CS 1674: Intro to Computer Vision
Sequential Data: Language and Vision; Video and Motion

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University of Pittsburgh
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Plan for this lecture

• Language and vision
  – Image captioning
  – Tool: Recurrent neural networks
  – Video captioning
  – Visual question answering

• Motion and video
  – Modeling and replicating motion
  – Tracking how an object moves
Motivation: Descriptive Text for Images

“It was an arresting face, pointed of chin, square of jaw. Her eyes were pale green without a touch of hazel, starred with bristly black lashes and slightly tilted at the ends. Above them, her thick black brows slanted upward, cutting a startling oblique line in her magnolia-white skin—that skin so prized by Southern women and so carefully guarded with bonnets, veils and mittens against hot Georgia suns”

Scarlett O’Hara described in Gone with the Wind
This is a picture of one sky, one road and one sheep. The gray sky is over the gray road. The gray sheep is by the gray road.

Here we see one road, one sky and one bicycle. The road is near the blue sky, and near the colorful bicycle. The colorful bicycle is within the blue sky.

This is a picture of two dogs. The first dog is near the second furry dog.
Some pre-RNN bad results

Missed detections:
Here we see one potted plant.

False detections:
There are one road and one cat. The furry road is in the furry cat.

Incorrect attributes:
This is a photograph of two sheeps and one grass. The first black sheep is by the green grass, and by the second black sheep. The second black sheep is by the green grass.

This is a picture of one tree, one road and one person. The rusty tree is under the red road. The colorful person is near the rusty tree, and under the red road.

This is a photograph of two horses and one grass. The first feathered horse is within the green grass, and by the second feathered horse. The second feathered horse is within the green grass.

Kulkarni et al., CVPR 2011
Results with Recurrent Neural Networks

"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."

Karpathy and Fei-Fei, CVPR 2015
Recurrent Networks offer a lot of flexibility:

- one to one
- one to many
- many to one
- many to many
- many to many

vanilla neural networks
Recurrent Networks offer a lot of flexibility:

- One to one
- One to many
- Many to one
- Many to many
- Many to many

e.g. **image captioning**
image -> sequence of words
Recurrent Networks offer a lot of flexibility:

e.g. sentiment classification
sequence of words -> sentiment

Andrej Karpathy
Recurrent Networks offer a lot of flexibility:

- **One to one**
- **One to many**
- **Many to one**
- **Many to many**

Example: **machine translation**

seq of words -> seq of words

Andrej Karpathy
Recurrent Networks offer a lot of flexibility:

- one to one
- one to many
- many to one
- many to many

e.g. video classification on frame level
Recurrent Neural Network
Recurrent Neural Network

usually want to output a prediction at some time steps

Adapted from Andrej Karpathy
Recurrent Neural Network

We can process a sequence of vectors $\mathbf{x}$ by applying a recurrence formula at every time step:

$$h_t = f_W(h_{t-1}, x_t)$$

new state

old state

input vector at some time step

some function with parameters $W$
Recurrent Neural Network

We can process a sequence of vectors $\mathbf{x}$ by applying a recurrence formula at every time step:

$$h_t = f_W(h_{t-1}, x_t)$$

Notice: the same function and the same set of parameters are used at every time step.
(Vanilla) Recurrent Neural Network
The state consists of a single “hidden” vector $h$:

$$h_t = f_W(h_{t-1}, x_t)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$
Character-level language model example

Vocabulary: [h,e,l,o]

Example training sequence: “hello”
Example

Character-level language model example

Vocabulary: [h,e,l,o]

Example training sequence: "hello"
Example

Character-level language model example

Vocabulary:
[h,e,l,o]

Example training sequence:
“hello”
**Example**

**Character-level language model example**

**Vocabulary:** [h,e,l,o]

**Example training sequence:** “hello”

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<th>target chars:</th>
<th>“e”</th>
<th>“l”</th>
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<td>0.2</td>
</tr>
<tr>
<td></td>
<td>2.2</td>
<td>0.3</td>
<td>0.5</td>
<td>-1.5</td>
</tr>
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<td></td>
<td>-3.0</td>
<td>-1.0</td>
<td>1.9</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>4.1</td>
<td>1.2</td>
<td>-1.1</td>
<td>2.2</td>
</tr>
</tbody>
</table>

| hidden layer  | 0.3 | 1.0 | 0.1 | W_{hh} |
|               | -0.1| 0.3 | -0.5| -0.3  |
|               | 0.9 | 0.1 | -0.3| 0.9   |

| input layer   | 1   | 0   | 0   | W_{xh} |
|               | 0   | 1   | 0   |        |
|               | 0   | 0   | 1   |        |

<table>
<thead>
<tr>
<th>input chars:</th>
<th>“h”</th>
<th>“e”</th>
<th>“l”</th>
<th>“l”</th>
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</table>
Extensions

• Vanishing gradient problem makes it hard to model long sequences
  – Multiplying together many values between 0 and 1 (range of gradient of sigmoid, tanh)
• One solution: Use RELU
• Another solution: Use RNNs with gates
  – Adaptively decide how much of memory to keep
  – Gated Recurrent Units (GRUs), Long Short Term Memories (LSTMs)
Generating poetry with RNNs

Sonnet 116 – Let me not ...

by William Shakespeare

Let me not to the marriage of true minds
Admit impediments. Love is not love
Which alters when it alteration finds,
Or bends with the remover to remove:
O no! it is an ever-fixed mark
That looks on tempests and is never shaken;
It is the star to every wandering bark,
Whose worth's unknown, although his height be taken.
Love's not Time's fool, though rosy lips and cheeks
Within his bending sickle's compass come:
Love alters not with his brief hours and weeks,
But bears it out even to the edge of doom.
If this be error and upon me proved,
I never writ, nor no man ever loved.
Generating poetry with RNNs

at first:

tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e plia tkrlgd t o idoe ns,smtt h ne etie h,hregtrs nigike,aoenms lng

train more

"Tmont thithey" fomesserliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome
canoiogennc Phe lism thond hon at. MeiDimorotion in ther thize."

train more

Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and ofter.

train more

"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.

More info: http://karpathy.github.io/2015/05/21/rnn-effectiveness/
Generating poetry with RNNs

PANDARUS:
Alas, I think he shall be come approached and the day
When little strain would be attain’d into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCEN'TIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I’ll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not ays, not a many and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father’s world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master’s ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder’d at the deeds,
So drop upon your lordship’s head, and your opinion
Shall be against your honour.

I'll drink it.
Image Captioning

CVPR 2015:
Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei
Show and Tell: A Neural Image Caption Generator, Vinyals et al.
Long-term Recurrent Convolutional Networks for Visual Recognition and Description, Donahue et al.
Learning a Recurrent Visual Representation for Image Caption Generation, Chen and Zitnick

Adapted from Andrej Karpathy
Image Captioning

Recurrent Neural Network

Convolutional Neural Network

Andrej Karpathy
Image Captioning

test image
test image
before:
\[ h = \tanh(W_{xh} * x + W_{hh} * h) \]

now:
\[ h = \tanh(W_{xh} * x + W_{hh} * h + W_{ih} * im) \]
Image Captioning

Andrej Karpathy
Image Captioning

test image

downsample
sample!

Andrej Karpathy
Image Captioning

Andrej Karpathy
Adapted from Andrej Karpathy

Image Captioning

Caption generated: “straw hat”

<START>

<END> token

=> finish.
Image Captioning

- "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."
- "a young boy is holding a baseball bat."
- "a cat is sitting on a couch with a remote control."
- "a woman holding a teddy bear in front of a mirror."
- "a horse is standing in the middle of a road."

Andrej Karpathy
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Video Captioning

Generate descriptions for events depicted in video clips

A monkey pulls a dog’s tail and is chased by the dog.

Venugopalan et al., “Translating Videos to Natural Language using Deep Recurrent Neural Networks”, NAACL-HTL 2015
Video Captioning

Key Insight:
Generate feature representation of the video and “decode” it to a sentence

Venugopalan et al., “Translating Videos to Natural Language using Deep Recurrent Neural Networks”, NAACL-HTL 2015
Video Captioning

Input Video  →  Sample frames @1/10

Forward propagate Output: “fc7” features (activations before classification layer)

fc7: 4096 dimension “feature vector”
Video Captioning

Input Video

Convolutional Net

\[ \frac{1}{n} \sum \]

Mean across all frames

Recurrent Net

\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)
\( \text{LSTM} \rightarrow \text{LSTM} \)

Output

\( A \)
\( \text{boy} \)
\( \text{is} \)
\( \text{playing} \)
\( \text{golf} \)
\( \text{<EOS>} \)

Venugopalan et al., “Translating Videos to Natural Language using Deep Recurrent Neural Networks”, NAACL-HTL 2015
Video Captioning

FGM: A person is dancing with the person on the stage.
YT: A group of men are riding the forest.
I+V: **A group of people are dancing.**
GT: Many men and women are dancing in the street.

FGM: A person is cutting a potato in the kitchen.
YT: A man is slicing a tomato.
I+V: **A man is slicing a carrot.**
GT: A man is slicing carrots.

FGM: A person is walking with a person in the forest.
YT: A monkey is walking.
I+V: **A bear is eating a tree.**
GT: Two bear cubs are digging into dirt and plant matter at the base of a tree.

FGM: A person is riding a horse on the stage.
YT: A group of playing are playing in the ball.
I+V: **A basketball player is playing.**
GT: Dwayne wade does a fancy layup in an allstar game.
Video Captioning

Venugopalan et al., “Sequence to Sequence - Video to Text”, ICCV 2015
Video Captioning

Encoding stage

Decoding stage

A man is talking...

Venugopalan et al., “Sequence to Sequence - Video to Text”, ICCV 2015
Task: Given an image and a natural language open-ended question, generate a natural language answer.

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?

Visual Question Answering (VQA)

Image Embedding

Question Embedding

“How many horses are in this image?”

Visual Question Answering (VQA)

Figure 2. Our proposed framework: given an image, a CNN is first applied to produce the attribute-based representation $V_{att}(I)$. The internal textual representation is made up of image captions generated based on the image-attributes. The hidden state of the caption-LSTM after it has generated the last word in each caption is used as its vector representation. These vectors are then aggregated as $V_{cap}(I)$ with average-pooling. The external knowledge is mined from the KB (in this case DBpedia) and the responses encoded by Doc2Vec, which produces a vector $V_{know}(I)$. The 3 vectors $V$ are combined into a single representation of scene content, which is input to the VQA LSTM model which interprets the question and generates an answer.
Visual Question Answering (VQA)

https://vqa.cloudcv.org/

Ask any question about this image

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Motion: Why is it useful?
Motion: Why is it useful?

- Even “impoverished” motion data can evoke a strong percept

Modeling Motion: Optical Flow

Walker et al., “Dense Optical Flow Prediction from a Static Scene”, ICCV 2015
Transferring Motion

Key idea: Generate videos with similar flow patterns as source videos (+ many details).
Transferring Motion
Transferring Motion

Baking

Blooming
Tracking: some applications

- Body pose tracking, activity recognition
- Censusing a bat population
- Video-based interfaces
- Medical apps
- Surveillance

Kristen Grauman
Tracking examples

Traffic: https://www.youtube.com/watch?v=DiZHQ4peqjg

Soccer: http://www.youtube.com/watch?v=ZqQlItFAnxg

Face: http://www.youtube.com/watch?v=i_bZNVmhJ2o

Body: https://www.youtube.com/watch?v=_Ahy0Gh69-M

Eye: http://www.youtube.com/watch?v=NCTyDUEMotg

Gaze: http://www.youtube.com/watch?v=-G6Rw5cU-1c
Things that make visual tracking difficult

- Erratic movements, moving very quickly
- Occlusions, leaving and coming back
- Surrounding similar-looking objects

Adapted from Amin Sadeghi
Strategies for tracking

• Tracking by repeated detection
  – Works well if object is easily detectable (e.g., face or colored glove) and there is only one
  – Need some way to link up detections
Strategies for tracking

- Tracking w/ dynamics: Using model of expected motion, *predict* object location in next frame
  - Restrict search for the object
  - Measurement noise is reduced by trajectory smoothness
  - Robustness to missing or weak observations
  - Assumptions: Camera is not moving instantly to new viewpoint, objects do not disappear/reappear in different places in the scene
General model for tracking

- **State** \( X \): The actual state of the moving object that we want to estimate but cannot observe
  - E.g. position, velocity
- **Observations** \( Y \): Our actual measurement or observation of state \( X \), which can be very noisy
- At each time \( t \), the state changes to \( X_t \) and we get a new observation \( Y_t \)
- Our goal is to recover the most likely state \( X_t \) given:
  - All observations so far, i.e. \( y_1, y_2, ..., y_t \)
  - Knowledge about dynamics of state transitions

Adapted from Amin Sadeghi and Kristen Grauman
Steps of tracking

- **Prediction:** What is the next state of the object given past measurements?

\[
P(X_t | Y_0 = y_0, \ldots, Y_{t-1} = y_{t-1})
\]
Steps of tracking

- **Prediction:** What is the next state of the object given past measurements?

\[
P(X_t | Y_0 = y_0, \ldots, Y_{t-1} = y_{t-1})
\]

- **Correction:** Compute an updated estimate of the state from prediction and measurements

\[
P(X_t | Y_0 = y_0, \ldots, Y_{t-1} = y_{t-1}, Y_t = y_t)
\]
Problem statement

• We have models for

  Likelihood of next state given current state (dynamics model):
  \[ P(X_t | X_{t-1}) \]

  Likelihood of observation given the state (observation or measurement model):
  \[ P(Y_t | X_t) \]

• We want to recover, for each \( t \):
  \[ P(X_t | y_0, \ldots, y_t) \]
Example: Constant velocity (1D points)
Example: Constant velocity (1D points)

- State vector: position $p$ and velocity $v$

\[
x_t = \begin{bmatrix} p_t \\ v_t \end{bmatrix} \quad p_t = p_{t-1} + (\Delta t)v_{t-1} + \xi \\
\]

\[
v_t = v_{t-1} + \xi
\]

\[
x_t = D_t x_{t-1} + \text{noise} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} p_{t-1} \\ v_{t-1} \end{bmatrix} + \text{noise}
\]

- Measurement is position only

\[
y_t = M x_t + \text{noise} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} p_t \\ v_t \end{bmatrix} + \text{noise}
\]
The Kalman filter

• Linear dynamics model: state undergoes linear transformation plus Gaussian noise

• Observation model: measurement is linearly transformed state plus Gaussian noise

• Predicted/corrected state distributions are Gaussian
  – You only need to maintain the mean and covariance
  – The calculations are easy
Prediction and correction

Prediction:

\[ P(X_t \mid y_0, \ldots, y_{t-1}) = \int P(X_t \mid X_{t-1})P(X_{t-1} \mid y_0, \ldots, y_{t-1})dX_{t-1} \]

Correction:

\[ P(X_t \mid y_0, \ldots, y_t) = \frac{P(y_t \mid X_t)P(X_t \mid y_0, \ldots, y_{t-1})}{\int P(y_t \mid X_t)P(X_t \mid y_0, \ldots, y_{t-1})dX_t} \]

Adapted from Amin Sadeghi
Example w/ constant velocity

Kalman filter processing

- $o$ state
- $x$ measurement
- * predicted mean estimate
- + corrected mean estimate

bars: variance estimates

Adapted from Kristen Grauman
Example w/ constant velocity

Ground Truth  Observation  Correction