Statistical Dialogue Systems

NPFL099 Statistické Dialogové systémy

12. Multimodal Systems

(+a few words about domain adaptation)

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http://ufal.cz/npfl099

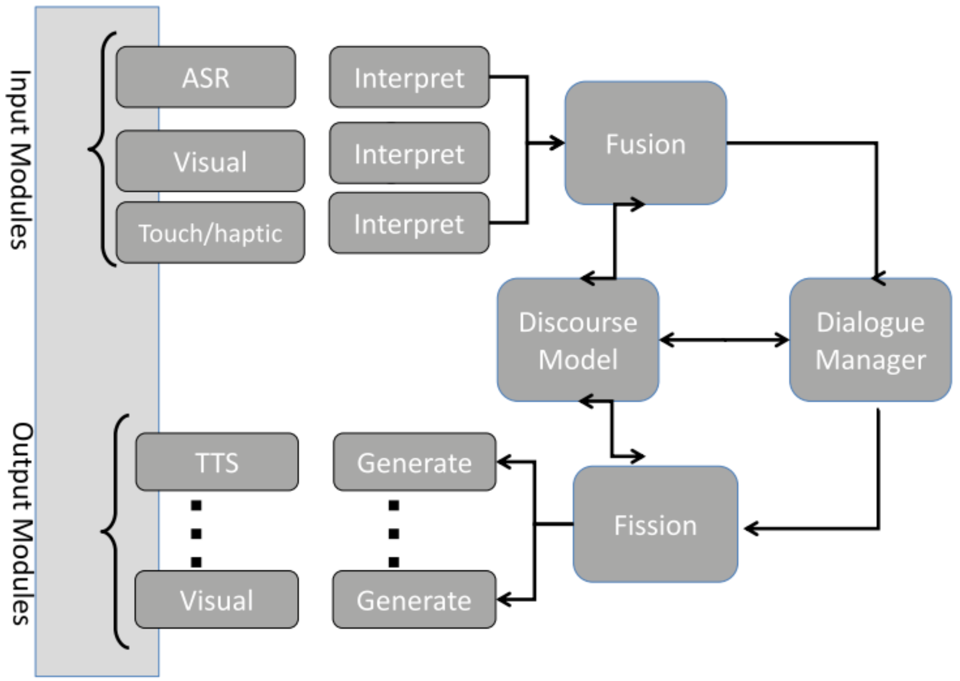
9. 1. 2020

Multimodal Dialogue Systems

- adding more modalities to voice/text
  - input:
    - touch
    - drawing
    - gaze, gestures, facial expressions
    - voice pitch/tone
    - image
  - output:
    - graphics
    - gaze, gestures, facial expressions, body movement
- either traditional/modular and mostly rule-based systems, or very experimental (not much use in practice)

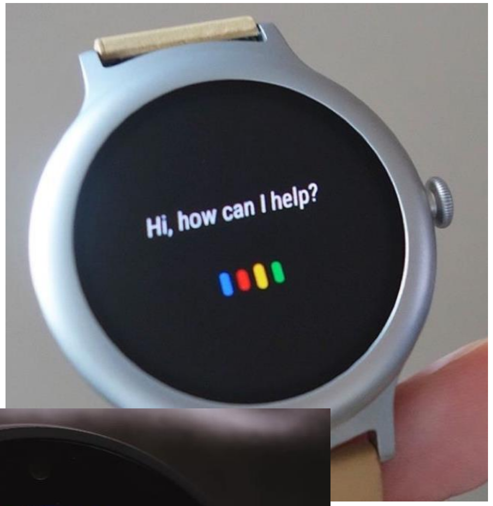
Standard Multimodal DS Schema

- basically the same as voice/text DSs
- adding multiple input modules
  - for multiple modalities
  - each with its own NLU-like interpretation
  - interpretations are merged
- multiple output modules
  - each with its own generation
  - dialogue manager output is split
- typically ready-made off-the-shelf modules
  - it’s too complex/costly to build these custom



Smart Devices

- Phones, wearables, smart speakers with a display
  - incl. Google Assistant, Alexa & Siri
  - admittedly not so much dialogue, more of commands
  - cloud-based operation for most
- Input
  - touch: active & passive gestures (touch/accelerometer)
    - “raise to speak”
    - rarely visually sensing gestures
    - doesn’t support gaze
- Output
  - graphics: card interface
  - generation functions rule-based/low-level

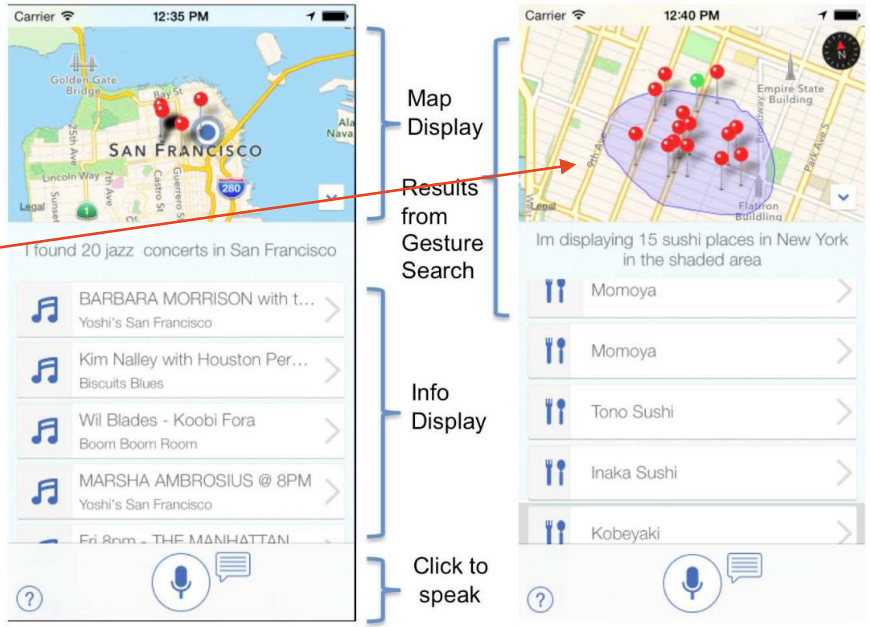


https://www.wareable.com/android-wear/how-to-use-voice-commands-on-android-wear
https://www.cnet.com/reviews/amazon-echo-spot-review/
https://www.macrumors.com/how-to/use-siri-raise-to-speak-watchos-5/

“Classical” Multimodal Systems

- closed-domain task-oriented dialogue systems
- map-based: town information with map input & output
  - touch / pen – drawing, map display
    - reacting to zooming, area selection
    - handwriting recognition (as alternative input)
  - similar to Google Assistant, but more interactive
- in-car: voice & button control
- custom architectures
  - off-the-shelf modules
  - rule-based touch input processing

what about here?



S: *I found 3 albums by The Beatles in your collection*
<shows listing on screen>
U: *Play the third one.*
U: *Which songs are on this one?*
<selects an album from listing on screen>

(Johnston et al., 2002) https://www.aclweb.org/anthology/P02-1048/
(Johnston et al., 2014) https://www.aclweb.org/anthology/W14-4335
(Becker et al., 2006) https://www.aclweb.org/anthology/P06-4015

Virtual Agents

https://youtu.be/ejczMs6b1Q4
https://vhtoolkit.ict.usc.edu/

- character face/full body
  - on screen or 3D projected (FurHat)
- a lot more outputs
  - full motion video – facial expressions, gaze, gestures, body movement
    - a lot of it “automatic”,
      designed to look natural/match what’s said
- additional inputs – gaze & facial expression
  - checking user engagement/sentiment
- dialogue management mostly rule-based
  - retrieval with non-linguistic inputs (Virtual Humans/SimSensei)
  - limited-domain custom rules (FurHat)
- tutoring/training, healthcare

FurHat

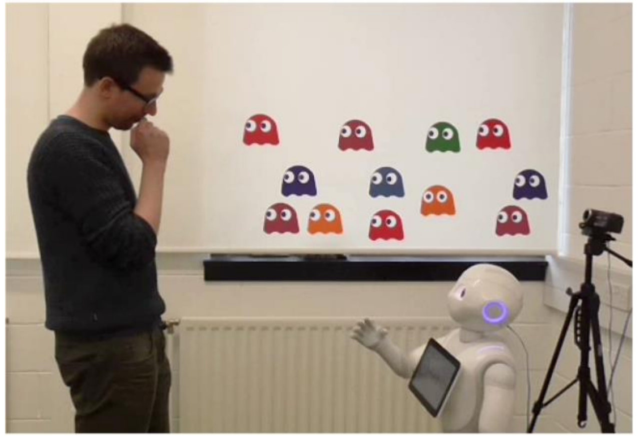
Virtual Humans

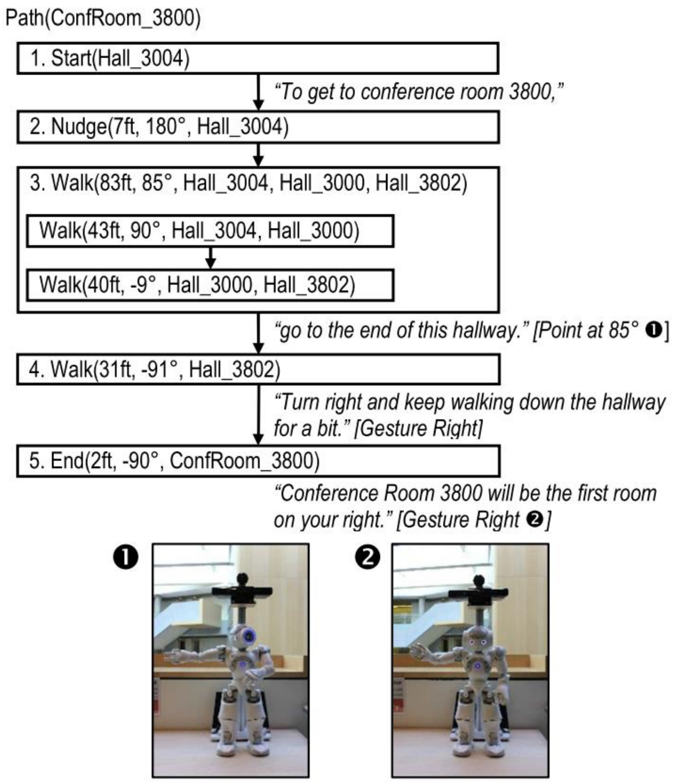
SimSensei

(Al Moubayed et al., 2012) https://doi.org/10.1007/978-3-642-34584-5_9
(Rushforth et al., 2009) https://doi.org/10.1007/978-3-642-04380-2_82
(DeVault et al., 2014) https://dl.acm.org/doi/10.5555/2615731.2617415

Robots

- similar to virtual agents, but with actual hardware
  - different user's perception
    - body gestures more prominent
    - touching the robot is possible
  - situated deployment – need to track user engagement
    - is the user still talking to the robot?
  - hardware limitations
    - mostly no facial expr./gaze output, some sensors missing etc.
- off-the-shelf robots (Nao, Pepper)
  - built-in & additional sensors (e.g. Kinect)
  - custom rule-based gesture generation
  - controlled via a computer (not autonomous)
- "receptionist" – directions, information

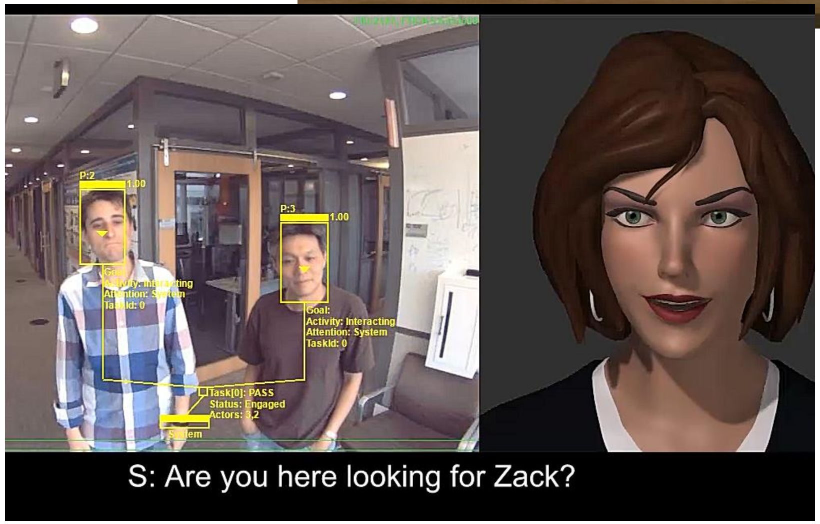




(Novikova et al., 2017) http://arxiv.org/abs/1706.02757
(Bohus et al., 2014) https://dl.acm.org/doi/10.5555/2615731.2615835

Multi-party Dialogue

- Relevant for both virtual agents & robots
  - supported by most previously mentioned projects
- How to handle multiple counterparts?
  - users or other robots/virtual agents
- gaze/engagement/speech detection
  - who's speaking/looking etc.
- rules for multiple counterparts
  - switching gaze to address them
    - here, 3D is better than 2D (otherwise gaze ambiguous)
  - telling one to wait for another
- customer service, information



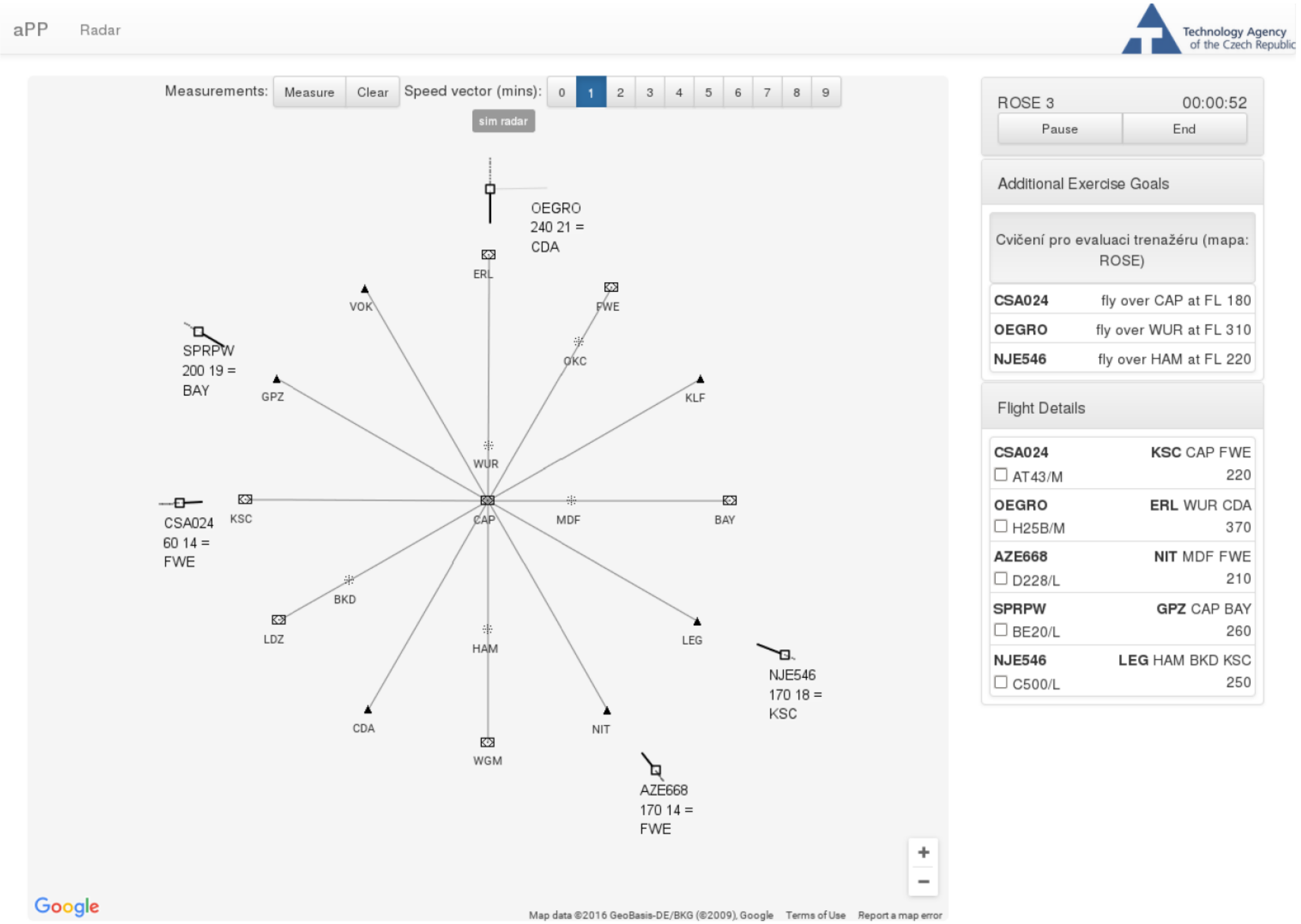
Interaction 1 (Socially inappropriate)	**Interaction 2 (Socially appropriate)**
One person, A, approaches the bar and turns towards the bartender	
Robot (to A): How can I help you?	Robot (to A): How can I help you?
A: A pint of cider, please.	A: A pint of cider, please.
A second person, B, approaches the bar and turns towards the bartender	
Robot (to B): How can I help you?	Robot (to B): One moment, please.
B: I'd like a pint of beer.	Robot: (Serves A)
Robot: (Serves B)	Robot (to B): Thanks for waiting. How can I help you?
Robot: (Serves A)	B: I'd like a pint of beer.
	Robot: (Serves B)

https://youtu.be/oOp4XP_ziMw
http://www.danbohus.com/

(Foster et al., 2012) http://dl.acm.org/citation.cfm?doid=2388676.2388680
(Bohus et al., 2014) https://dl.acm.org/doi/10.5555/2615731.2615835
(Skantze & Al Moubayed, 2012) https://doi.org/10.1145/2388676.2388698

Specific uses

- Air traffic controller training – radar as a modality
  - multiple agents/systems representing pilots
  - radar charting each agent's behavior
  - single ASR, many TTSs
    - varied accents
  - all rule-based
    - very limited domain
    - bearings, flight levels



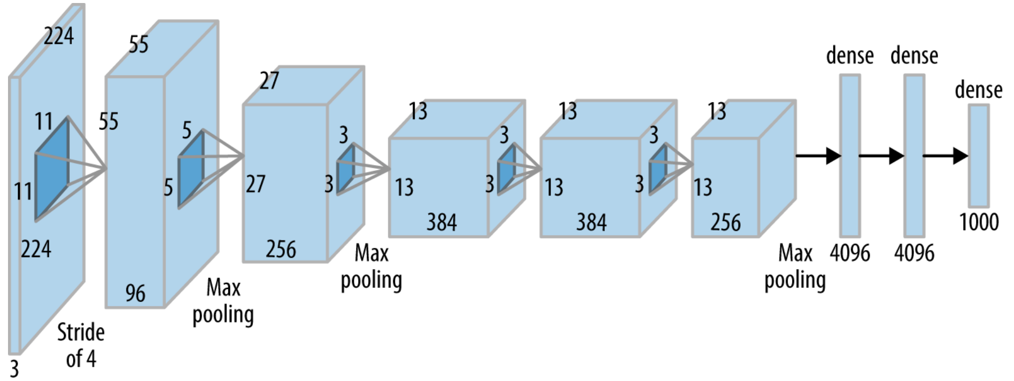
(Šmídl et al., 2016) https://www.isca-speech.org/archive/Interspeech_2016/abstracts/2002.html

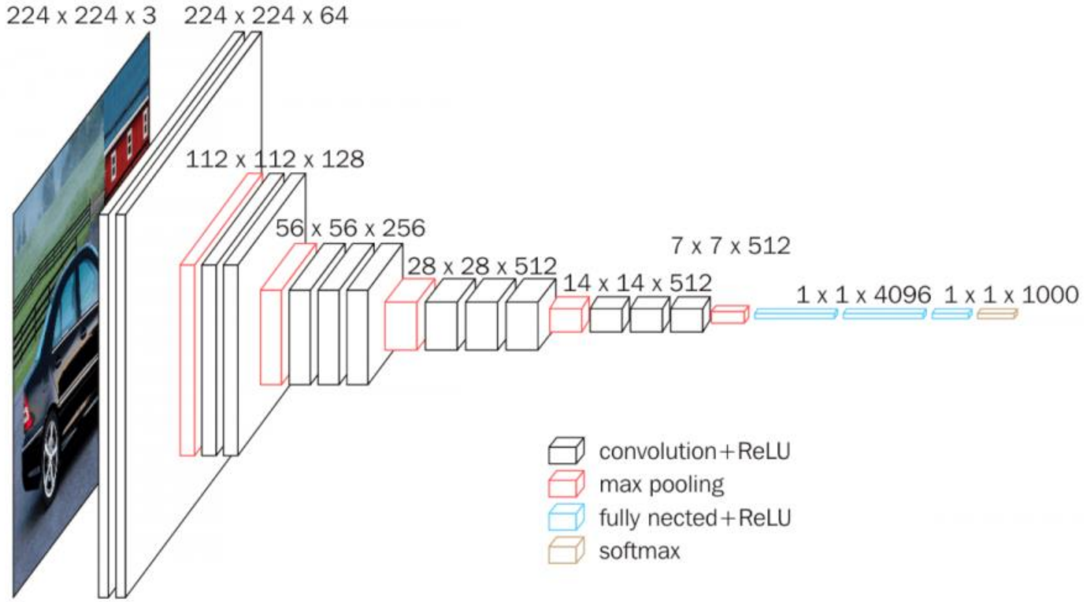
End-to-end Multimodal

- recent, experimental
- enhancing end-to-end DS architectures with image input
  - no video input
  - no avatars, facial expressions, gestures etc.
  - not much graphics output either
- also using off-the-shelf components
  - especially for image recognition – ready-made convolutional architectures
  - textual parts based on known architectures (HRED, MemNN etc.)
- mostly just end-to-end prediction
  - pretrained image recognition parts are kept fixed, no end-to-end training

Pretrained convolutional nets

- Data: ImageNet Challenge
  - >1M images, 1000 classes
  - just classify the object in the image
  - CNNs are way better than anything that came before them
- **AlexNet** – 1st deep CNN
  - 5 conv layers, ReLU activations, max pooling & 3 dense layers
- **VGGNet** – improvement
  - more layers, smaller CNN kernels (3x3, 2x2 pooling with stride 2)
    - reduces # of parameters, same function



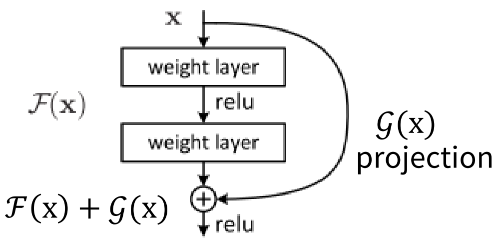


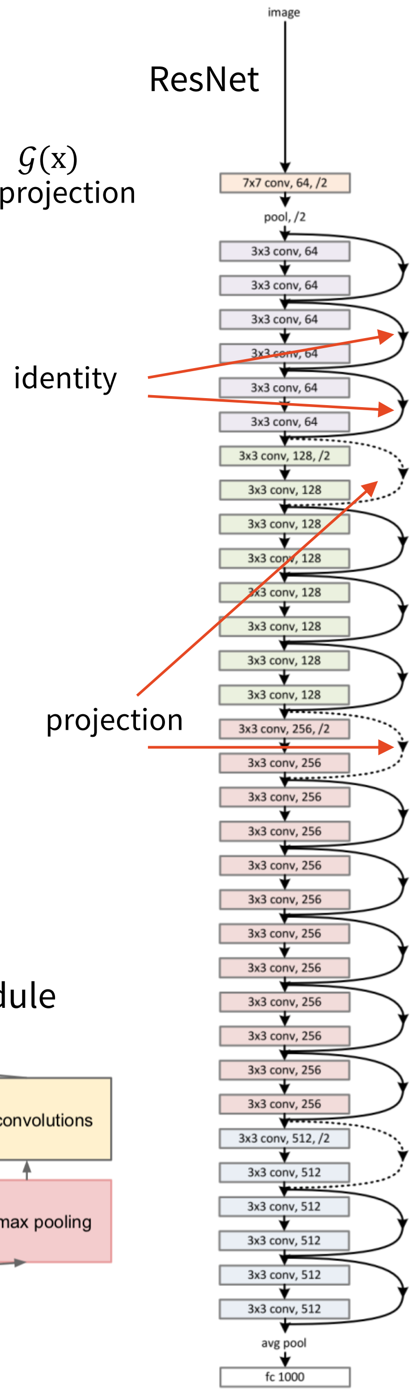
https://towardsdatascience.com/the-w3h-of-alexnet-vggnet-resnet-and-inception-7baaaecccc96

(Krizhevsky et al., 2012) https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks
(Simonyan & Zisserman, 2015) http://arxiv.org/abs/1409.1556

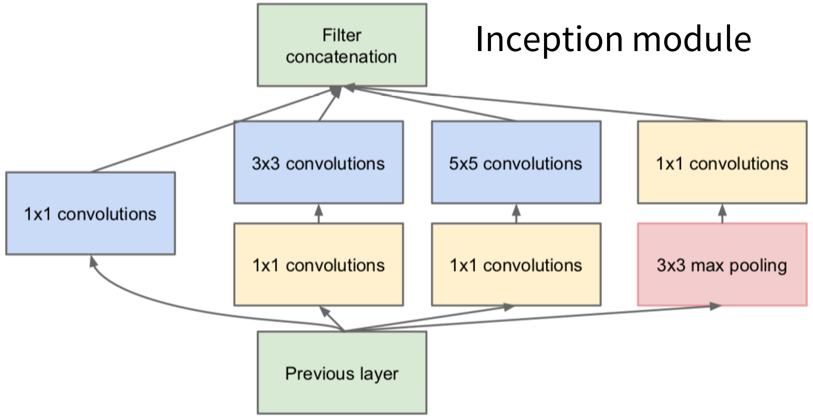
Pretrained CNNs

- **ResNet** – residual networks
  - trying to simplify the mappings found by CNNs
    - with regular CNNs, deeper might not be better (vanishing gradient problem)
  - “shortcuts”: adding identity / linear projection to convolutions
    - learning a **residual** CNN mapping (“what projection can’t handle”)
  - allows much deeper networks – alleviates vanishing gradients





- **Inception** – more CNN kernels in parallel
  - for detecting different-sized object features
  - 1x1 depth reductions, depth-wise concatenations
  - better results with shallower networks



https://towardsdatascience.com/the-w3h-of-alexnet-vggnet-resnet-and-inception-7baaaecccc96

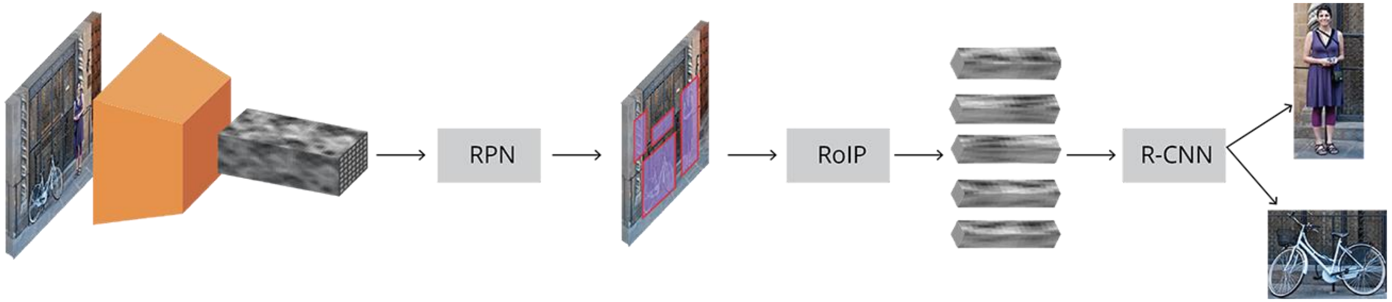
(He et al., 2016) https://arxiv.org/abs/1512.03385
(Szegedy et al., 2015) http://arxiv.org/abs/1409.4842

Pretrained CNNs

(Girschick, 2015) http://arxiv.org/abs/1504.08083
(Ren et al., 2015) https://arxiv.org/abs/1506.01497

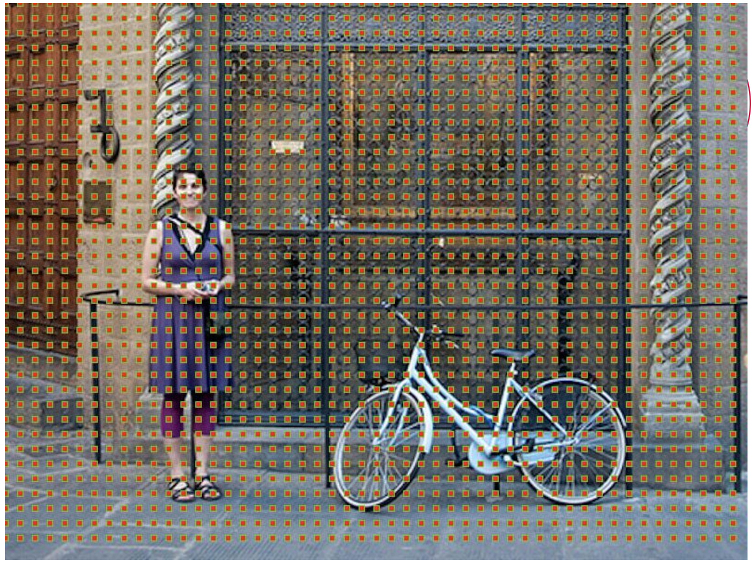
https://tryolabs.com/blog/2018/01/18/faster-r-cnn-down-the-rabbit-hole-of-modern-object-detection/

- **Faster R-CNN**
  - object detection – harder task
  - detecting boxes (regions) for multiple objects in image
- Pipeline:
  - Region prediction network (detect salient boxes)
  - Region-of-interest pooling (consolidate features)
  - Region-based CNN (classify)

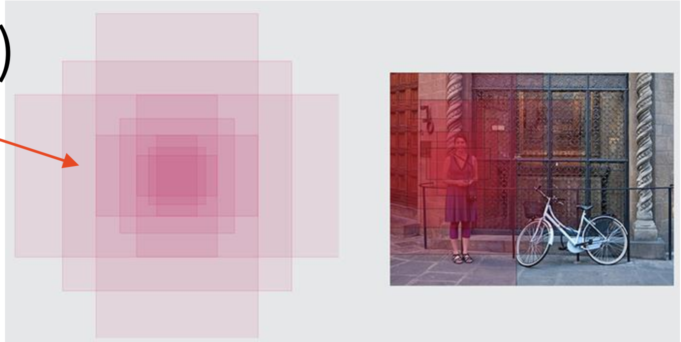


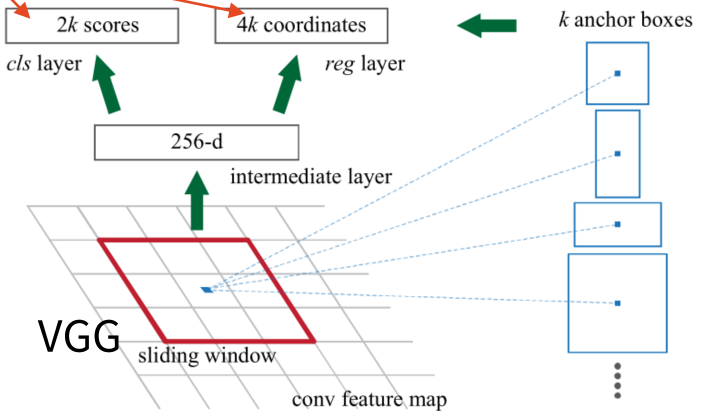
Region prediction

- pretrained VGG as feature extraction
  - features for each of the anchor points (regularly spaced in the image)



- for each anchor point, predict:
  - anchor base size & h/w ratio (e.g. 64-128-256px, 0.5/1/1.5)
  - p(this is object) & p(this is background)
  - anchor $\Delta x, \Delta y, \Delta h, \Delta w$
  - all of this via convolutions ☺
- trained using object/non-object anchors
- overlapping predictions unified



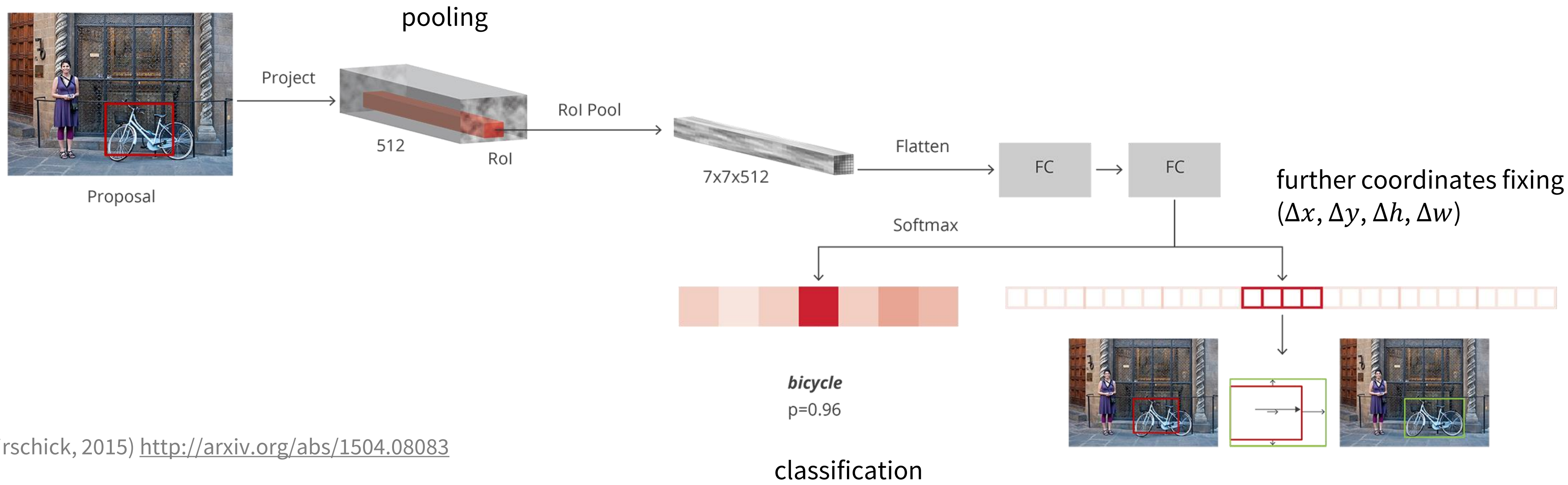


(Ren et al., 2015) https://arxiv.org/abs/1506.01497

https://tryolabs.com/blog/2018/01/18/faster-r-cnn-down-the-rabbit-hole-of-modern-object-detection/

R-CNN classification

- basically the same as image classification (given region)
  - with one more box coordinates fix
- sharing VGG features from RPN
  - this makes it much faster (only the pooling & prediction layers are new)



(Girschick, 2015) http://arxiv.org/abs/1504.08083

https://tryolabs.com/blog/2018/01/18/faster-r-cnn-down-the-rabbit-hole-of-modern-object-detection/

Visual Dialogue

https://visualdialog.org/
(Das et al., 2017) http://arxiv.org/abs/1611.08669

- **Task**: have a meaningful dialogue about an image
  - close to visual QA: **human asks, system responds**
  - but VD is multi-turn & human doesn't see the image (just a caption)
    - follow-up questions possible – coreference
    - people are not primed by the image when asking questions
- not much realistic purpose other than to test the models
  - dataset of 10-turn dialogues on 120k images
    - collected via crowdsourcing
      - connecting 2 people live to talk about an image
  - shared challenges

Caption: A man and woman on bicycles are looking at a map.
Person A (1): where are they located
Person B (1): in city
Person A (2): are they on road
Person B (2): sidewalk next to 1
Person A (3): any vehicles
Person B (3): 1 in background
Person A (4): any other people
Person B (4): no
Person A (5): what color bikes
Person B (5): 1 silver and 1 yellow
Person A (6): do they look old or new
Person B (6): new bikes
Person A (7): any buildings
Person B (7): yes
Person A (8): what color
Person B (8): brick
Person A (9): are they tall or short
Person B (9): i can't see enough of them to tell
Person A (10): do they look like couple
Person B (10): they are

Caption:
A sink and toilet in a small room.

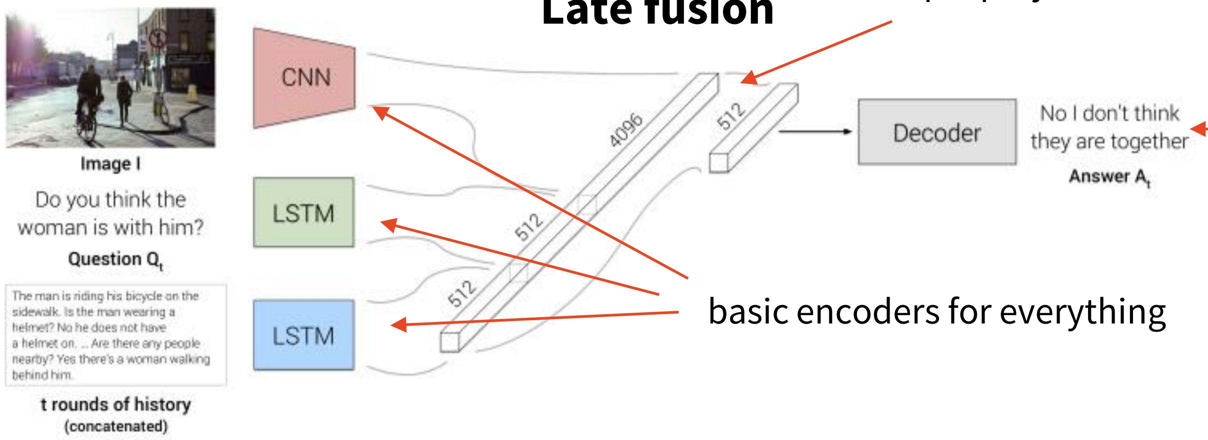
Q3: can you see anything else ?
A3: there is a shelf with items on it
Q4: is anyone in the room ?
A4: nobody is in the room
Q5: can you see on the outside ?
A5: no, it is only inside
Q6: what color is the sink ?
A6: the sink is white
Q7: is the room clean ?
A7: it is very clean
Q8: is the toilet facing the sink ?
A8: yes the toilet is facing the sink
Q9: can you see a door ?
A9: yes, I can see the door
Q10 what color is the door ?
A10 the door is tan colored

Base Visual Dialogue Models

(Das et al., 2017) http://arxiv.org/abs/1611.08669

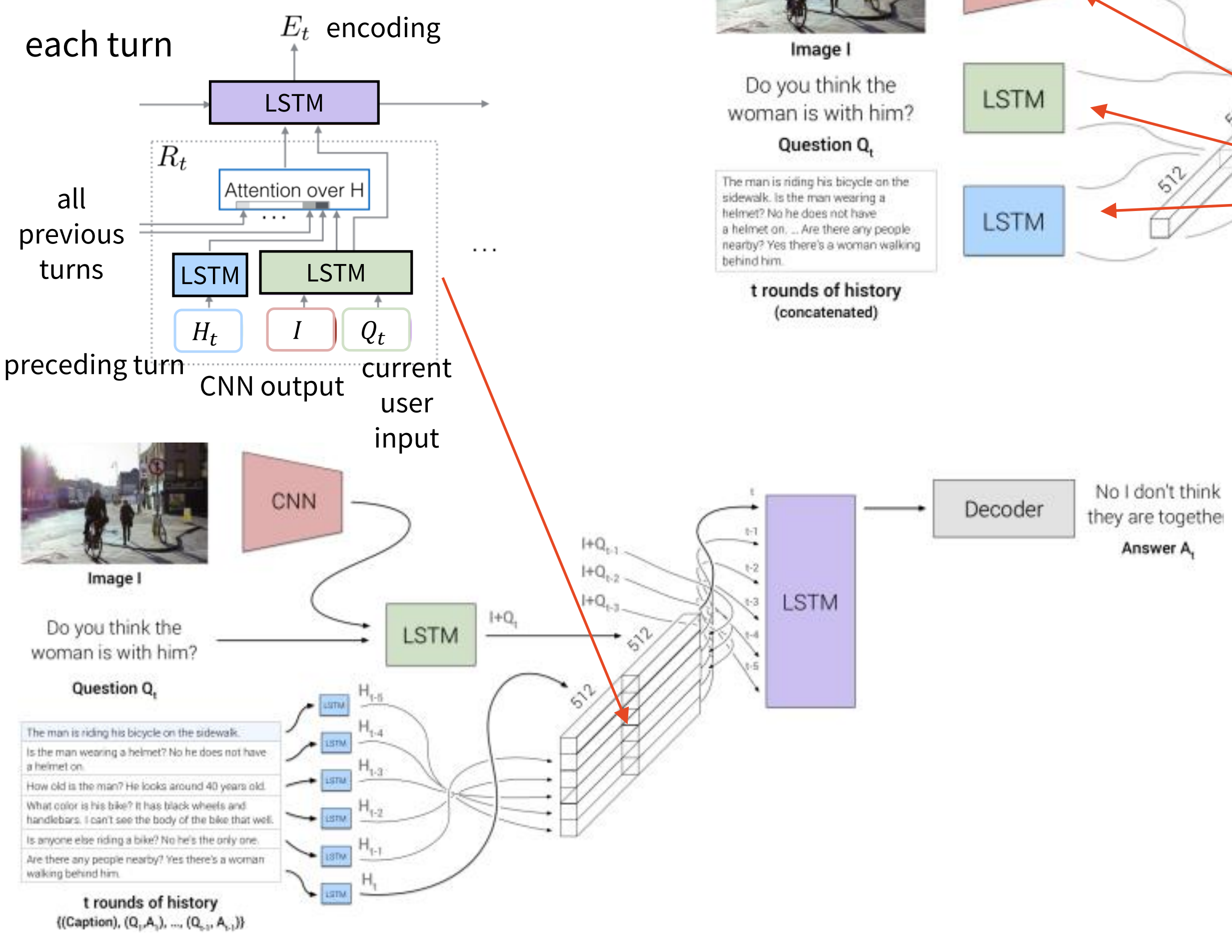
Late fusion

simple projection to initialize decoder



LSTM decoder (same for all)

basic encoders for everything



each turn

all previous turns

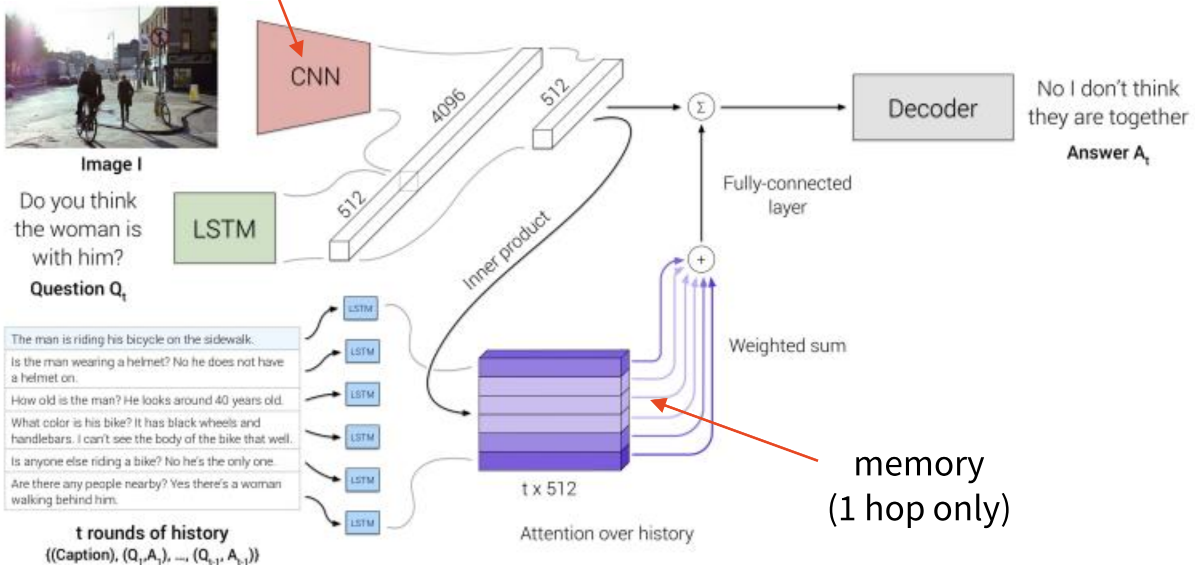
preceding turn

CNN output

current user input

VGG (same for all)

Memory Network



memory (1 hop only)

Hierarchical Recurrent Encoder

Visual Dialogue Evaluation

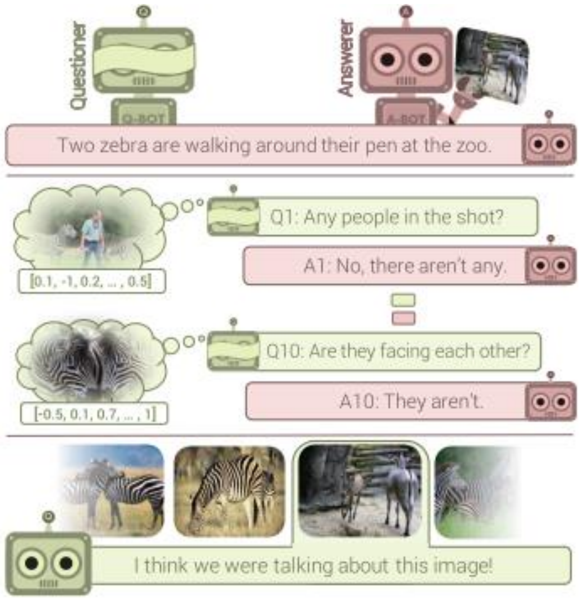
- BLEU etc. possible but not used here
- IR setup used instead
  - system given ground-truth dialogue history + user input & 100 candidate answers to score/rank
- IR metrics:
  - **ground-truth response rank** (average)
  - **recall@k** (% cases where ground-truth is included in top *k*)
  - **mean reciprocal rank**: Ø $\frac{1}{\text{ground truth rank}}$ (1 if ground truth is first, 0.5 if second etc.)
  - **normalized discounted cumulative gain**
    - for multiple acceptable answers out of the 100 candidates
    - DCG: $\sum_{i=1}^{100} \frac{c_i \text{ relevant?}}{\log_2(i+1)}$, normalize by highest possible DCG (all good answers on top)
- problem: images only give modest gain over text-only models

https://visualdialog.org/challenge/2019#evaluation

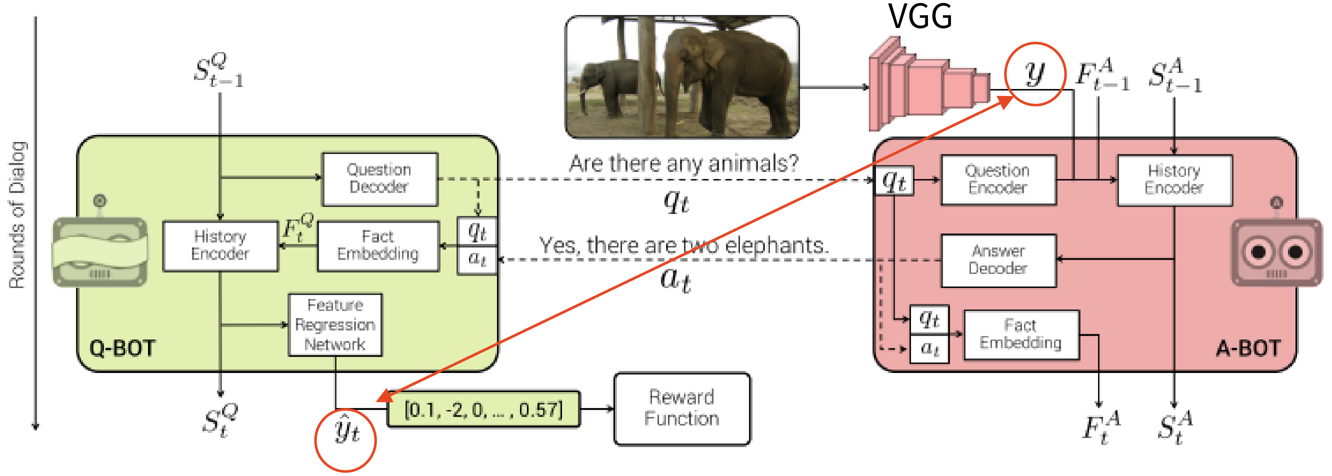
https://en.wikipedia.org/wiki/Discounted_cumulative_gain
https://medium.com/@_init_/notes-on-the-ndcg-metric-used-in-the-visual-dialog-challenge-2019-90cf443b93dc

RL for Visual Dialogue

(Das et al., 2017)
http://arxiv.org/abs/1703.06585



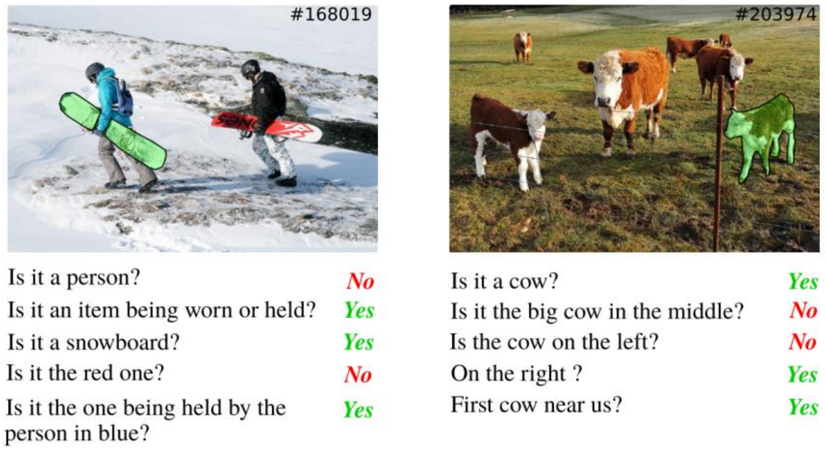
- human questioner replaced by “Q-bot”
  - Q-bot needs to guess an image
- using HRE architecture for both
  - Q-bot produces a VGG-like image representation
  - both trained via REINFORCE
  - same reward for both: lowered difference of Q-bot’s predicted representation to the ground-truth image
    - per turn
  - curriculum learning
    - start with fully supervised
    - use RL only for last k turns
    - increase k
  - combination with supervised works best

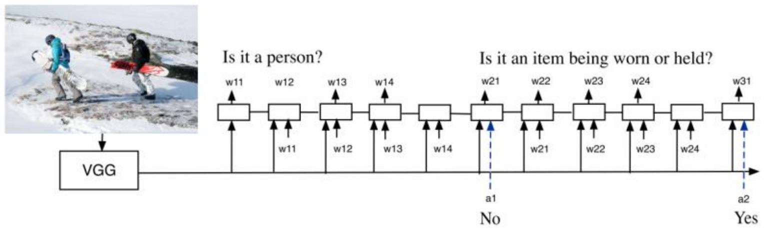


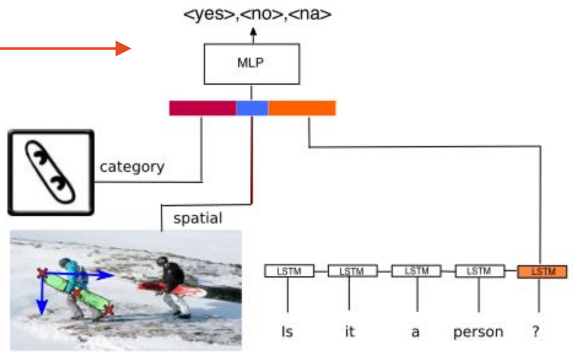
Guess What

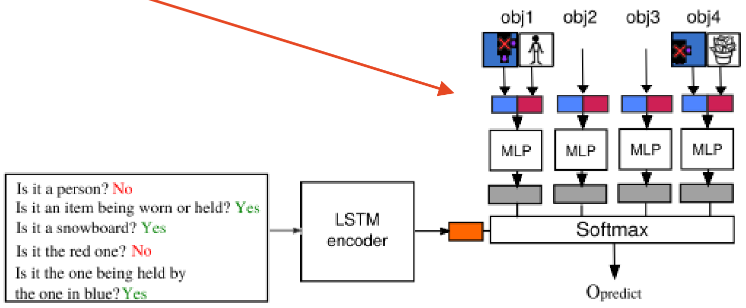
(Strub et al., 2017)
https://www.ijcai.org/proceedings/2017/385

- guessing one of the objects in an image
    - GuessWhat data (150k guessing dialogues)
- 3 models:
    - question generation – LSTM
        - running through all previous questions
        - conditioned on VGG image features & previous replies
    - “oracle” – reply generation (Y/N/NA)
        - feed-forward from LSTM question encoding + object category + object size & position in image
    - guesser – select object from list of candidates
        - dot product & softmax over last LSTM generator state + candidate objects categories & sizes/positions
        - triggered at the end of the dialogue









Guess What

(Strub et al., 2017)
https://www.ijcai.org/proceedings/2017/385

- training via RL
  - optimize the sequence of questions to find the object
  - states = each word
    - <?> = answer retrieved, <stop> = end of dialogue, guesser applied
  - simple 0/1 reward (guesser found the correct object at the end or not)
- supervised pretraining
- only question generator trained using RL (REINFORCE)
  - learns to stop after 4.1 questions on average
    - without penalty
    - guesser might be less accurate for long dialogues

		New Objects	New Images
Supervised	Sampling	39.2% ± 0.2	38.0% ± 0.1
	Greedy	40.7% ± 0.1	39.4%
	BSearch	46.1% ± 0.0	44.8%
REINFORCE	Sampling	**53.3% ± 0.3**	**52.3% ± 0.2**
	Greedy	49.5% ± 0.0	48.5%
	BSearch	44.9% ± 0.1	45.8%
Human		84.4%	
Human with Guesser		63.8%	
Random		18,1%	

Image Chat

(Shuster et al, 2018)
http://arxiv.org/abs/1811.00945

- Open chat about an image
  - no particular task
  - specific personality traits of both participants
- Crowdsourced data
  - ~200k dialogues, 3 turns per dialogue (A-B-A)
  - A & B have predefined personalities
- Evaluation: recall@1 (out of 100 candidates)

A: Fearful *B: Miserable*

A: I just heard something out there and I have no idea what it was.

B: It was probably a Wolf coming to eat us because you talk too much.

A: I would never go camping in the woods for this very reason.

A: Stylish *B: Fatalistic*

A: Riding a mechanical bull in a skirt is just my style.

B: You'd probably fall off and get hurt.

A: And everyone would be copying me for it! It'll be trendy!

A: Money-Minded *B: Glamorous*

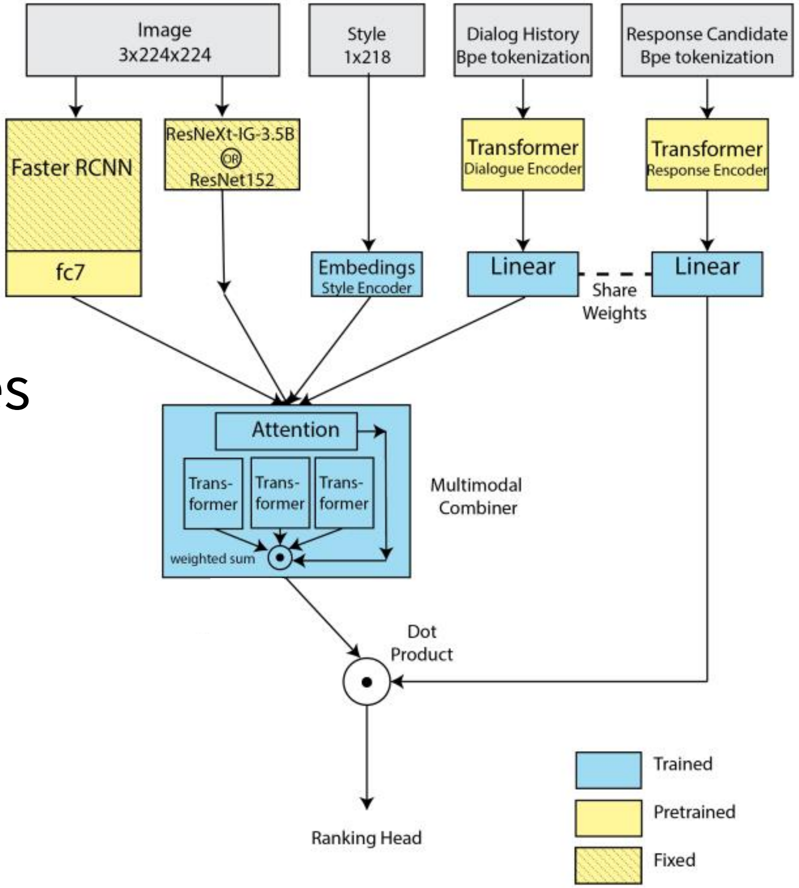
A: You know money doesn't grow on trees.

B: I could see some high society ladies having their brunch over looking this canal.

A: I could see them spending way too much on avocado toast here.

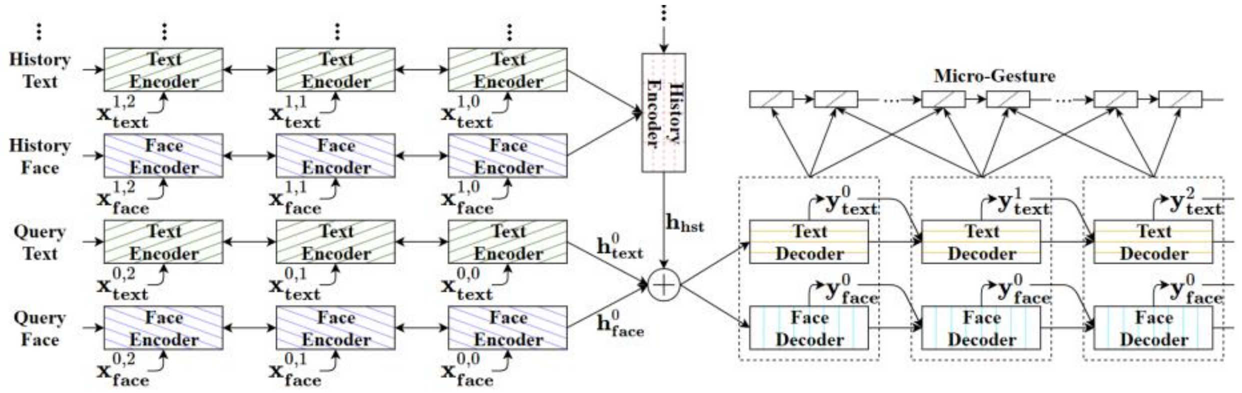
Image Chat

(Ju et al., 2019)
http://arxiv.org/abs/1912.12394

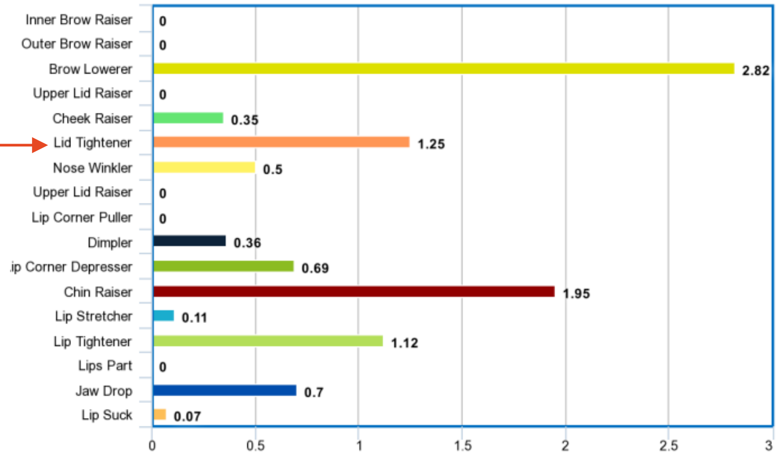


- Pretrained input components
  - concatenating ResNet & Faster R-CNN image features
  - Transformer encoders pretrained on Reddit
    - 1 encoder for the dialogue context
    - 1 encoder for candidate response
- personality embedding
- multimodal combiner
  - concatenate all inputs except candidate & self-attend (transformer)
    - using 3 transformers, then summing them (~ensemble)
- dot product with candidate encoding for ranking (ranking only!)
- the same model can also do captioning and visual QA

Chat with Facial Expressions



- Data collected from movie clips
  - selected scenes with single face on screen
  - automatically annotated FACS facial features
    - movements of 18 muscles + 3 head position features
  - 48k utterances (=pretraining needed)



- facial features clustered & synced with words
  - 200 facial expression “templates”
- HRED-like setup
  - parallel encoders – words & facial in sync (+ turn-level encoders)
  - parallel decoders + fine-grained micro-gesture generator (frame-level LSTM)
  - training: supervised, RL (word F1 as reward), GAN (human/machine discriminator)
- avatar with external ASR/TTS

(Chu et al., 2018)
https://arxiv.org/abs/1812.01525
https://vimeo.com/248025147
http://www.cs.toronto.edu/face2face

Shopping Dialogues

(Saha et al., 2018)
http://arxiv.org/abs/1704.00200

- a more practical task: fashion e-shop
  - both user & system can show images
  - user can reference/talk about images
- semi-automatic data (150k dialogues)
  - 84 predefined intents
  - generated dialogue flows
    - based on predefined state automata over intents
  - utterances for each intent written by annotators
  - backed by a large manually curated DB of fashion items with images (1M items)
    - taxonomy (*man > apparel > lower body > trousers*)
    - (generated) celebrity profiles/endorsements

SHOPPER: Hello

AGENT: Hello, is there anything i can help you with today?

SHOPPER: show me some espadrilles in beige/blue within $200.

AGENT: Sure. let me just quickly browse through my catalogue

AGENT: 

AGENT: What you can see in the fifth item, michael michael kors brings you an effortless weekend look with the wrapped espadrille heel and crisscross styling of these dana flats. And what you see in the 3rd item, steve madden, the company, was founded by steve madden, the man, in 1990 in brooklyn, where he started out making trend-advancing shoes one pair at a time.

SHOPPER: List more in the upper material as in the 5th image and style as the 3rd and the 5th

AGENT: 

AGENT: The 2nd one, viscata espadrilles are 100% authentic and handcrafted in spain inspired by the mediterranean, viscata shoes are lightweight and made of natural jute rope, premium leathers, suedes and woven cloth.

SHOPPER: Can you list images of the 1st result from all orientations?

AGENT: Image from the front,right and back orientations respectively

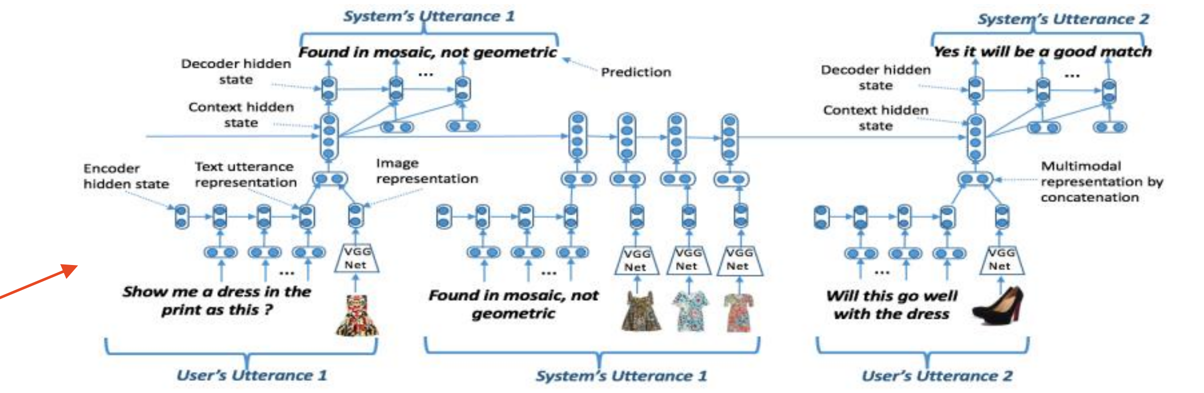
SHOPPER: And the 3rd one?

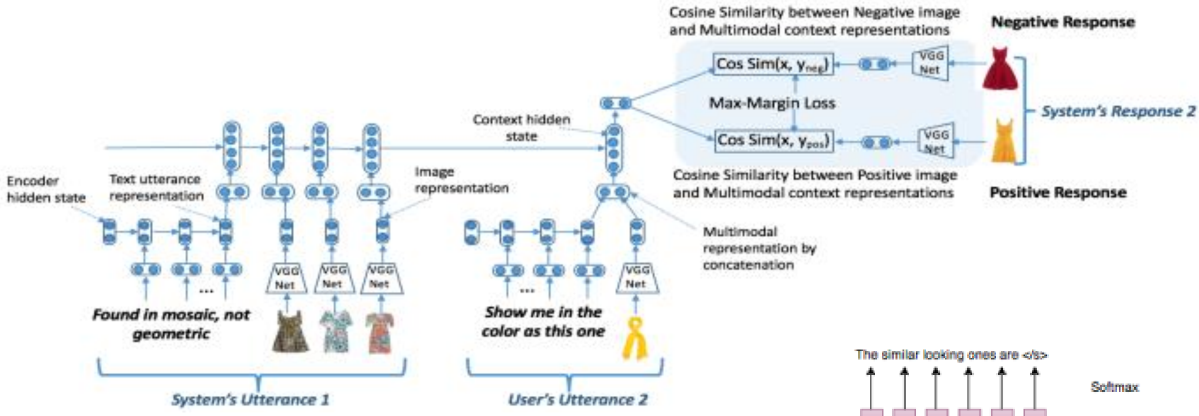
AGENT: Image from the front,right,back and left orientations respectively

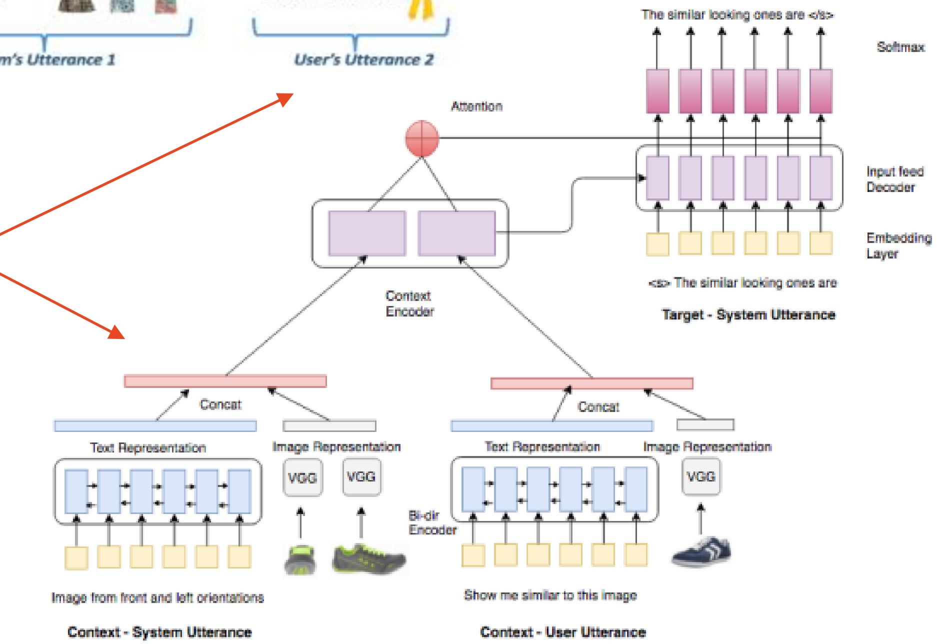
Id	Automata State Type	State Description
1	**greeting**	Shopper greets
2	**self-info**	Shopper gives information about him/herself
3	**give-criteria**	describes his requirements
4	**show-image**	Agent shows relevant responses for the Shopper's query
5	**give-image-description**	Agent generates short description of the product, using visual and catalog information
6	**Like/Dislike specific items / overall items, show-more**	Shopper expresses negative or positive preference specifically towards one or more items previously or currently shown, or a overall general preference towards all the items and optionally shows a new image to possibly modify his requirements and wants to see more
7	**show-orientation**	Shopper wants to see an item from different orientations
8	**show-similar**	Shopper wants to see similar to a particular item

Shopping Dialogues

- Models similar to visual dialogue
  - variants of multimodal HRED
  - VGG image input
- image input
  - turn-level
  - concatenated with utterance
    - seems to work better (fewer turns)
- text/image responses
  - shared encoder
  - text generation (word-by-word)
  - image ranking (needs rough retrieval)
    - so far just “select 1 out of 5”







(Saha et al., 2018) http://arxiv.org/abs/1704.00200
(Agarwal et al., 2018) http://aclweb.org/anthology/W18-6514

Domain Adaptation

- pretraining
  - BERT, but also any other model
  - weight sharing: copy weights for similar slots in target domain
- delexicalization
  - assuming your domains are similar (e.g. TVs → PCs)
- pseudo in-domain data selection
  - find data similar to your domain in the source domain
- forcing shared latent space (see few-shot end-to-end models)
- multi-task training
  - your task in source domain & different task in target domain
- partial handcrafting (see Hybrid Code Networks)

Summary

- “traditional” multimodal systems, with components
  - combination of off-the-shelf components
    - parallels for ASR/NLU & NLG/TTS in I/O modalities
  - dialogue typically quite simple
  - modalities: static graphics / touch / gaze / facial expr. / avatars / robots
  - often support multi-party dialogue
- end-to-end multimodal systems
  - mostly experimental, based on HRED with pretrained CNNs
    - VGG, ResNet, Inception (just image classification), Faster R-CNN (+object detection)
  - visual dialogue: questions & answers about an image
  - guessing: finding an object in image
  - image chat: open-domain, based on image
  - task-oriented: shopping dialogue with product images

Thanks

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or on Slack

Get the slides here:

http://ufal.cz/npfl099

References/Inspiration/Further:

- Volha Pethukova’s course (Uni Saarland): https://www.lsv.uni-saarland.de/multimodal-dialogue-systems-summer-2019/
- McTear et al. (2016): The Conversational Interface – Talking to Smart Devices
- Delgado & Araki (2005): Spoken, Multilingual and Multimodal Dialogue Systems: Development and Assessment
- papers referenced on slides

Exam

- Written test, ~10 questions
  - 60 % = pass (C), 73+% = B, 88+% = A
  - points might be adapted based on your overall performance
  - expected 1 hr, but you'll be given at least 2hrs (no pressure on time)
- Covering all lectures
- Question format
  - you'll need to write stuff on your own (not a-b-c-d)
  - explanation of terms/concepts
    - no exact formulas needed (if needed, they might be provided)
    - but you should know the principles of how stuff works
  - relationships between concepts ("what's the difference between X & Y")
  - "how would you build X"
  - focused on "important" stuff – see summaries at the end of each lecture