

# We Are Humor Beings: Understanding and Predicting Visual Humor

Shuai Wang

University of Toronto

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- ▶ An adult laughs 18 times a day
- ▶ A good sense humor
  - ▶ is related to communication competence
  - ▶ helps raise an individual's social status & popularity
  - ▶ even helps attract compatible mates
  - ▶ makes yourself happier :)

What makes an image funny?



# Humor Techniques

- ▶ Animal doing something unusual
- ▶ Person doing something unusual
- ▶ Somebody getting hurt
- ▶ Somebody getting scared

## Animal doing something unusual



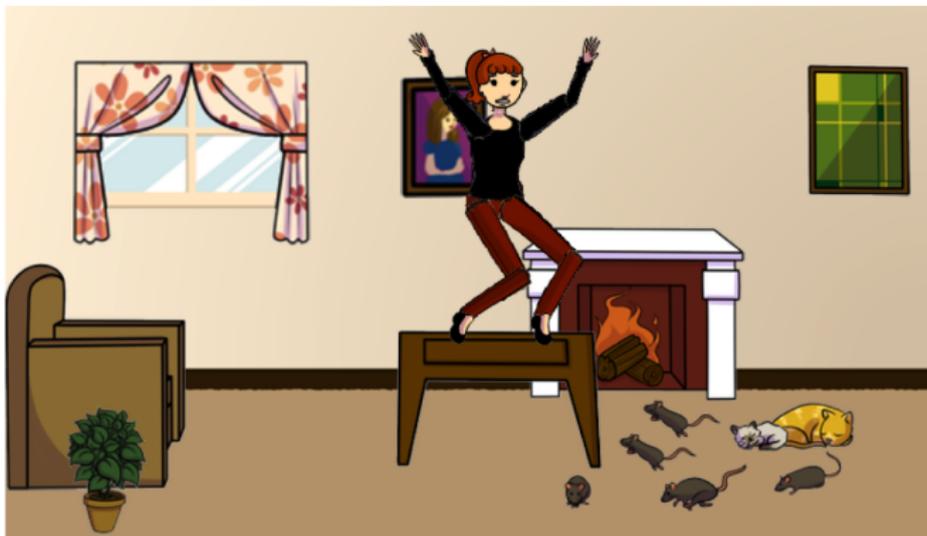
## Person doing something unusual



# Somebody getting hurt



## Somebody getting scared



Changing objects can alter the funniness of a scene

## Removing Incongruities



An elderly person kicking a football while skateboarding is incongruous, but a young girl doing so is not



## Adding Incongruities



Add incongruities (and humor)  
by replacing the expected with  
the unexpected



## Two Tasks to Understand Visual Humor

- ▶ Predicting how funny a given scene is (scene-level)
- ▶ Changing the funniness of a scene (object-level)

## Object-level Features

- ▶ **Object embedding** (150-d): captures the context in which an object usually occurs
- ▶ **Local embedding** (150-d): weighted sum of object embeddings of all other instances

## Scene-level Features

- ▶ **Cardinality** (150-d): bag-of-words representation of how many instances of each object are in the scene
- ▶ **Location** (300-d): horizontal and vertical coordinates of every object (closest to the center if multiple instance)
- ▶ **Scene embedding** (150-d): sum of object embeddings of all objects in the scene

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- ▶ Support Vector Regressor (SVR) on scene-level features
- ▶ Metric: average relative error

$$\frac{1}{N} \sum_{i=1}^N \frac{|Predicted F_i - Ground Truth F_i|}{Ground Truth F_i}$$

## Predicting Funniness Score: Ablation Analysis

Different feature subsets perform about the same: slightly better than baseline (average score of the training scenes)

<b>Feautres</b>	<b>Avg. Rel. Err.</b>
Avg. Prediction Baseline	0.3151
Embedding	0.2516
Cardinality	0.2450
Location	0.2400
Cardinality + Location	0.2435
Embedding + Location	0.2435
Cardinality + Embedding	0.2435
Embedding + Cardinality + Location	0.2400

## Alter Funniness of a Scene

- ▶ Detect the objects that do (or do not) contribute to humor
- ▶ Identify which objects should replace the objects from step 1

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- ▶ On average, the model replaces 3.67 objects (2.54 ground truth) → this bias towards replace ensures a large 'margin'
- ▶ Animate objects like humans and animals are more likely sources of humor → tends to replace these objects

# Funny → Unfunny

Old man dancing → young boy dancing  
Hawk stealing meat → baseball



# Funny → Unfunny

Cute puppy → Insect

Watermelon → Ax



# Unfunny → Funny

Couple having dinner at the table → Puppies having dinner at the table



# Unfunny → Funny

Cating playing around → Raccoon driving motorcycle



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- ▶ Dataset is small: 6,400 images
- ▶ Feature representation can be improved

