Today: Outline

- Logistics
- Model Selection and Evaluation
- Explainable Al

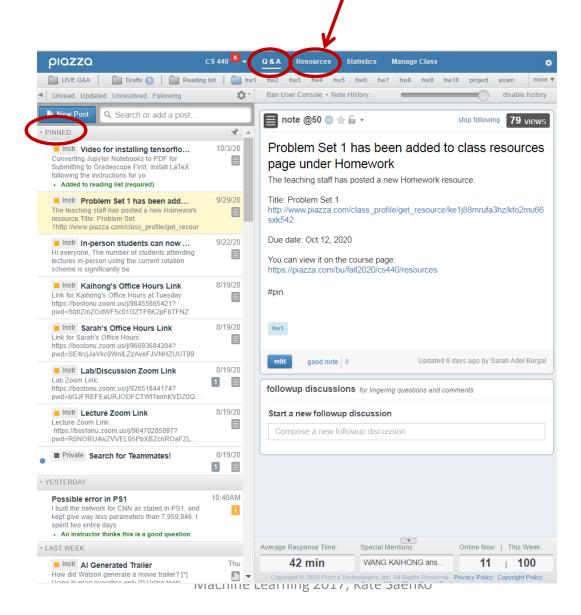
• Reminders:

- Problem Set 1, due: Oct 12 by midnight
- Midterm Exam, in class, Oct 20 (Practice problems will be posted)

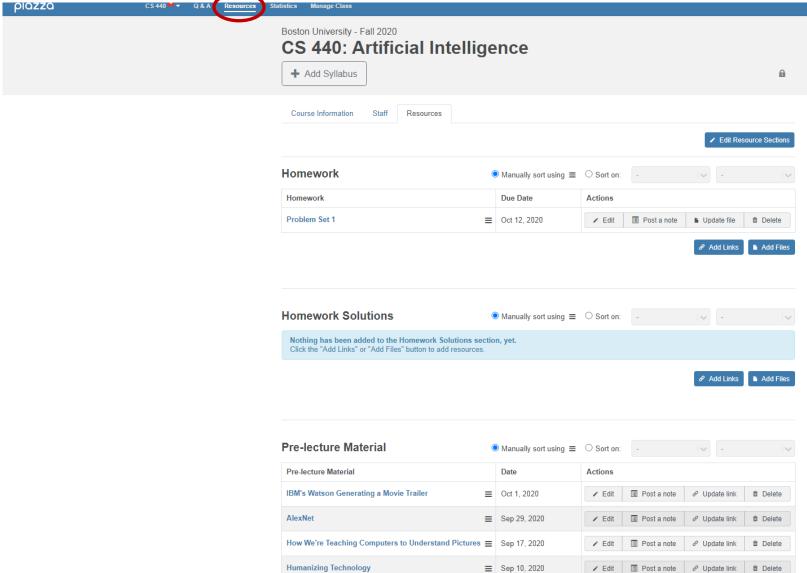
Announcements:

- Lab on Fri Oct 9 will be a chance to get help with PS1
- No class on Oct 13 per BU Calendar (Substitute Mon Schedule of Classes)

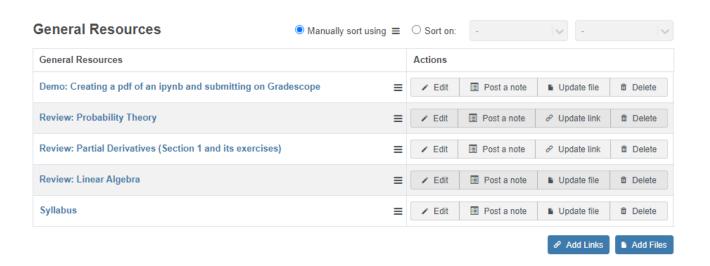
Piazza – Posts

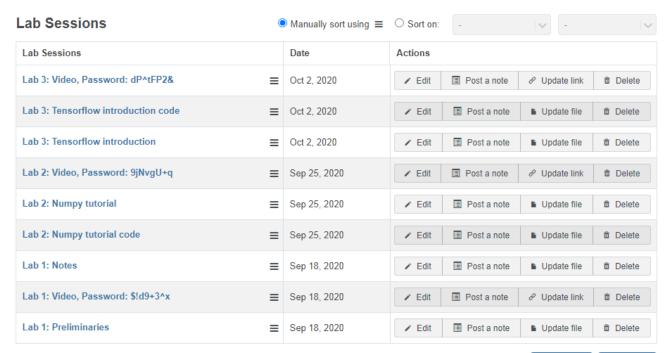


Piazza - Resources



Lecture Notes		Manually sort using ≡	O Sort on:	-	-	\ <u>\</u>
Lecture Notes		Lecture Date	Actions			
Lecture 9: Video, Password: ICQ!.X2c	=	Oct 1, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 9: Neural Networks V	=	Oct 1, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 8: Video, Password: x!8x+V?\$	=	Sep 29, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 8: Neural Networks IV	≡	Sep 29, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 7: Video, Password: RhT^+IX0	≡	Sep 24, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 7: Neural Networks III	≡	Sep 24, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 6: Video, Password: 7!VG.88g	≡	Sep 22, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 6: Neural Networks II	≡	Sep 22, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 5: Video, Password: DyA&1MTF	=	Sep 17, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 5: Neural Networks I	=	Sep 17, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 4: Video, Password: N7fSvw8!	=	Sep 15, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 4: Learning from Examples II	≡	Sep 15, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 3: Video, Password: ctq\$1ShM	≡	Sep 10, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 3: Learning from Examples I	≡	Sep 10, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 2: Video, Password: 44Wq9Z8&	=	Sep 8, 2020	✓ Edit	Post a note	∂ Update link	□ Delete
Lecture 2: Ethics in Al	≡	Sep 8, 2020	✓ Edit	Post a note	■ Update file	□ Delete
Lecture 1: Video, Password: j=5HJCF!	≡	Sep 3, 2020	✓ Edit	Post a note	∂ Update link	a Delete
Lecture 1: Logistics and Intro	=	Sep 3, 2020	✓ Edit	Post a note	■ Update file	□ Delete





Video Demo

- Installing Tensorflow
- Converting ipynb to pdf
- Submitting pdf on gradescope

https://www.youtube.com/watch?v=gxR012ZAR4o

Gradescope

Please join the Gradescope with your BU email

https://www.gradescope.com/courses/186182%E2%80%A9Entry

Entry Code: 95Y7JG



Your Courses

Welcome to Gradescope! Click on one of your courses to the right, or on the Account menu below. Your Courses

Fall 2020

CS 440

Introduction to Artificial Intelligence

1 assignment

Dry Run

- Create a pdf from the current notebook with no solutions
- Submit it now in gradescope as a dry run
- Do not wait until you have completed solving the assignment to try out the submission system
- This will give you ample time to ask any questions you have about the submission process before the deadline and will make your future submissions smooth

Important!

- Keep a copy of your ipynb with unchanged last date of modification
 - Graders might need it, and would be requesting it by email cc ing me

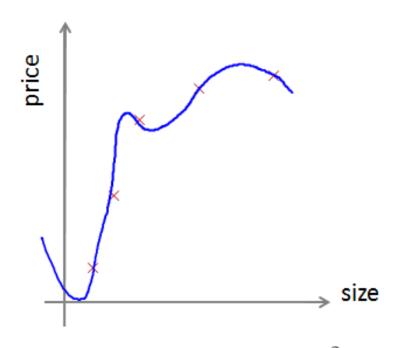
Friday's Lab:
 brief demo + office hour for help with PS1

 We encourage you to make best use of Piazza and Office Hours



Model Selection Training/Validation/Test Sets

Overfitting example



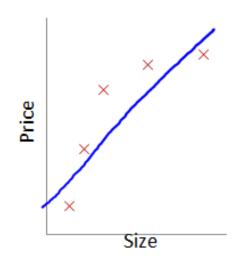
$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

Once parameters $(\theta_0, \theta_1, ..., \theta_4)$ were fit to some set of data (training set), the error of the parameters as measured on that data (the training error $J(\theta)$) is likely to be lower than the actual generalization error.

One solution is to regularize, but how can we choose the regularization weight λ ?

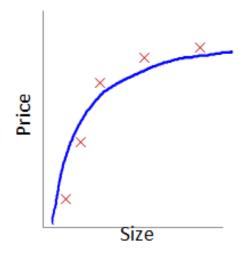
Choosing weight λ

$$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$



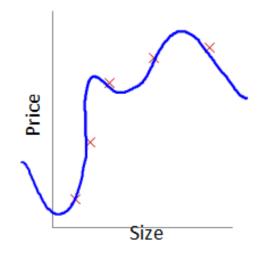
$$\lambda = 100$$

High bias (underfit)



$$\lambda = 1$$

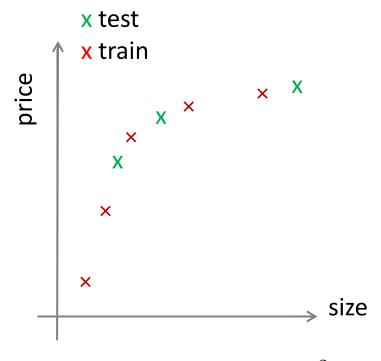
"Just right"



$$\lambda = 0.01$$

High variance (overfit)

Model selection



$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

Hyperparameters (e.g., degree of polynomial, regularization weight, learning rate) must be selected prior to training.

How to choose them?

Try several values, choose one with the lowest test error?

Problem: test error is likely an overly optimistic estimate of generalization error because we "cheat" by fitting the hyperparameter to the actual test examples.

Train/Validation/Test Sets

, <u> </u>	Size	Price		
train	2104	400		
	1600	330		
	2400	369		
	1416	232		
	3000	540		
validation	1985	300		
	1534	315		
	1427	199		
test	1380	212		
	1494	243		

Solution: split data into three sets.

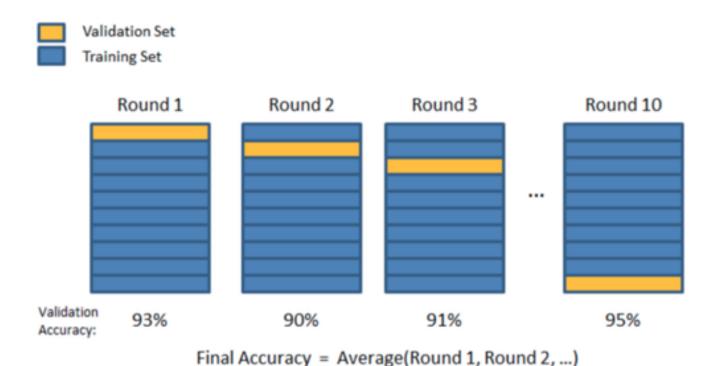
For each value of a hyperparameter, train on the train set, evaluate learned parameters on the validation set.

Pick the model with the hyper parameter that achieved the lowest validation error.

Report this model's test set error.

N-Fold Cross Validation

- What if we don't have enough data for train/test/validation sets?
- Solution: use N-fold cross validation.
- Split training set into train/validation sets N times.
- Report average predictions over N val sets, e.g. N=10:



Confusion Matrix

 A performance measurement for machine learning classification problem where output can be two or more classes.

• True Positive:

predicted positive and it's true

True Negative:

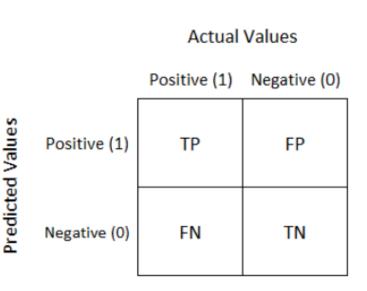
predicted negative and it's true

False Positive:

predicted positive and it's false

False Negative:

predicted negative and it's false



Recall

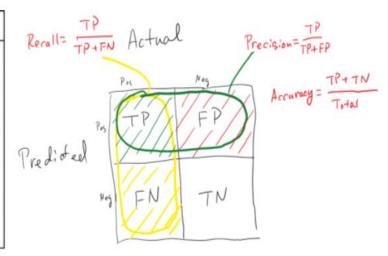
• Out of all the positive classes, how much we predicted correctly. It should be high as possible.

Precision

 Out of all the positive classes we have predicted, how many are actually positive.

Example

у	y pred	output for threshold 0.6	Recall	Precision	Accuracy	
0	0.5	0		2/3		
1	0.9	1	1/2		4/7	
0	0.7	1				
1	0.7	1				
1	0.3	0	1000	1885	7.53	
0	0.4	0				
1	0.5	0				



F-measure

• F-score helps to measure Recall and Precision at the same time.



Neural Networks VI

Explainability

Importance of Explainability

 An important action to be detected in the vision systems of autonomous vehicles is: Pedestrian Crossing





Importance of Explainability

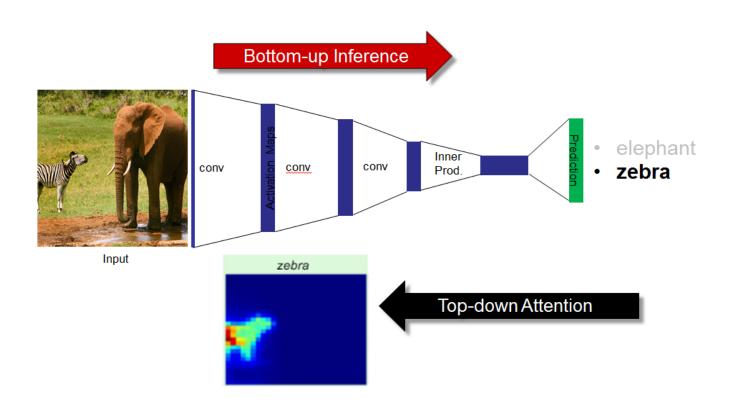
Sample Misclassification



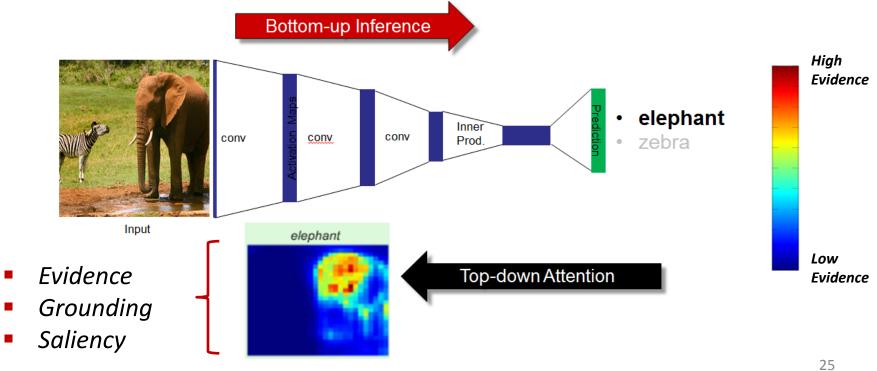
Ground Truth:BabyCrawling

Classified as: Pushups

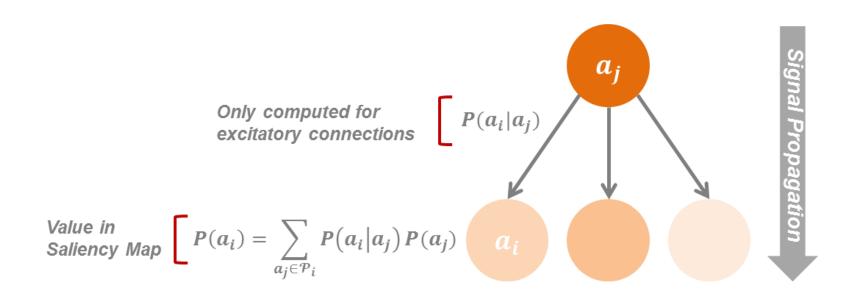
Spatial Grounding



Spatial Grounding



Excitation Backprop (EB)



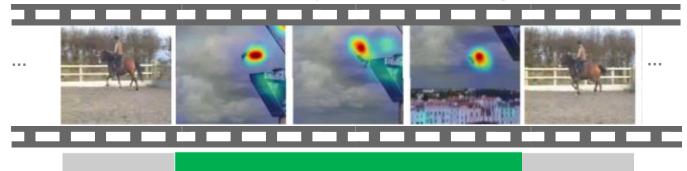
[Jianming Zhang, Zhe Lin, Jonathan Brandt, Xiaohui Shen, Stan Sclaroff. "Top-down Neural Attention by Excitation Backprop., ECCV'16]

Spatiotemporal Grounding

Input Video Sequence

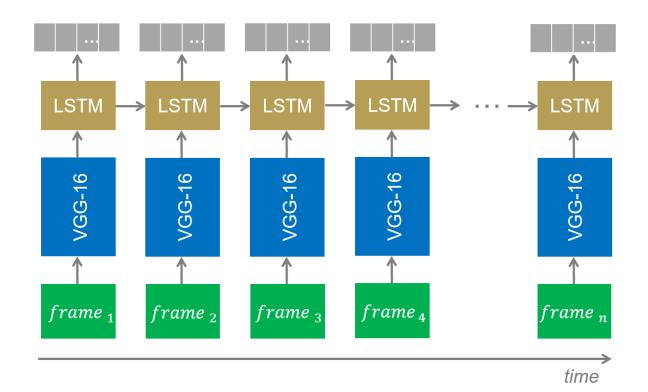


Spatio-temporal Saliency for *CliffDiving*



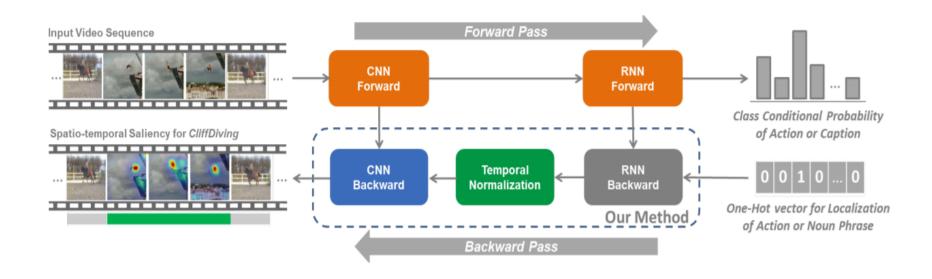
Architecture: Forward Pass

- CNN-LSTM is trained for the action recognition task.
- Resulting grounding is weakly-supervised.

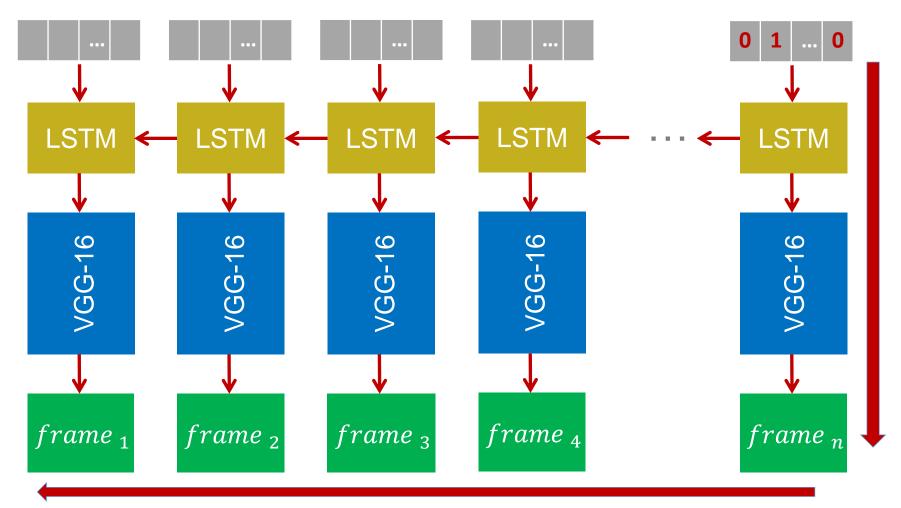


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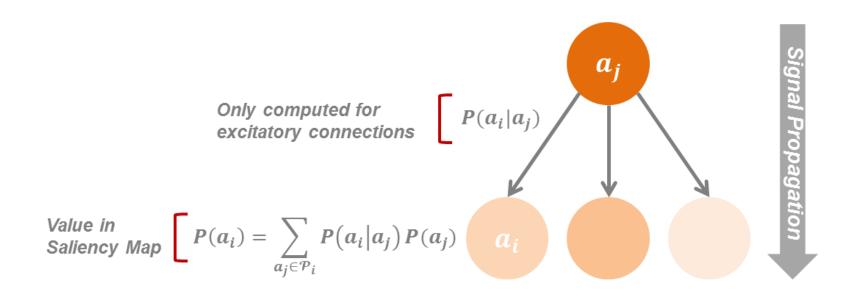
Excitation Backprop in RNNs



Architecture: Backward Grounding Pass



Excitation Backprop (EB)



[Jianming Zhang, Zhe Lin, Jonathan Brandt, Xiaohui Shen, Stan Sclaroff. "Top-down Neural Attention by Excitation Backprop., ECCV'16]

Applications

Action Detection (videos)

- Caption Grounding (images, videos)
- Reflecting the Abstraction Capability of Models

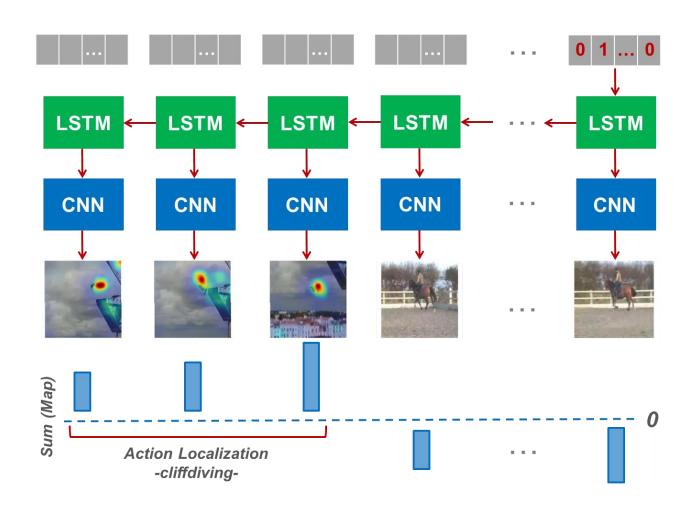
Applications

Action Detection (videos)

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Reflecting the Abstraction Capability of Models

Spatiotemporal Action Detection



Applications

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Caption Grounding (images, videos)

Reflecting the Abstraction Capability of Models

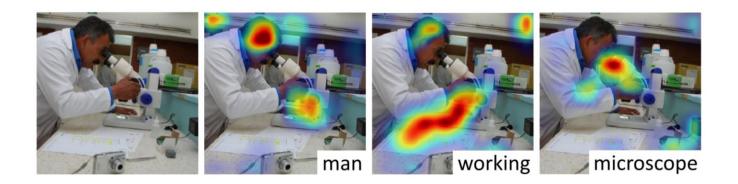
Flicker30kEntities Dataset: Grounding Words of an Image Caption

image caption: A man in a lab coat is working on a microscope.



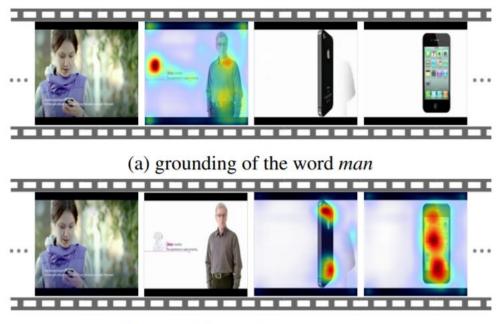
Flicker30kEntities Dataset: Grounding Words of an Image Caption

image caption: A man in a lab coat is working on a microscope.



MSRVTT Dataset: Grounding Words of a Video Caption

video caption: "A man is talking about a phone"



(b) grounding of the word phone

Applications

Action Detection (videos)

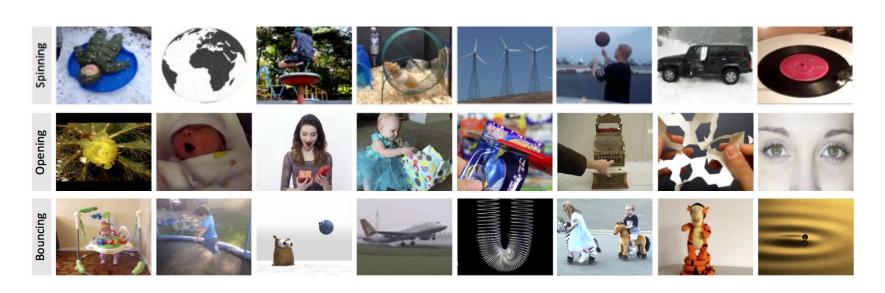
- Caption Grounding (images, videos)
- Reflecting the Abstraction Capability of Models

Reflecting the Abstraction Capability of Models

Moments in Time Dataset

M. Monfort, A. Andonian, B. Zhou, K. Ramakrishnan, S. A. Bargal, T. Yan, L. Brown, Q. Fan, D. Gutfruend, C. Vondrick, A. Oliva. "Moments in Time Dataset: one million videos for event understanding." *TPAMI*, 2019.

Videos of abstract dynamical events performed by various actors.



Moments in Time Dataset

• Typically, classification accuracy is reported to summarize the recognition capability of models.

 However, classification accuracy alone is not representative as to whether the models are really modeling this diversity of actors.

 A classifier may be incorrectly classifying a whole subset of cases/actors.

Moments in Time Dataset

• Class: Opening



