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Predicting Event Memorability from Contextual Visual Semantics

Qianli Xu[1], Fen Fang[1], Ana Garcia del Molino[2], Vigneshwaran Subbaraju[3], Joo-Hwee Lim[1,4]

1. Institute for Infocomm Research, A*STAR, Singapore
2. ByteDance AI Lab, Singapore
3. Institute of High Performance Computing, A*STAR, Singapore
4. Nanyang Technological University

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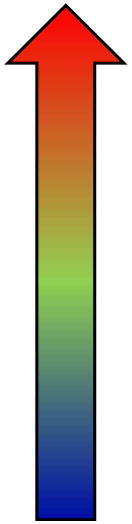
Background

Image Memorability (Isola et al., 2011) [1]

“Memorable”



“Forgettable"

Image source [1]

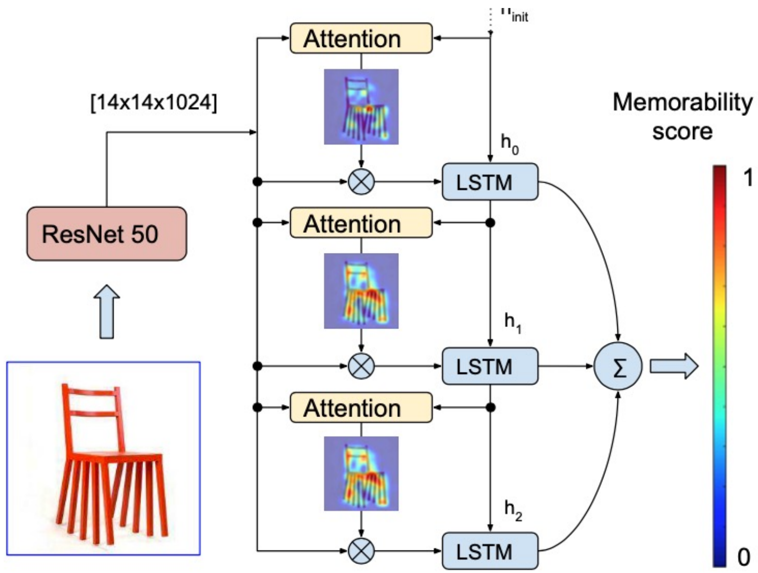


Image source [8]

Motivation

Event Memorability

Event memorability ≠ **Image** memorability

- What factors affect event memorability?
- **Can we predict a person's memory of individual events?**
- [Future work] Can we design cognitive intervention programs to enhance subjects' episodic memory by leveraging on the knowledge of event memorability?

Related works

- Image Memorability
  - What makes an [image/object/graph/scene/] memorable? [1-5]
  - Video memorability [6,7]
- Dataset
  - SUN-Mem [1], LaMem [2], FIGRIM [3], Mem-Cat [4], LNSIM [5]
- Predictive models
  - MemNet [2], AMNet [8], DeepNSM [5], ICNet [9]
- Event Memorability
  - Neuro-psychological studies [10]: only study memorability of event categories
  - Neural imaging [11,12]: intrusive and expensive, difficult to get data

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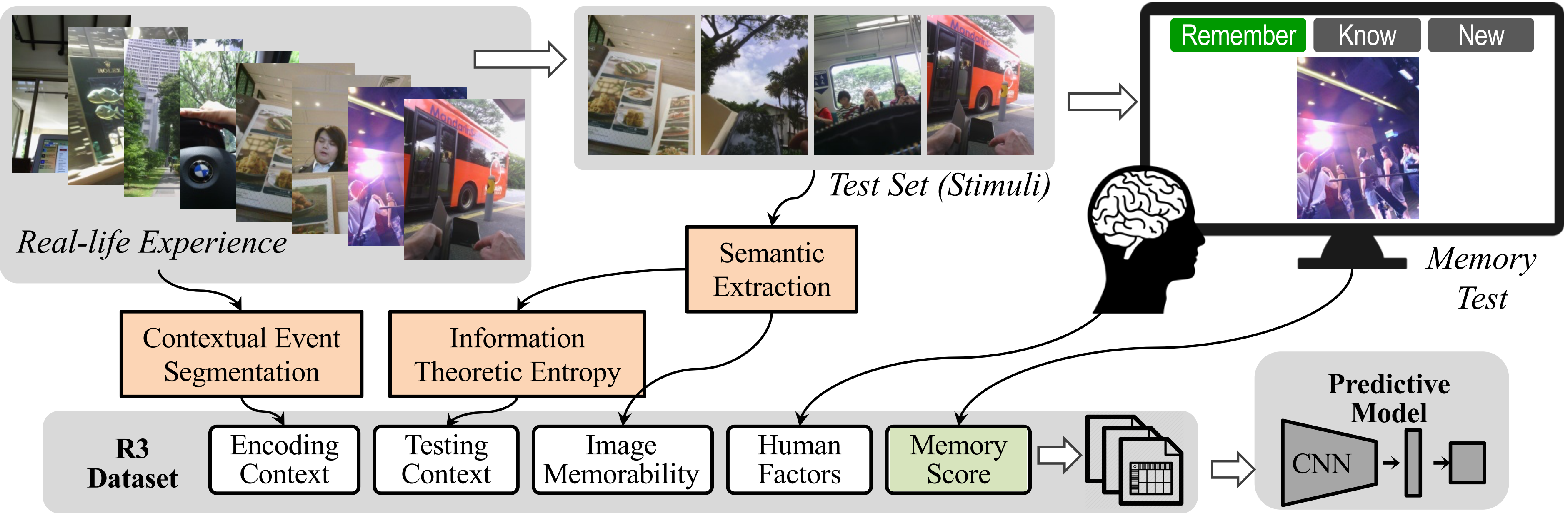
Our Approach



- ***An experiment protocol***: lifelogging, systematic training, standardized testing
- ***A dataset (R3)***: Sophisticated mechanisms to extract visual semantic features
- ***A predictive model***: compute item-wise event memorability

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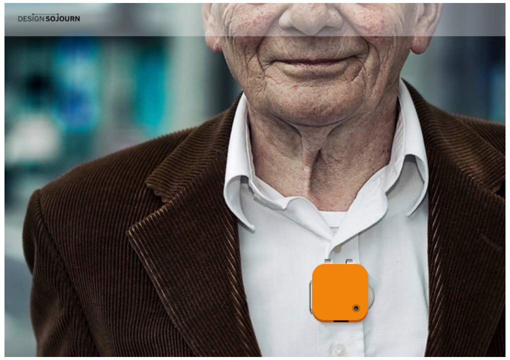
Experiment design and dataset

Phase I			Phase II			Phase III	
14 days Recording	3 days	Test 1	14 days Recording	3 days	Test 2	7 wks	Test 3



8 s

Memory Type

- Remember
- Know
- New

3 s

Memory Level

- R: 1 2 3 4
- K: 1 2 3 4
- N: perhaps vs. certain

3 s

- Pilot study (8 young + 5 old); formal study (47 old, reported in this study)
- 1 month lifelog recording from each subject; >13K hours, >1.5M photos with meta-data
- >10K samples of event recall (reported in this study; privacy sensitive information removed)

Visual Semantic Features in Context

- Intrinsic (pure visual; from image cue)
  - Saliency: image memorability, multiple benchmarking models used
  - Face: presence of human face
  - Human: presence of human body
- Extrinsic
  - Encoding context
    - Event distinctiveness: Rare events are remembered better (Hunt and Worthen, 2006); computed using CES method (del Molino et al., 2018)
    - Event boundary condition: Event segmentation theory (Gold et al. 2017)
    - Activity: Manually annotated based on local context
    - Place: Manually annotated based on local context
  - Testing context
    - Event distinctiveness: computed based on information-theoretic entropy (Bylinskii et al., 2015)
    - Encode-test interval: time between event occurrence and testing
    - Training (treatment): event has been re-consolidated before
  - Demographic
    - Age
    - gender
    - Etc.

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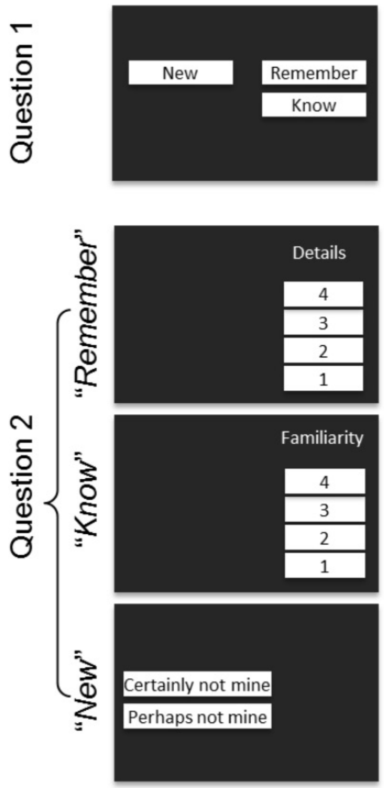
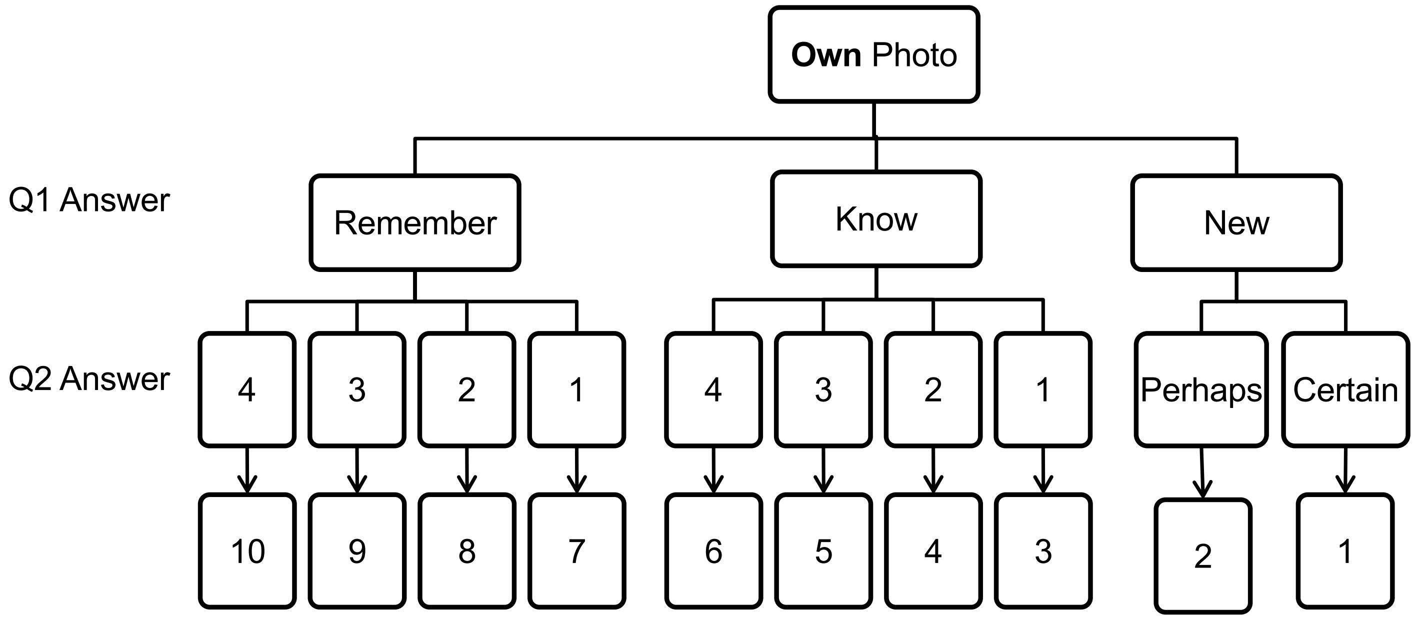
Memory Mnemonics





(b) Encode test outcome as 10-level graded memory types

Linear regression analysis

Hypothesis: event memorability is dependent on both intrinsic and extrinsic features

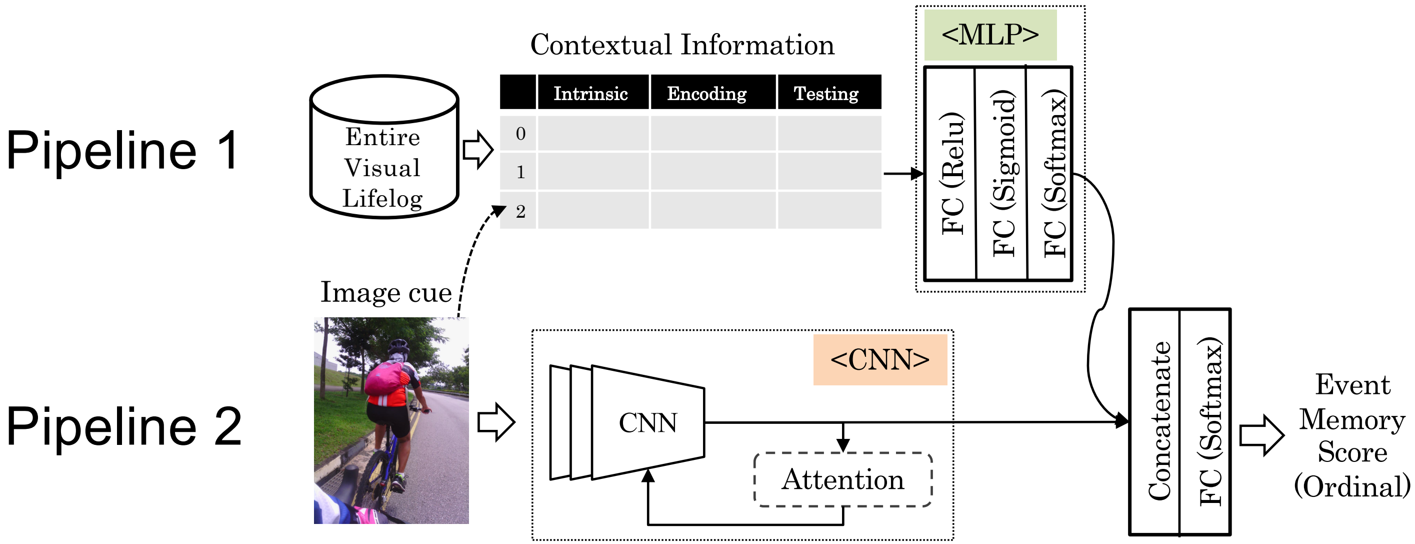
- Intrinsic feature (i.e., image memorability) predicts event memory to vary extends based on different predictive models.
  - MemNet [28]: $r = 0.02$, $p = 0.04$,
  - DeepNSM [33]: $r = 0.01$, $p = 0.54$
  - **AMNet [15]: $r = 0.19$, $p < 0.001$**

- Linear mixed-effect analysis: features are used as fixed effects and "subject" modelled as a random effect.

Intrinsic Factors	t-statistics	**Encoding Context**	t-statistics	**Testing Context**	t-statistics
Image memorability	**11.14**	Encode distinctiveness	**7.45**	Test distinctiveness	**3.93**
Presence of faces	**10.55**	Boundary condition	-0.73	Treatment	**10.00**
Presence of human	**2.08**	Activities	**7.34**	Interval	**-14.22**
		Places	1.38		

Table 1: Factors that affects event memorability. t-value in bold font means the factor significantly correlated with memory ($p < 0.05$).

CEMNet – Predicting item-wise event memory



Pipeline	AMNet	ICNet	MLP	CEMNet wt AMNet	CEMNet wt ICNet
1	-	-	MLP	MLP	MLP
2	AMNet[8]	ICNet[9]	-	AMNet	ICNet

Code available @ https://github.com/ffzzy840304/Predicting-Event-Memorability

Experiment results

Method	Input Features	Precision↑	Recall↑	F1↑	Mean error↓
AMNet [8]	Image	0.171	0.179	0.150	3.03
ICNet[9]	Image	0.153	0.155	0.140	3.11
MLP	Extrinsic Features*	0.389	0.385	0.333	0.91
CEMNet w/t AMNet	Intrinsic + Extrinsic	**0.408**	**0.414**	**0.368**	**0.85**
CEMNet w/t ICNet	Intrinsic + Extrinsic	0.369	0.340	0.340	0.97

Table 2: Comparing performance of models. *Intrinsic features, *i.e.*, human face & body, are included.

- Intrinsic features (i.e., using only image cues) have limited predictive power; above chance accuracy.
- Extrinsic features (MLP model) can predict event memorability with considerable accuracy.
- Combining intrinsic and extrinsic gives best prediction outcome; Especially using more comprehensive DCNN model (e.g., AMNet)

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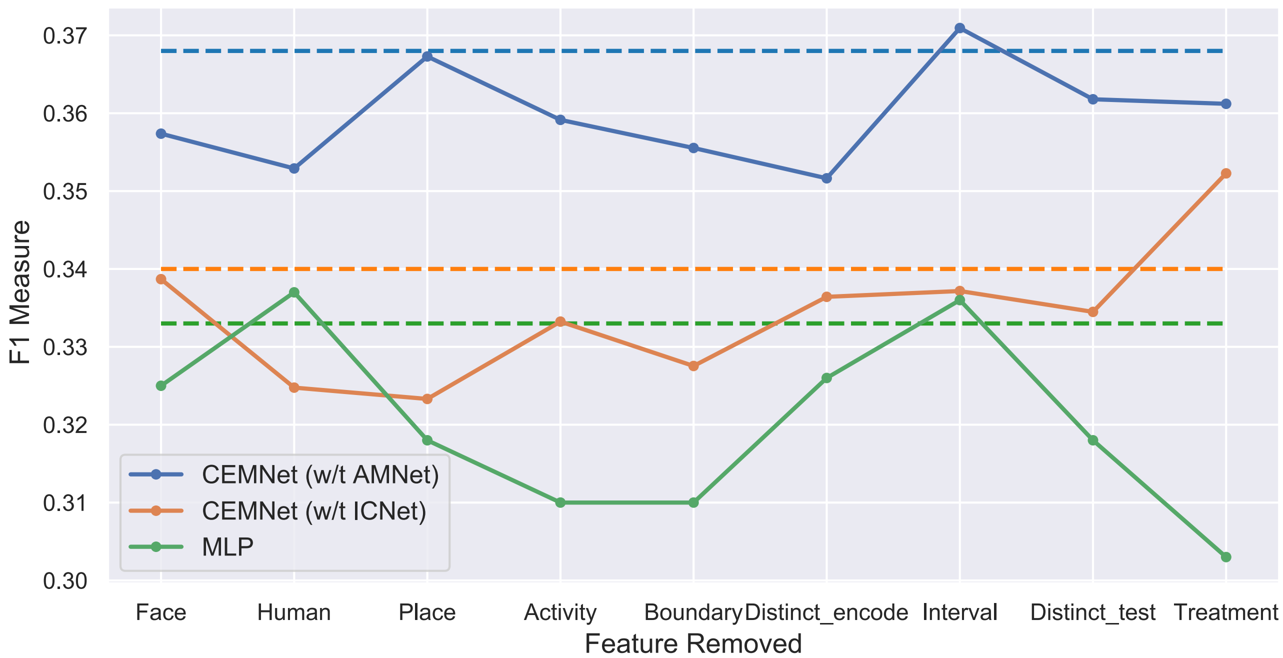
Ablation Study – *which feature has higher predictive value?*



- Using all features generally gives better performance
- Most features are conducive to the performance, except “human” and “interval”
- Some factors co-vary with each other, which may have caused inconsistent outcome. No causal relationship is established.

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Summary

- Event memory can be effectively predicted with intrinsic + extrinsic factors
- Extrinsic factors are more important in event memory prediction

- R3 experiment and dataset may inspire new experiments to investigate on event memory
- We can leverage on the outcome of predicted event memory to design memory intervention programs

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THANK YOU

qxu@i2r.a-star.edu.sg

www.a-star.edu.sg

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