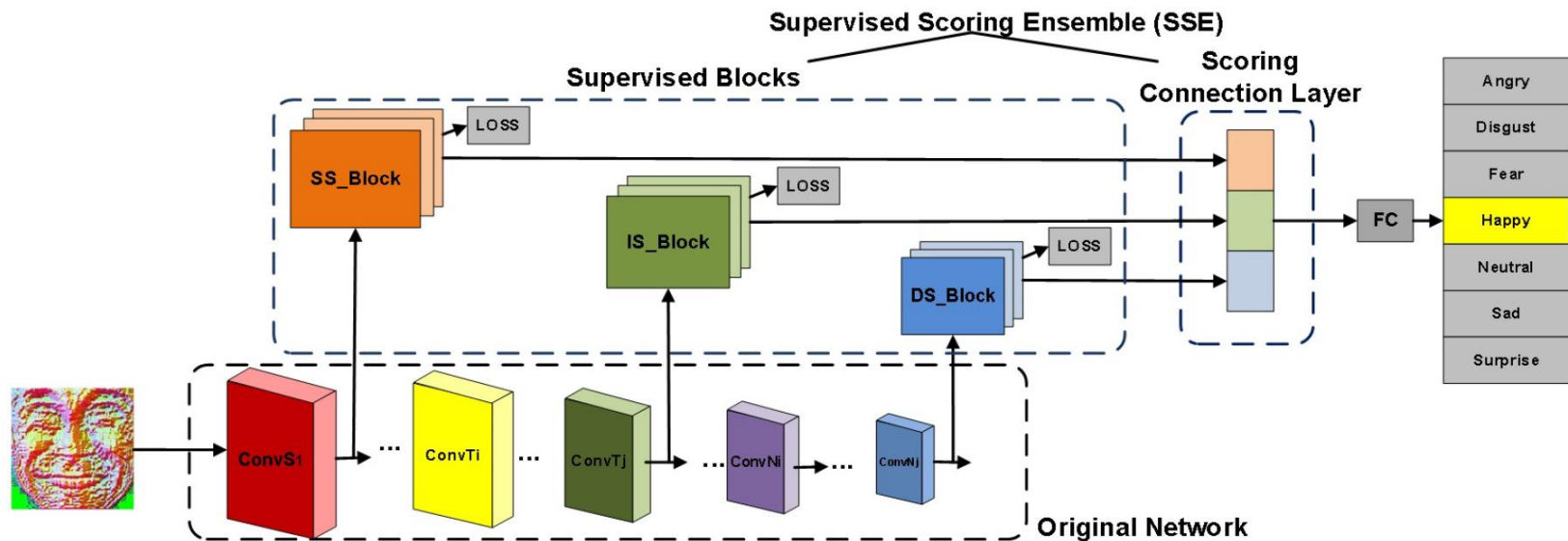
# Affect recognition Challenges

- EmotiW 2016 winner
- Video-based Emotion Recognition Using CNN-RNN and C3D Hybrid Networks



# Affect recognition Challenges

- EmotiW 2017 winner
- Learning Supervised Scoring Ensemble for Emotion Recognition in the Wild



# Media description

---

- Given a piece of media (image, video, audio-visual clips) provide a free form text description



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



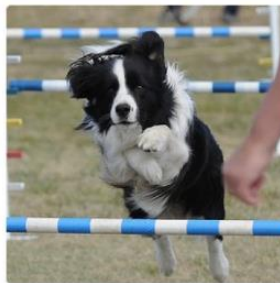
"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."



"girl in pink dress is jumping in air."



"black and white dog jumps over bar."



"young girl in pink shirt is swinging on swing."



"man in blue wetsuit is surfing on wave."

# Media description dataset 1 – MS COCO (B1)

---

- Microsoft Common Objects in COntext ([MS COCO](#))
- 120000 images
- Each image is accompanied with five free form sentences describing it (at least 8 words)
- Sentences collected using crowdsourcing (Mechanical Turk)
- Also contains object detections, boundaries and keypoints



The man at bat readies to swing at the pitch while the umpire looks on.



A large bus sitting next to a very tall building.

# Media description dataset 1 – MS COCO (B1)

---

- Has an evaluation server
  - Training and validation - 80K images (400K captions)
  - Testing – 40K images (380K captions), a subset contains more captions for better evaluation, these are kept privately (to avoid over-fitting and cheating)
- Evaluation is difficult as there is no one “correct” answer for describing an image in a sentence
- Given a candidate sentence it is evaluated against a set of “ground truth” sentences



## Evaluating Image Captioning Results - MS COCO (B1)

---

- A challenge was done with actual human evaluations of the captions ([CVPR 2015](#))

M1	Percentage of captions that are evaluated as better or equal to human caption.
M2	Percentage of captions that pass the Turing Test.
M3	Average correctness of the captions on a scale 1-5 (incorrect - correct).
M4	Average amount of detail of the captions on a scale 1-5 (lack of details - very detailed).
M5	Percentage of captions that are similar to human description.

## Evaluating Image Captioning Results - MS COCO (B1)

---

- A challenge was done with actual human evaluations of the captions ([CVPR 2015](#))

	M1	↓ M2	M3	M4	M5
Human <sup>[5]</sup>	0.638	0.675	4.836	3.428	0.352
Google <sup>[4]</sup>	0.273	0.317	4.107	2.742	0.233
MSR <sup>[8]</sup>	0.268	0.322	4.137	2.662	0.234
Montreal/Toronto <sup>[10]</sup>	0.262	0.272	3.932	2.832	0.197
MSR Captivator <sup>[9]</sup>	0.250	0.301	4.149	2.565	0.233
Berkeley LRCN <sup>[2]</sup>	0.246	0.268	3.924	2.786	0.204
m-RNN <sup>[15]</sup>	0.223	0.252	3.897	2.595	0.202
Nearest Neighbor <sup>[11]</sup>	0.216	0.255	3.801	2.716	0.196

## Evaluating Image Captioning Results - MS COCO (B1)

---

	<b>CIDEr-D</b>	<b>↓ F</b>	<b>Meteor</b>	<b>ROUGE-L</b>	<b>BLEU-1</b>	<b>BLEU-2</b>
Google <sup>[4]</sup>	0.943	0.254	0.53	0.53	0.713	0.542
MSR Captivator <sup>[9]</sup>	0.931	0.248	0.526	0.526	0.715	0.543
m-RNN <sup>[15]</sup>	0.917	0.242	0.521	0.521	0.716	0.545
MSR <sup>[8]</sup>	0.912	0.247	0.519	0.519	0.695	0.526
Nearest Neighbor <sup>[11]</sup>	0.886	0.237	0.507	0.507	0.697	0.521
m-RNN (Baidu/ UCLA) <sup>[16]</sup>	0.886	0.238	0.524	0.524	0.72	0.553
Berkeley LRCN <sup>[2]</sup>	0.869	0.242	0.517	0.517	0.702	0.528
Human <sup>[5]</sup>	0.854	0.252	0.484	0.484	0.663	0.469

## Media description dataset 2 - Video captioning (B2&B3)

---

- MPII Movie Description dataset (B2)
  - [A Dataset for Movie Description](#)
- Montréal Video Annotation dataset (B3)
  - [Using Descriptive Video Services to Create a Large Data Source for Video Annotation Research](#)



**AD:** Abby gets in the basket.



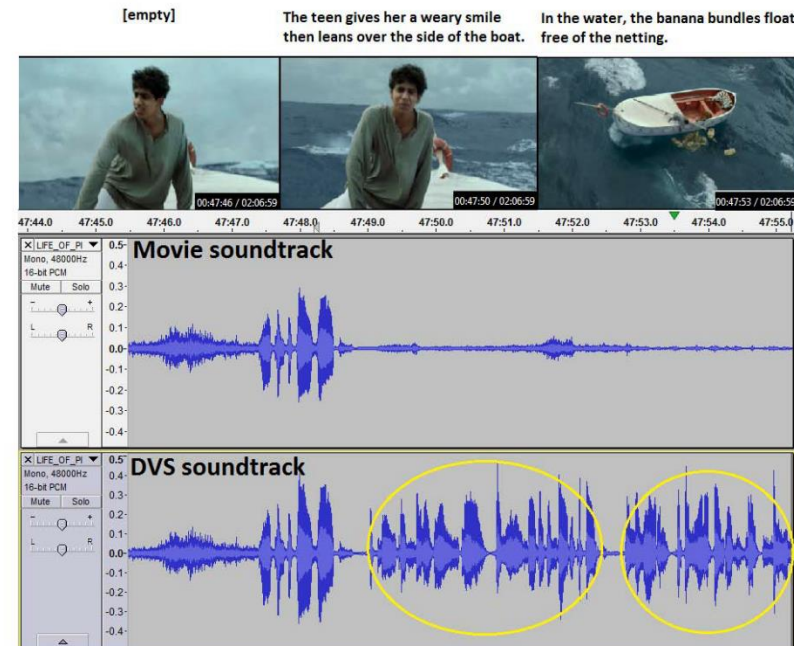
Mike leans over and sees how high they are.



Abby clasps her hands around his face and kisses him passionately.

## Media description dataset 2 - Video captioning (B2&B3)

- Both based on audio descriptions for the blind (Descriptive Video Service - DVS tracks)
- MPII – 70k clips (~4s) with corresponding sentences from 94 movies
- Montréal – 50k clips (~6s) with corresponding sentences from 92 movies
- Not always well aligned
- Quite noisy labels
- Single caption per clip



# Media description dataset 2 - Video captioning (B4)

---

- Large Scale Movie Description and Understanding Challenge ([LSMDC](#)) hosted at [ECCV 2016](#) and [ICCV 2015](#)
- Combines both of the datasets and provides three challenges
  - Movie description
  - Movie annotation and Retrieval
  - Movie Fill-in-the-blank
- Nice challenge, but beware
  - Need a lot of computational power
  - Processing will take space and time



# Charades Dataset –video description dataset (B5)

- <http://allenai.org/plato/charades/>
- 9848 videos of daily indoors activities
- 267 different users
- Recording videos at home
- Home quality videos

## Sampled Words

### *Kitchen*

vacuum  
groceries  
chair  
refrigerator  
pillow

laughing  
drinking  
putting  
washing  
closing

AMT

## Scripts

"A person is washing their refrigerator. Then, opening it, the person begins putting away their groceries."

"A person opens a refrigerator, and begins drinking out of a jug of milk before closing it."

AMT

## Recorded Videos



AMT

## Annotations

"A person stands in the kitchen and cleans the fridge. Then start to put groceries away from a bag"

Opening a refrigerator

Putting groceries somewhere

Closing a refrigerator

"person drinks milk from a fridge, they then walk out of the room."

Opening a refrigerator

Drinking from cup/bottle



# Media Description dataset 3 – VQA (B6)

---

- Task - Given an image and a question, answer the question (<http://www.visualqa.org/>)



What color are her eyes?  
What is the mustache made of?



How many slices of pizza are there?  
Is this a vegetarian pizza?



Is this person expecting company?  
What is just under the tree?



Does it appear to be rainy?  
Does this person have 20/20 vision?



# Media Description dataset 3 – VQA (B6)

## Real images


- 200k MS COCO images
- 600k questions
- 6M answers
- 1.8M plausible answers

## Abstract images

- 50k scenes
- 150k questions
- 1.5M answers
- 450k plausible answers

8653. COCO\_train2014\_000000450914

Image On/Off



Open-Ended/Multiple-Choice/Ground-Truth/Common-Sense

Q: Are these veggies or fruits?

Ground Truth Answers:

(1) Fruits	(6) Fruit
(2) fruits	(7) fruits
(3) fruits	(8) fruits
(4) fruits	(9) fruits
(5) fruits	(10) fruits

Q: What is in the white bowl?

Ground Truth Answers:

(1) strawberries	(6) strawberries
(2) strawberries	(7) strawberry
(3) strawberry	(8) strawberries
(4) strawberries	(9) strawberries
(5) fruits	(10) strawberries



Is this person expecting company?  
What is just under the tree?

## VQA Challenge 2016 and 2017 (B6)

---

- Two challenges organized these past two years ([link](#))
- Currently good at yes/no question, not so much free form and counting

	By Answer Type			Overall ▾
	Yes/No ▾	Number ▾	Other ▾	
UC Berkeley & Sony <sup>[14]</sup>	83.79	38.9	58.64	66.9
Naver Labs <sup>[10]</sup>	83.78	37.67	54.74	64.89
DLAIT <sup>[5]</sup>	83.65	39.18	52.62	63.97
snubi-naverlabs <sup>[25]</sup>	83.64	38.43	51.61	63.4
POSTECH <sup>[11]</sup>	81.85	38.02	53.12	63.35
Brandeis <sup>[3]</sup>	82.53	36.54	51.71	62.8
VTComputerVison <sup>[19]</sup>	80.31	37.87	52.16	62.23
MIL-UT <sup>[7]</sup>	82.39	36.7	49.76	61.82

# VQA 2.0

---

- Just guessing without an image lead to ~51% accuracy
  - So the V in VQA “only” adds 14% increase in accuracy
- [VQA v2.0](#) is attempting to address this

Who is wearing glasses?

man



woman

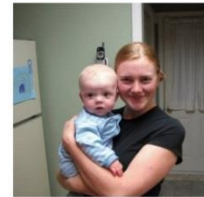


Where is the child sitting?

fridge



arms



Is the umbrella upside down?

yes



no



How many children are in the bed?

2



1



# Media Description – other VQA datasets



COCOQA

Q: What is the color of the desk?

A: white

Q: What are on the white desk?

A: computers



COCOQA

Q: What is the color of the dresses?

A: purple

Q: What are three women dressed up and on?

A: phones



DAQUAR

Q: What is the object close to the wall?

A: whiteboard

Q: What is the object in front of the sofa?

A: table



DAQUAR

Q: What is the largest object?

A: sofa

Q: How many windows are there?

A: 2



VQA

Q: How many bikes are there?

A: 2

Q: What number is the bus?

A: 48



VQA

Q: How many pickles are on the plate?

A: 1

Q: What is the shape of the plate?

A: round



VQA

Q: What does the sign say?

A: stop

Q: What shape is this sign?

A: octagon



VQA

Q: What type of trees are here?

A: palm

Q: Is the skateboard airborne?

A: yes

## Media Description – Other VQA datasets (B7&B8)

---

- DAQUAR (B7)
  - Synthetic QA pairs based on templates
  - 12468 human question-answer pairs
  
- COCO-QA (B8)
  - Object, Number, Color, Location
  - Training: 78736
  - Test: 38948

# Media Description – other VQA datasets (B9)

## ■ Visual Madlibs

- Fill in the blank Image Generation and Question Answering
- 360,001 focused natural language descriptions for 10,738 images
- collected using automatically produced fill-in-the-blank templates designed to gather targeted descriptions about: people and objects, their appearances, activities, and interactions, as well as inferences about the general scene or its broader context



1. This place is a park.
2. When I look at this picture, I feel competitive.
3. The most interesting aspect of this picture is the guys playing shirtless.
4. One or two seconds before this picture was taken, the person caught the frisbee.
5. One or two seconds after this picture was taken, the guy will throw the frisbee.
6. Person A is wearing blue shorts.
7. Person A is in front of person B.
8. Person A is blocking person B.
9. Person B is a young man wearing an orange hat.
10. Person B is on a grassy field.
11. Person B is holding a frisbee.
12. The frisbee is white and round.
13. The frisbee is in the hand of the man with the orange cap.
14. People could throw the frisbee.
15. The people are playing with the frisbee.

# Media Description – other VQA datasets (B10)

## ■ Textbook Question Answering

- Multi-Modal Machine Comprehension
- Context needed to answer questions provided and composed of both text and images
- 78338 sentences, 3455 images
- 26260 questions

Multi-modal Machine Comprehension (M<sup>2</sup>C)

Training Set → No content overlap → Testing Set


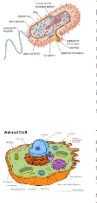
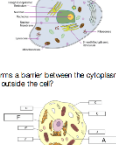
Textbook Question Answering (TQA)

1076 lessons from middle school curricula

78,338 sentences  
3,455 images  
26,260 questions

Life Science | Earth Science | Physical Science

Lessons in TQA

Cell Structures	Cell Membrane Structure	Instructional Diagrams	Questions						
<p><b>Introduction</b></p> <p>In some ways, a cell resembles a plastic bag full of jelly. Its basic structure is a cell membrane that sets cytoplasm, the cytoplasm of a eukaryotic cell is the jelly containing mixed fruit. It also contains a nucleus and other organelles.</p> <p><b>Cell Membrane</b></p> <p>The cell membrane is like the bag holding the jelly. It encloses the cytoplasm of the cell. It forms a barrier between the cytoplasm and the environment outside the cell. The function of the cell membrane is to protect and support the cell. It also controls what enters or leaves the cell. It allows only certain substances to pass through. It keeps other substances inside or outside the cell.</p> 	<p><b>Cell Membrane Structure</b></p> <p><b>Cytoplasm</b></p> <p><b>Organelles</b></p> <p><b>Lesson Summary</b></p> <ul style="list-style-type: none"><li>• The cell membrane consists of two layers of phospholipids.</li><li>• The cytoplasm consists of watery cytosol and cell structures.</li><li>• Eukaryotic cells contain a nucleus and other organelles.</li></ul> <p><b>Vocabulary</b></p> <table border="1"><tr><td>Cell Wall</td><td>rigid layer that surrounds the cell membrane of a plant cell or fungi cell and that supports and protects the cell</td></tr><tr><td>Cytoplasm</td><td>structure in a cell consisting of filaments and tubules that crisscross the cytoplasm and help maintain the cell's shape</td></tr><tr><td>Central Vacuole</td><td>large storage sac found in the cells of plants</td></tr></table>	Cell Wall	rigid layer that surrounds the cell membrane of a plant cell or fungi cell and that supports and protects the cell	Cytoplasm	structure in a cell consisting of filaments and tubules that crisscross the cytoplasm and help maintain the cell's shape	Central Vacuole	large storage sac found in the cells of plants	<p><b>Instructional Diagrams</b></p> <p>The image below shows the Prokaryotic cell. A prokaryote is a single-celled organism that lacks a membrane-bound nucleus (nucleus), mitochondria, or any other membrane-bound organelle. In the prokaryotes, all the intracellular, water-soluble components (proteins, DNA, and metabolites) are located together in the cytoplasm enclosed by the cell membrane, rather than in separate cellular compartments.</p> <p>This diagram shows the anatomy of an Animal Cell. Animal Cells have an outer boundary known as the plasma membrane. The nucleus and the organelles of the cell are bound by the membrane. The cell organelles have a vast range of functions to perform the homeostasis and enzyme production to proceed smoothly for the cells. They are of various sizes and have irregular shapes. Most of the cells size range between 1 and 100 micrometers and are visible only with help of microscope.</p> 	<p><b>Questions</b></p> <p>What is the outer surrounding part of the Nucleus?</p> <p>a. Nuclear Membrane b. Cell Body c. Cell Membrane d. Nucleolus</p> <p>Which component forms a barrier between the cytoplasm and the environment outside the cell?</p> <p>a. J b. L c. X d. U</p> <p>Which statement about the cell membrane is false?</p> <p>a. It encloses the cytoplasm b. It protects and supports the cell c. It keeps all external substances out of the cell d. none of the above</p> 
Cell Wall	rigid layer that surrounds the cell membrane of a plant cell or fungi cell and that supports and protects the cell								
Cytoplasm	structure in a cell consisting of filaments and tubules that crisscross the cytoplasm and help maintain the cell's shape								
Central Vacuole	large storage sac found in the cells of plants								

# Media Description – other VQA datasets (B11)

## ■ Visual7W

- Grounded Question Answering in Images
- 327,939 QA pairs on 47,300 COCO images
- 1,311,756 multiple-choices, 561,459 object groundings, 36,579 categories
- what, where, when, who, why, how and which

**Where does this scene take place?**  
A) In the sea. ✓  
B) In the desert.  
C) In the forest.  
D) On a lawn.

**What is the dog doing?**  
A) Surfing. ✓  
B) Sleeping.  
C) Running.  
D) Eating.

**Which paw is lifted?**

**Why is there foam?**  
A) Because of a wave. ✓  
B) Because of a boat.  
C) Because of a fire.  
D) Because of a leak.

**What is the dog standing on?**  
A) On a surfboard. ✓  
B) On a table.  
C) On a garage.  
D) On a ball.



# Media Description – Referring Expression datasets (B12)

---

## ■ Referring Expressions:

- Generation (Bounding Box to Text) and Comprehension (Text to Bounding Box)
- Generate / Comprehend a noun phrase which identifies a particular object in an image
- Many datasets!
  - RefClef
  - RefCOCO (+, g)
  - GRef

RefClef	RefCOCO	RefCOCO+
		
right rocks rocks along the right side stone right side of stairs	woman on right in white shirt woman on right right woman	guy in yellow dirbbling ball yellow shirt and black shorts yellow shirt in focus

# Media Description - Referring Expression datasets (B13)

## GuessWhat?!

- Cooperative two-player guessing game for language grounding
- Locate an unknown object in a rich image scene by asking a sequence of questions
- 821,889 questions+answers
- 66,537 images and 134,073 objects



### Questioner

- Is it a vase?
- Is it partially visible?
- Is it in the left corner?
- Is it the turquoise and purple one?

### Oracle

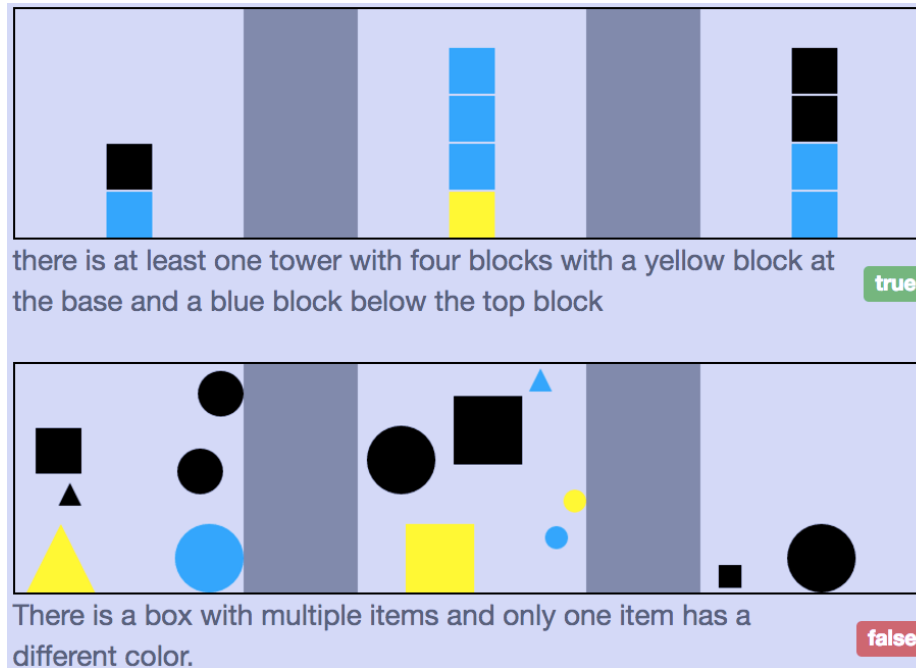
- Yes
- No
- No
- Yes

# Media Description – Visual Reasoning (B14)

---

## ■ Cornell NLVR

- 92,244 pairs of natural language statements grounded in synthetic images
- Determine whether a sentence is true or false about an image



The image displays two examples of visual reasoning tasks from the Cornell NLVR dataset. Each example consists of a synthetic image and a natural language statement with a true/false label.

**Example 1:** The image shows three towers of blocks. The first tower has a blue block at the base and a black block on top. The second tower has a yellow block at the base and three blue blocks stacked on top. The third tower has a blue block at the base, a black block in the middle, and another black block on top. The statement is: "there is at least one tower with four blocks with a yellow block at the base and a blue block below the top block". The label is "true".

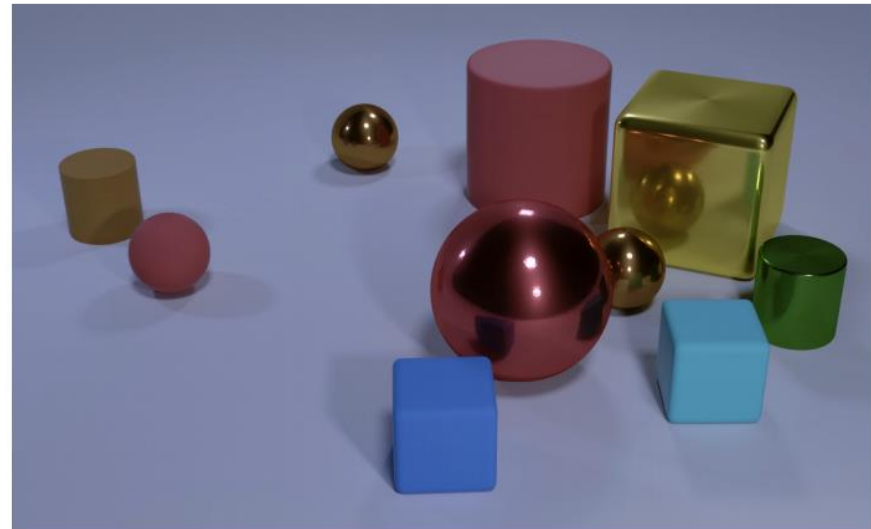
**Example 2:** The image shows a collection of various shapes and colors: a black square, a black triangle, a yellow triangle, a black circle, a blue circle, a black circle, a black square, a blue triangle, a yellow square, a blue circle, a yellow circle, a black square, a black circle, and a black circle. The statement is: "There is a box with multiple items and only one item has a different color." The label is "false".

# Media Description - Visual Reasoning (B15)

---

## ■ CLEVR

- A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning
- Tests a range of different specific visual reasoning abilities
- Training set: 70,000 images and 699,989 questions
- Validation set: 15,000 images and 149,991 questions
- Test set: 15,000 images and 14,988 questions



- Q: Are there an **equal number** of large things and metal spheres?  
Q: What size is the cylinder **that is left of the brown metal thing that is left of the big sphere**?  
Q: There is a sphere with the **same size as** the metal cube; is it **made of the same material as** the small red sphere?  
Q: **How many** objects **are either small cylinders or metal things**?

# Media Description - other datasets (B16)

## ■ Flickr30k Entities

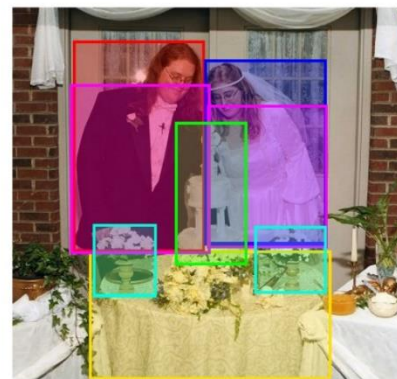
- Region-to-Phrase Correspondences for Richer Image-to-Sentence Models
- 158k captions
- 244k coreference chains
- 276k manually annotated bounding boxes



A man with **pierced ears** is wearing **glasses** and an **orange hat**.  
A man with **glasses** is wearing a **beer can crotched hat**.  
A man with **gauges** and **glasses** is wearing a **Blitz hat**.  
A man in an **orange hat** starring at **something**.  
A man wears an **orange hat** and **glasses**.



During a **gay pride parade** in an **Asian city**, **some people** hold up **rainbow flags** to show their **support**.  
A **group of youths** march down a **street** waving **flags** showing a **color spectrum**.  
**Oriental people** with **rainbow flags** walking down a **city street**.  
A **group of people** walk down a **street** waving **rainbow flags**.  
**People** are **outside** waving **flags**.

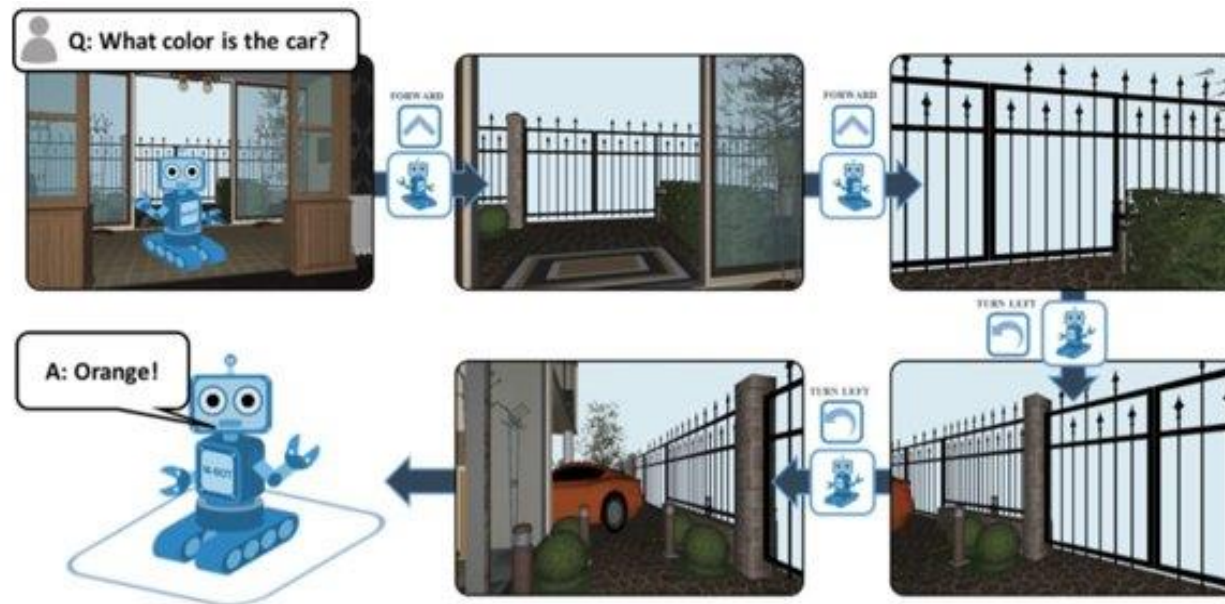


A couple in **their wedding attire** stand behind a **table** with a **wedding cake** and **flowers**.  
A **bride** and **groom** are standing in front of **their wedding cake** at their reception.  
A **bride** and **groom** smile as **they view their wedding cake** at a reception.  
A couple stands behind **their wedding cake**.  
**Man** and **woman** cutting **wedding cake**.

## Media Description: Embodied Question Answering (B17)

---

- An agent is spawned at a random location in a 3D environment and asked a question
- [EQA v1.0](#): 9,000 questions from 774 environments



# Media Description: Visual Dialog (B18)

- VisDial v0.9: total of ~1.2M dialog question-answer pairs (1 dialog with 10 question-answer pairs on ~120k images from MS-COCO)
- [VisDial v1.0](#) has also been released recently
- A Visual Dialog Challenge is organized at ECCV 2018



## Room-2-Room Navigation with NL instructions (B19)

---

- Visually grounded natural language navigation in real buildings
- [Room-2-Room](#): 21,567 open vocabulary, crowd-sourced navigation instructions



**Instruction:** Head upstairs and walk past the piano through an archway directly in front. Turn right when the hallway ends at pictures and table. Wait by the moose antlers hanging on the wall.



# CSI Corpus (B20)

---

- CSI-Corpus: 39 videos from the U.S. TV show “Crime Scene Investigation Las Vegas”
- Data: Sequence of inputs comprising information from different modalities such as text, video, or audio. The task is to predict for each input whether the perpetrator is mentioned or not.



**Peter Berglund:**

You're still going to have to convince a jury that I killed two **strangers** for no reason.



*Grissom doesn't look worried.*

*He takes **his** gloves off and puts them on the table.*



**Grissom:**

You ever been to the theater **Peter**? There 's a play called six degrees of separation.



It 's about how all the people in the world are connected to each other by no more than six people. All it takes to connect **you** to the **victims** is one degree.



*Camera holds on **Peter Berglund**'s worried look.*

# Multimodal Machine Translation (B21)

---

- Generate an image description in a target language, given an image and one or more descriptions in a source language
- <http://www.statmt.org/wmt16/multimodal-task.html>
- 30K multilingual captioned images (German and English)

1. Brick layers constructing a wall.

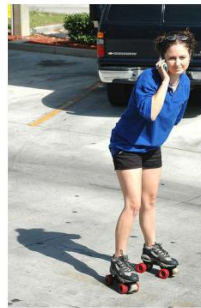


2. Maurer bauen eine Wand.

1. The two men on the scaffolding are helping to build a red brick wall.

2. Zwei Maurer mauern ein Haus zusammen.

1. Trendy girl talking on her cellphone while gliding slowly down the street



2. Ein schickes Mädchen spricht mit dem Handy während sie langsam die Straße entlangschwebt.

1. There is a young girl on her cellphone while skating.

2. Eine Frau im blauen Shirt telefoniert beim Rollschuhfahren.

(a) Translations

(b) Independent descriptions

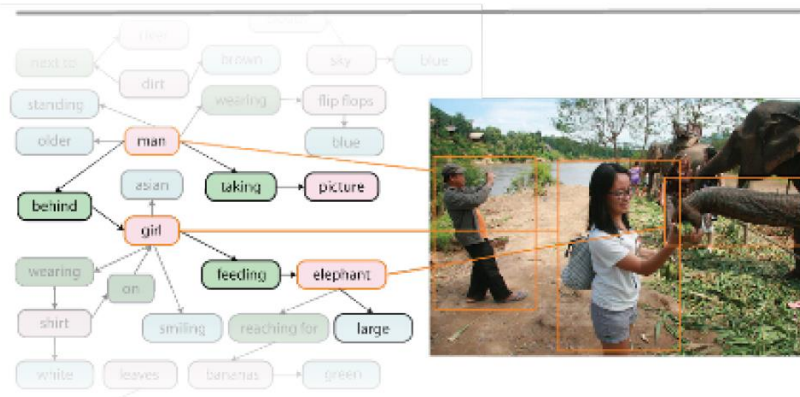
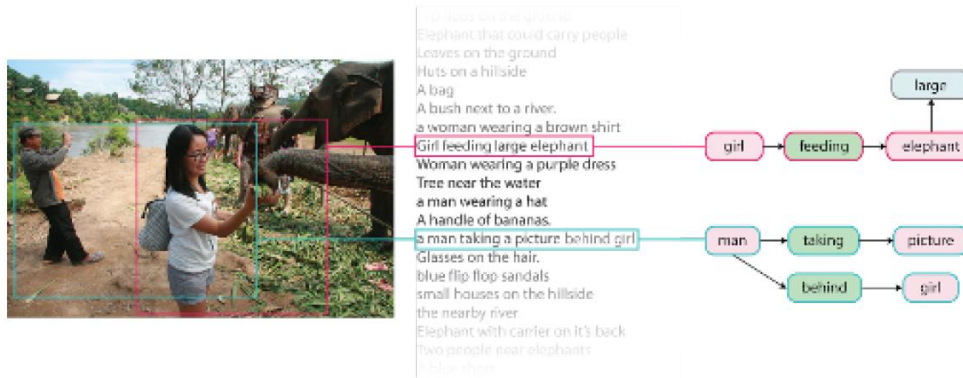
## Other Media Description Datasets (B22, B23, B24 & B25)

---

- [MVSO](#) (B22): Multilingual Visual Sentiment Ontology. There are multiple derivatives of this as well
- Dataset from the AAAI'16 [paper](#) 'Listen, Attend, and Walk: Neural Mapping of Navigational Instructions to Action Sequences'. The data is provided with the code [here](#).
- [Visual Relation](#) dataset (B23): learning relations between objects based on language priors.
- [Visual genome](#) (B24) Great resource for many multimodal problems.
- [Pinterest](#) (B25): Contains 300 million sentences describing over 40 million 'pins'

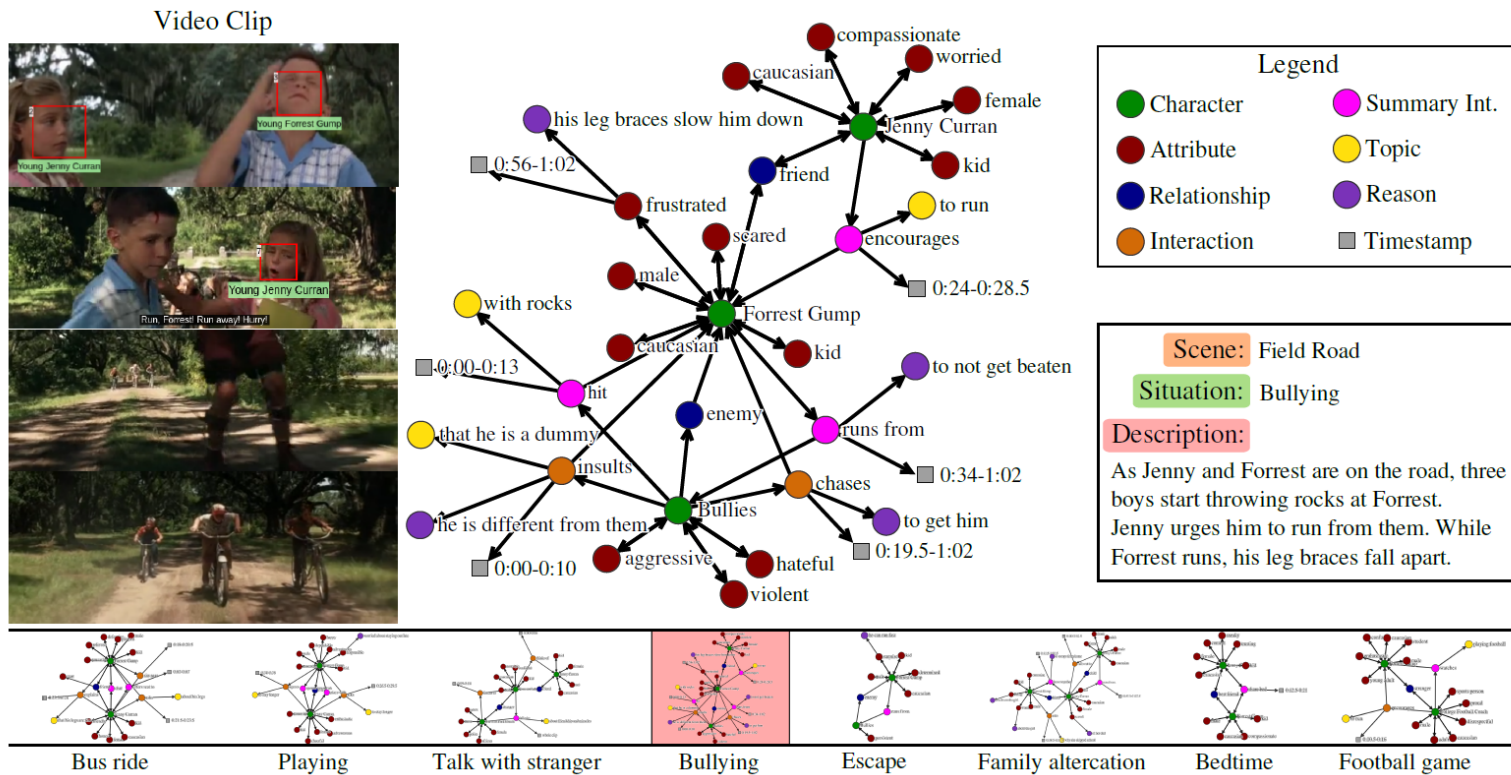
# Visual Genome (B24)

- <https://visualgenome.org/>



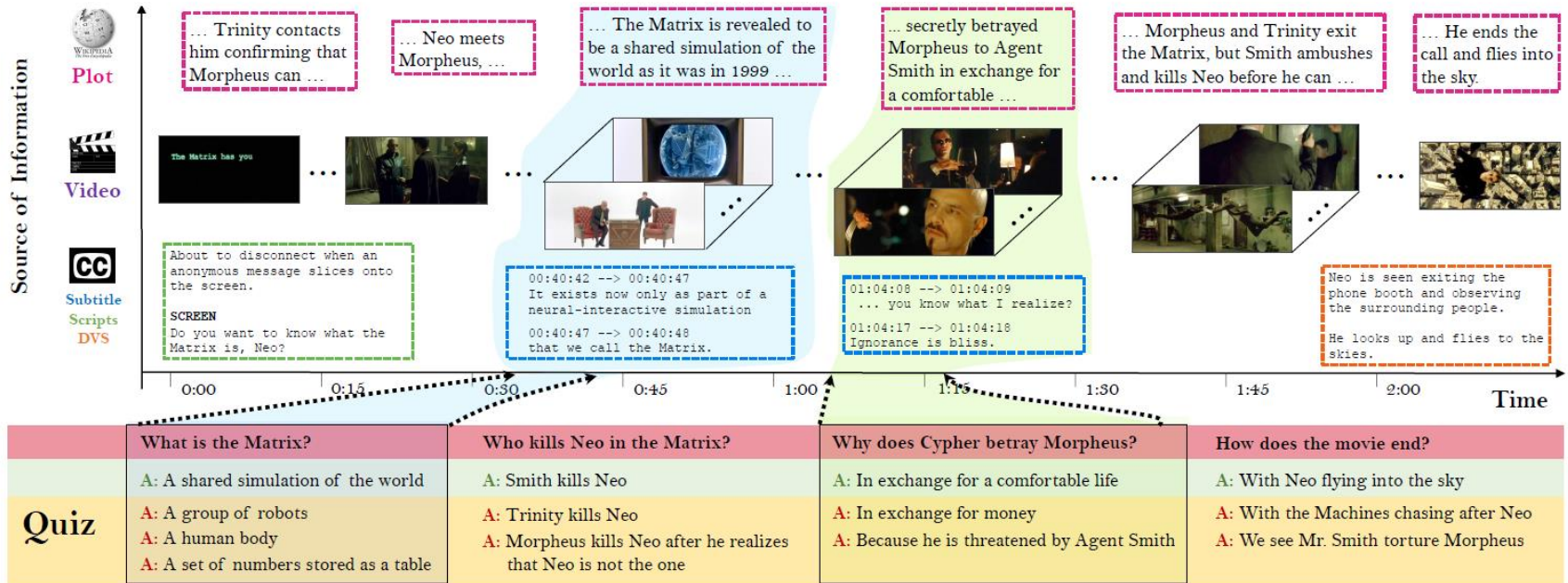
# MovieGraph dataset (B26)

- <http://moviegraphs.cs.toronto.edu/>



# Movie QA (B27)

- <http://movieqa.cs.toronto.edu/home/>



# Media description technical challenges

---

- What technical problems could be addressed?
  - Translation
  - Representation
  - Alignment
  - Co-training/transfer learning
  - Fusion



The man at bat readies to swing at the pitch while the umpire looks on.



A large bus sitting next to a very tall building.



AD: Abby gets in the basket.



Mike leans over and sees how high they are.



Abby clasps her hands around his face and kisses him passionately.



What color are her eyes?  
What is the mustache made of?



How many slices of pizza are there?  
Is this a vegetarian pizza?

# Event detection

- Given video/audio/ text detect predefined events or scenes
- Segment events in a stream
- Summarize videos



Action knead      Object dough      Run Hybrid      [SEARCH](#)

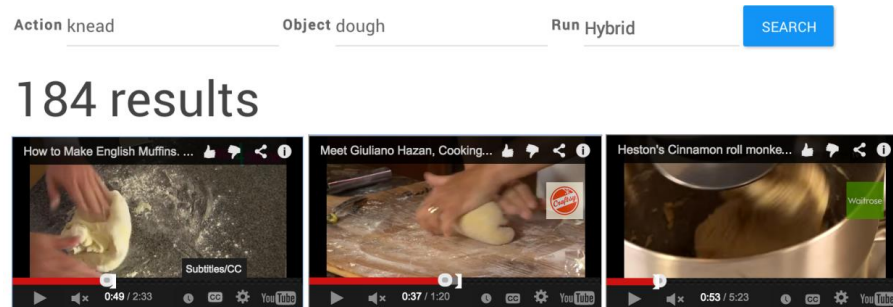
184 results





# Event detection dataset 1 (C1, C2, C3 & C4)

- [What's Cooking](#) (C1)- cooking action dataset
  - **melt butter, brush oil, etc.**
  - **taste, bake etc.**
- Audio-visual, ASR captions
  - 365k clips
  - Quite noisy
- Surprisingly many cooking datasets:
  - [TACoS](#) (C2), [TACoS Multi-Level](#) (C3), [YouCook](#) (C4)



# Event detection dataset 2 (C5)

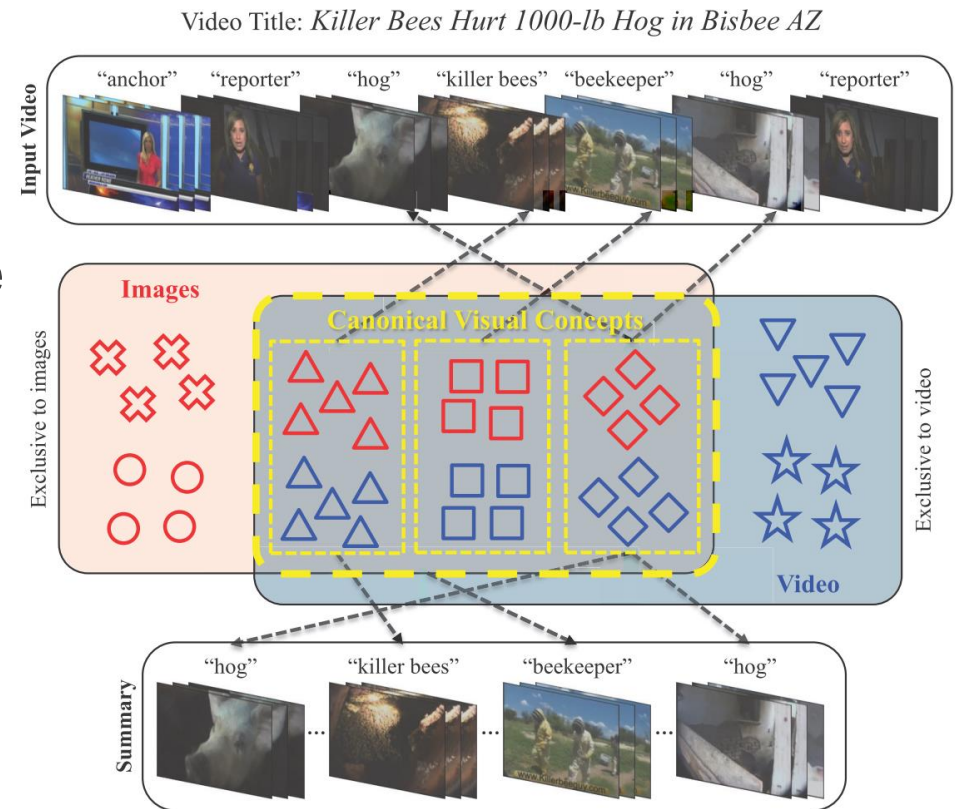
---

- Multimedia event detection
  - TrecVid Multimedia Event Detection ([MED](#)) 2010-2015
  - One of the six TrecVid tasks
  - Audio-visual data
  - Event detection



# Event detection dataset 3 (C6)

- [Title-based Video Summarization dataset](#)
- 50 videos labeled for scene importance, can be used for summarization based on the title



# Event detection dataset 4 (C7)

---

- [MediaEval](#) challenge datasets
  - Affective Impact of Movies (including Violent Scenes Detection)
  - Synchronization of Multi-User Event Media
  - Multimodal Person Discovery in Broadcast TV

# CrisisMMD: Natural Disaster Assessment (C8)

- [CrisisMMD](#) – Multimodal Dataset for Natural Disasters
- 16,097 Twitter posts with one or more images
- Annotations comprises of 3 types:
  - Informative vs. Uninformative for humanitarian aid purposes
  - Humanitarian aid categories
  - Damage Assessment

Informative



(a) Hurricane Maria turns Dominica into 'giant debris field' <https://t.co/rAISiAhMUy> by #AJEnglish via @c0nvey <https://t.co/l4zeuW4gkc>

Not informative



(d) @SueAikens hi su o back againe big hug FROM PUERTO RICO love you <https://t.co/HCEyIHB0QZ>

Rescue & volunteering



(g) Puerto Rico donation drive going on until 4 p.m. today and again on Oct. 28! <https://t.co/zXZBrHeLCQ> <https://t.co/2T9k2mTCIs>

# Event detection technical challenges

---

- What technical problems could be addressed?
  - Fusion
  - Representation
  - Co-learning
  - Mapping
  - Alignment (after misaligning)

# Cross-media retrieval

---

- Given one form of media retrieve related forms of media, given text retrieve images, given image retrieve relevant documents
- Examples:
  - Image search
  - Similar image search
- Additional challenges
  - Space and speed considerations

# IKEA Interior Design Dataset: Multimodal Retrieval (D1)

---

- [Interior Design Dataset](#) – Retrieve desired product using room photos and text queries.
- 298 room photos, 2193 product images/descriptions.

Room images:



Object images:



Description:

You sit comfortably thanks to the armrests.

There's a natural and living feeling of wood, as knots and other marks remain on the surface.

This lamp gives a pleasant light for dining and spreads a good directed light across your dining or bar table.



## Cross-media retrieval datasets (D2, D3, D4 & D5)

---

- [MIRFLICKR-1M](#) (D2)
  - 1M images with associated tags and captions
  - Labels of general and specific categories
- [NUS-WIDE dataset](#) (D3)
  - 269,648 images and the associated tags from Flickr, with a total number of 5,018 unique tags;
- [Yahoo Flickr Creative Commons 100M](#) (D4)
  - Videos and images
- [Wikipedia featured articles dataset](#) (D5)
  - 2866 multimedia documents (image + text)
- Can also use image and video captioning datasets
  - Just pose it as a retrieval task



## Other Multimodal Datasets (D6, D7, D8, D9 & D10)

---

- 1) Youtube 8M (D6)
  - <https://research.google.com/youtube8m/>
- 2) Youtube Bounding Boxes (D7)
  - <https://research.google.com/youtube-bb/>
- 3) Youtube Open Images (D8)
  - <https://research.googleblog.com/2016/09/introducing-open-images-dataset.html>
- 4) YFCC 100M (D9)
  - <https://webscope.sandbox.yahoo.com/catalog.php?datatype=i&did=67>
- 5) VIST (D10)
  - <http://visionandlanguage.net/VIST/>

# Cross-media retrieval challenges

---

- What technical problems could be addressed?
  - Representation
  - Translation
  - Alignment
  - Co-learning
  - Fusion

# Technical issues and support

# Challenges

---

- To those used to only dealing with text or speech
  - Space will become an issue working with image and video data
  - Some datasets are in 100s of GB (compressed)
- Memory for processing it will become an issue as well
  - Won't be able to store it all in memory
- Time to extract features and train algorithms will also become an issue
- Plan accordingly!
  - Sometimes tricky to experiment on a laptop (might need to do it on a subset of data)

# Available tools

---

- Use available tools in your research groups
  - Or pair up with someone that has access to them
- Find a GPU!
- We will be getting AWS credit for some extra computational power
  - Will allow for training in the cloud
- Google Cloud Platform credit as well



Google Cloud Platform



**amazon**  
**web services™**



## Before next class

---

- Let us know
  - what challenge and dataset interests you
  - What computational power you have available
  - Instructions how to do this are posted on Piazza
- Will reserve 15+ minutes next week for discussions to help you find project teammates
- Reading group assignment
  - [Representation Learning: A Review and New Perspectives](#)
    - Sections 1-3, 6-8, 11
  - [Multimodal Machine Learning: A Survey and Taxonomy](#)
    - Sections 1, 2 and 3
  - Questions announced on Friday
    - Answer using Gradescope (instructions will follow soon)
    - Everybody needs to submit their answers (even if you travel)

## Reference book for the course

---

- Good reference source
- Is not focused on multimodal but good primer for deep learning
- <http://www.deeplearningbook.org/>