



Language  
Technologies  
Institute

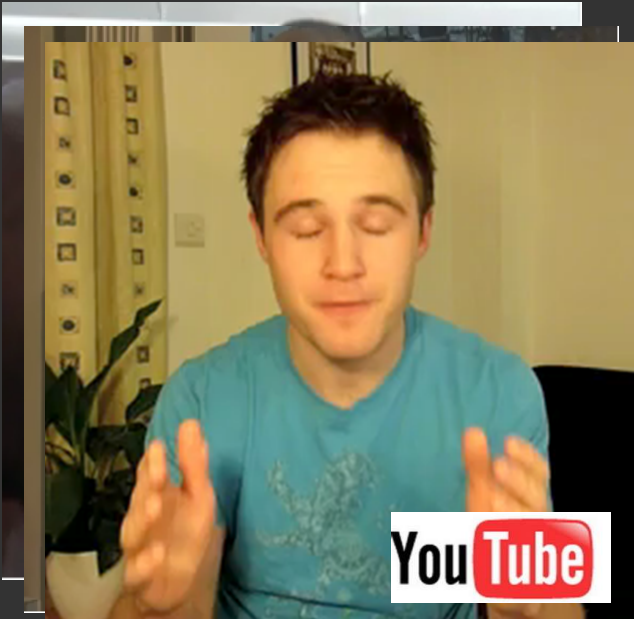
Carnegie  
Mellon  
University

# Multimodal Sentiment Analysis with Word-Level Fusion and Reinforcement Learning

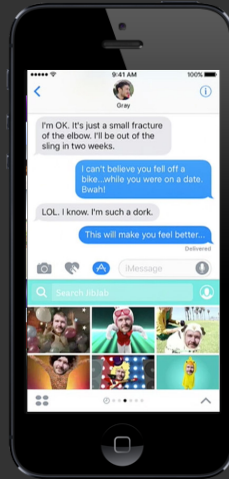
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Tadas Baltrusaitis, Amir Zadeh, Louis-Philippe Morency

# Natural Computer Interaction

## Parasocial Interactions (e.g., multimedia content)



## Intelligent Personal Assistant



## Robots and Virtual Agents



# Multimodal Communicative Behaviors

## Verbal

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

## Vocal

- **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



## Sentiment

- Positive
- Negative

## Emotion

- Anger
- Disgust
- Fear
- Happiness
- Sadness
- Surprise

## Social

- Empathy
- Engagement
- Dominance



# Multimodal Sentiment Analysis

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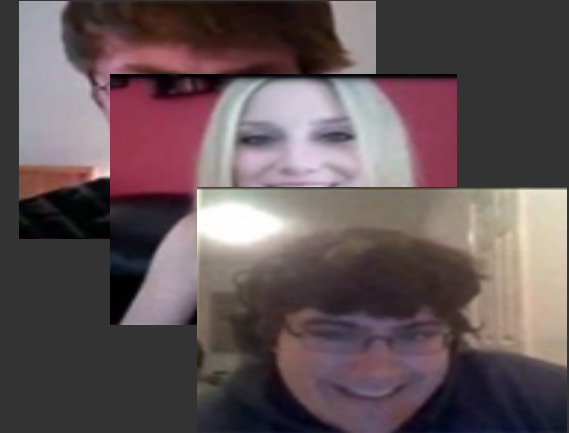
## Sentiment

- Highly positive
- Positive
- Weakly positive
- Neutral
- Weakly negative
- Negative
- Highly negative

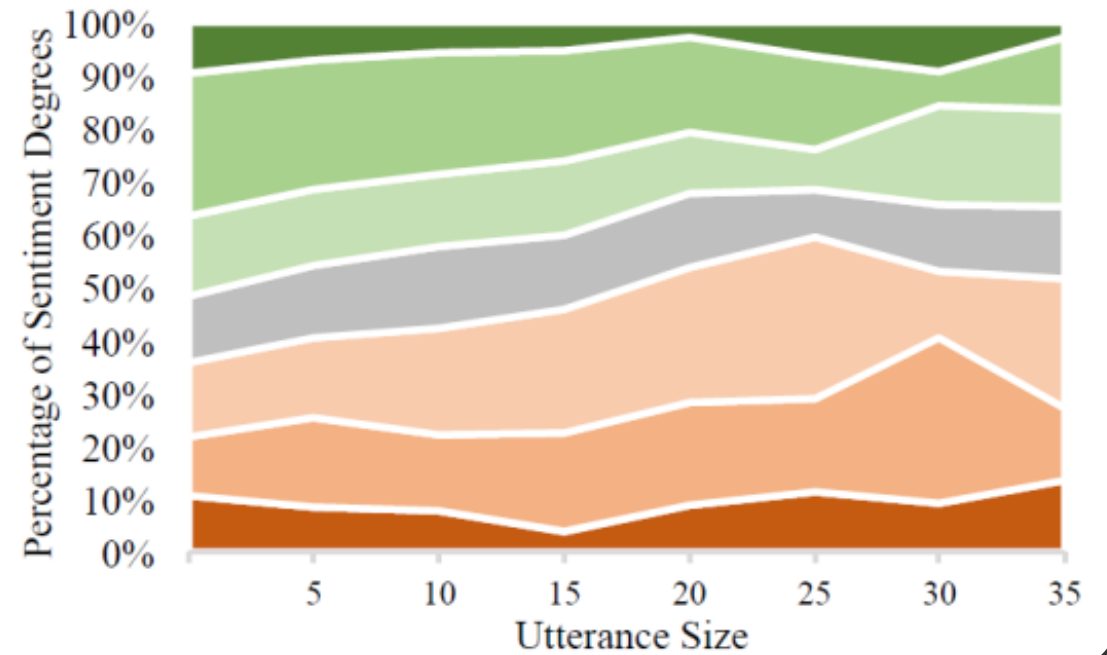
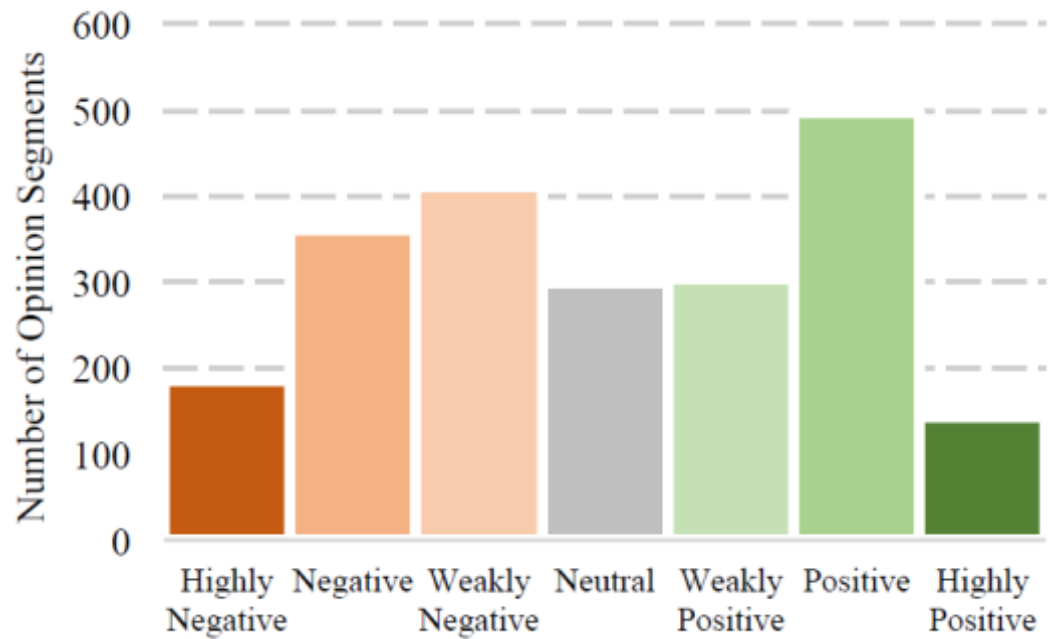
# CMU-MOSI Dataset

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- 93 videos of movie reviews
  - 89 distinct speakers
  - 48 male and 41 female speakers
- 2199 opinion segments
  - Average length: 4.2 sec
  - Average word count: 12
- 5 different annotators for each opinion segment
  - Krippendorff's Alpha: 0.77



# CMU-MOSI Dataset



# Three Main Challenges Addressed in This Work

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1

## What granularity should we use?

- Conventional approach summarizes features for the whole video
- But some multimodal interactions happen at the word level:
  - ❑ The word “crazy” with smile: Positive
  - ❑ The word “crazy with frown: Negative



# Three Main Challenges Addressed in This Work

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2

What if a modality is noisy (e.g., occlusion)?

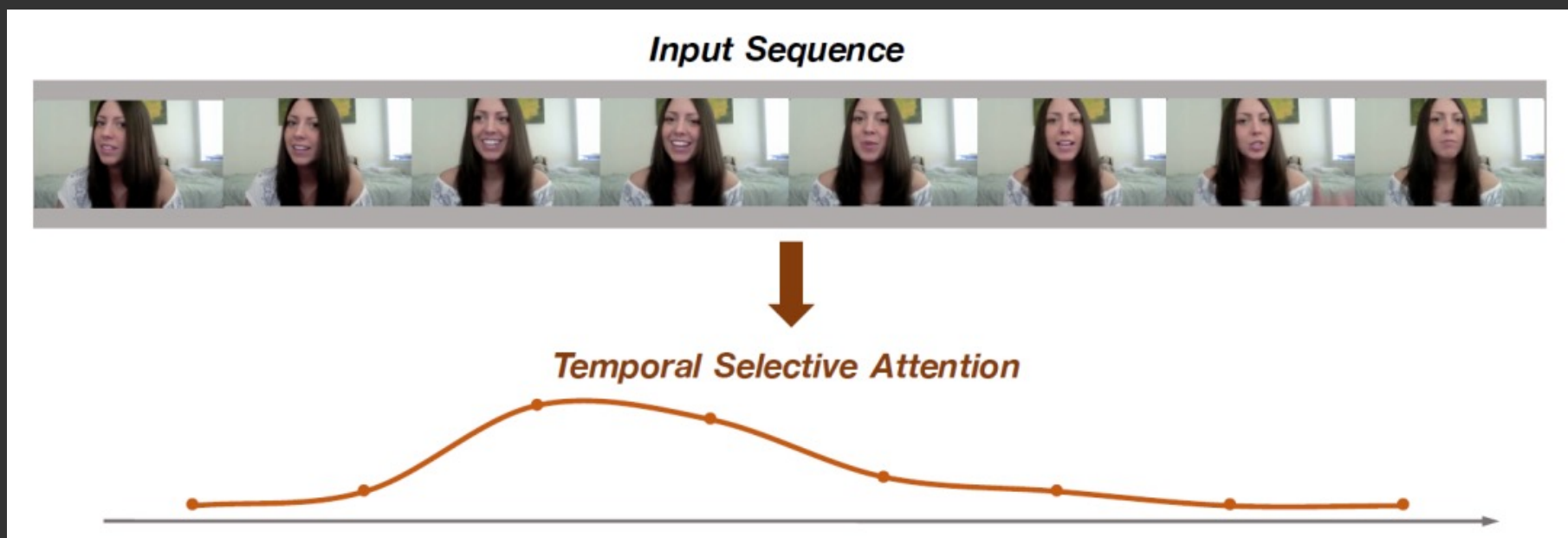




# Three Main Challenges Addressed in This Work

3

What part of the video is relevant for the prediction task?



# Main Contributions

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1 What granularity should we use?

 Word-level feature representation

2 What if a modality is noisy (e.g., occlusion)?

 Modality-specific “on/off gate”

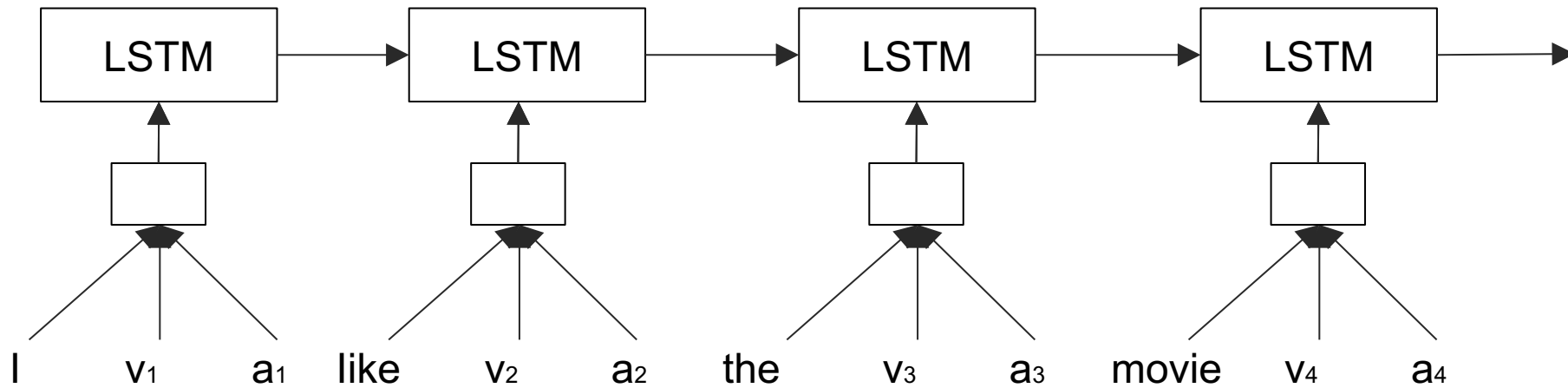
3 What part of the video is relevant for the prediction task?

 Temporal attention

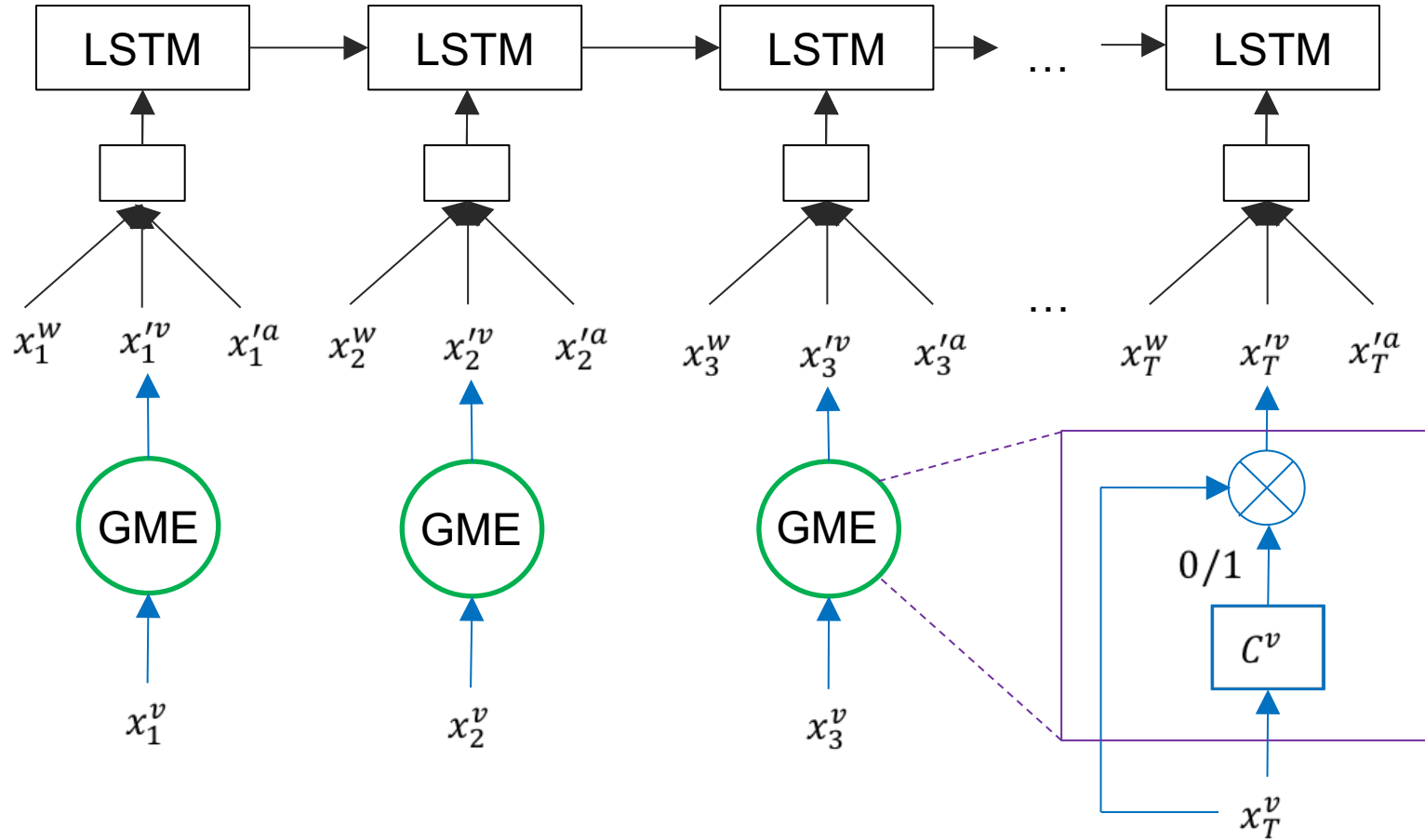


# Challenge 1: LSTM with Word-Level Fusion

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# Challenge 2: Gated Multimodal Embedding (GME)



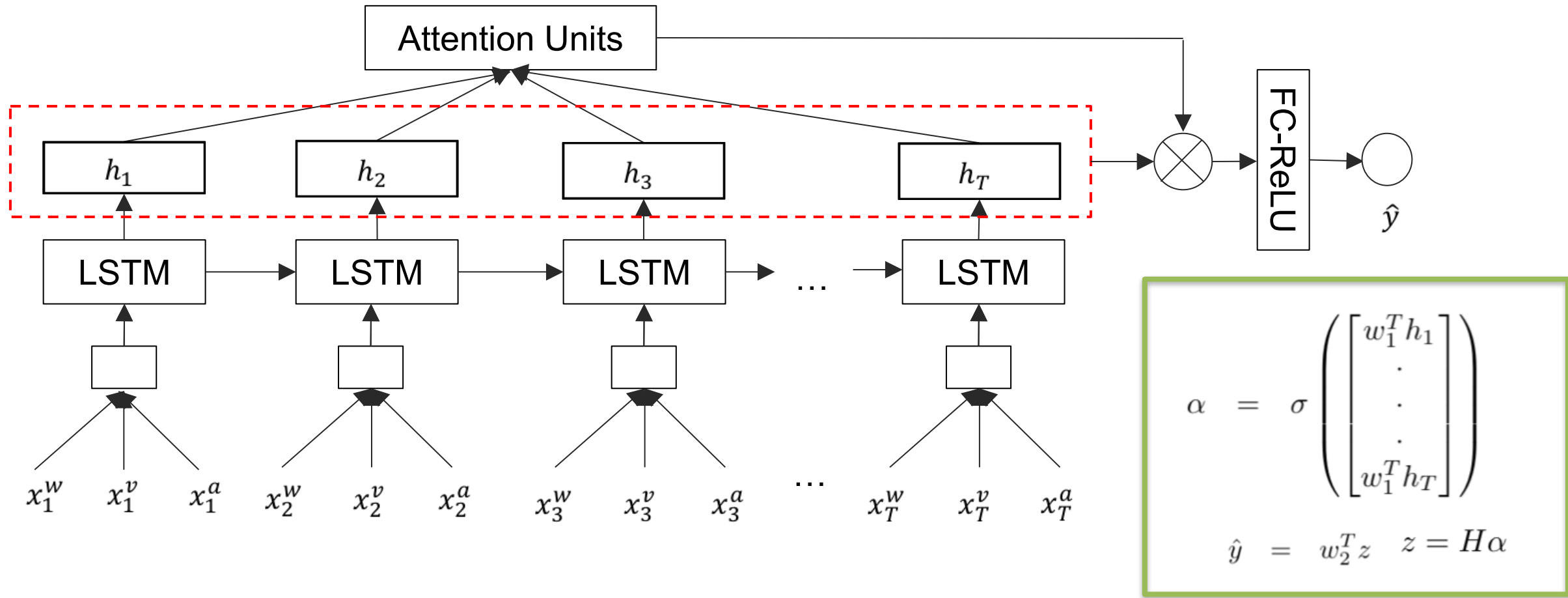
$$x_t^{lw} = x_t^w$$

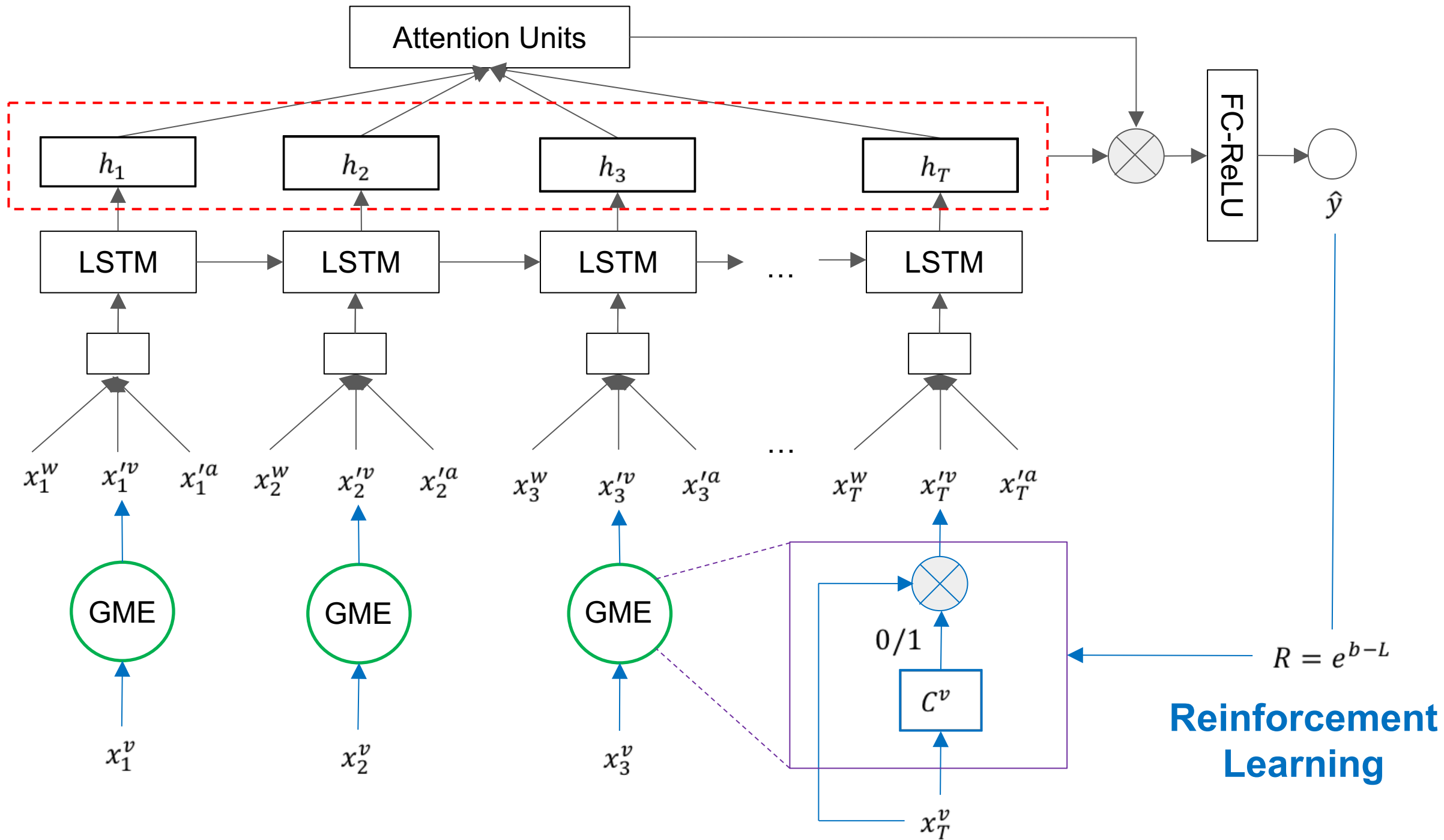
$$x_t^{la} = c_t^a \cdot x_t^a = C^a(x_t^a) \cdot x_t^a$$

$$x_t^{lv} = c_t^v \cdot x_t^v = C^v(x_t^v) \cdot x_t^v$$



# Challenge 3: LSTM with Temporal Attention





# Experiments

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## Text

- Transcripts of videos as well as pre-trained Glove word embeddings

## Audio

- Covarep to extract acoustic features

## Video

- Facet and Openface to extract facial landmarks, head pose, gaze tracking etc.



# Baseline Models

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- **C-MKL**: Convolutional Multi-Kernel Learning model. CNN to extract textual features and uses for fusion. ([Poria et al., 2015](#))
- **SAL-CNN**: Select-Additive Learning. Reduces impact of identity-specific information. ([Wang et al., 2016](#))
- **SVM-MD**: Support Vector Machine with Multimodal Dictionary. Multimodal features using early fusion. ([Zadeh et al., 2016b](#))
- **RF**: Random Forest

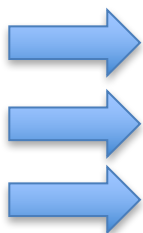




# Results – Multimodal Predictions

Method	Acc	F-score	MAE
Random	50.2	48.7	1.880
SAL-CNN	73.0	-	-
SVM-MD	71.6	72.3	1.100
C-MKL	73.5	-	-
RF	57.4	59.0	-
LSTM	69.4	63.7	1.245
LSTM(A)	75.7	72.1	1.019
<b>GME-LSTM(A)</b>	<b>76.5</b>	<b>73.4</b>	<b>0.955</b>
Human	85.7	87.5	0.710
$\Delta^{SOTA}$	3.0 ↑	1.1 ↑	0.145 ↓

No Attention  
Without GME  
Our model



# Results – Text Only

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Method	Acc	F-score	MAE
RNTN	(73.7)	(73.4)	(0.990)
DAN	70.0	69.4	-
D-CNN	69.0	65.1	-
SAL-CNN text	73.5	-	-
SVM-MD text	73.3	72.1	1.186
RF text	57.6	57.5	-
LSTM text	67.8	51.2	1.234
LSTM(A) text	71.3	67.3	1.062
<b>GME-LSTM(A)</b>	<b>76.5</b>	<b>73.4</b>	<b>0.955</b>



# LSTM with Word-Level Features

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Modalities	Acc	F-score	MAE
text	67.8	51.2	1.234
audio	44.9	61.9	1.511
video	44.9	61.9	1.505
text+audio	66.8	55.3	<b>1.211</b>
text+video	63.0	<b>65.6</b>	1.302
text+audio+video	<b>69.4</b>	63.7	1.245



# LSTM with Temporal Attention (LSTM(A))

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Modalities	Acc	F-score	MAE
text	71.3	67.3	1.062
audio	55.4	63.0	1.451
video	52.3	57.3	1.443
text+audio	73.5	70.3	1.036
text+video	74.3	69.9	1.026
text+audio+video	<b>75.7</b>	<b>72.1</b>	<b>1.019</b>



# Temporal Attention on Word features

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*But a lot of the footage was kind of **unnecessary**.*

*And she really **enjoyed** the film.*

*I thought it was **fun**.*

*So yes I really **enjoyed** it.*



# Example from LSTM with Temporal Attention

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Transcript: *He's not gonna be looking like a chirper bright young man but early thirties really you **want** me to buy that.*

Visual modality: **Looks disappointed**

LSTM sentiment prediction: **1.24**

LSTM(A) sentiment prediction: **-0.94**

Ground truth sentiment: **-1.8**



# Example for Gated Multimodal Embedding

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Transcript: *First of all I'd like to say little James or Jimmy he's so cute he's so xxx.*

LSTM(A) Attention: ***little*** (her mouth is covered by her hands)

GME-LSTM(A) Attention: ***cute***

LSTM(A) prediction: **-0.94**

GME-LSTM(A) prediction: **1.57**

Ground truth: **3.0**



# Video example showing the effect of GME

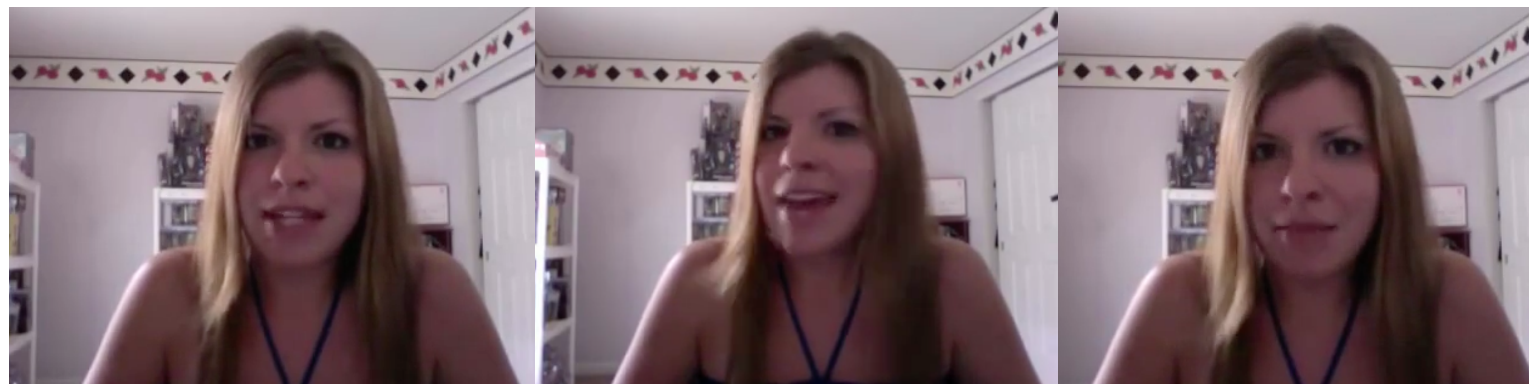
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# GME Analysis

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Visual RL Gate:                      Reject                      Pass                      Reject

LSTM(A) prediction: **-2.0032**

GME-LSTM(A) prediction: **1.4835**

Ground truth: **1.2**



# Main Contributions

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1 What granularity should we use?

 Word-level feature representation

2 What if a modality is noisy (e.g., occlusion)?

 Modality-specific “on/off gate”

3 What part of the video is relevant for the prediction task?

 Temporal attention



**MERCI !**