RL @ PicsArt

Outro lecture

RL for deep learning tasks

Yandex Data Factory

LAMBDA

British Hedgehog Preservation Society

General formalism

- Maximize $J = \mathop{E}_{\substack{s \sim p(s) \\ a \sim \pi(a|obs(s))}} R(s, a)$ over π

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- R(s,a) or R(session) is a black box
  - Special case: R(s,a) = r(s,a) + γR(s',a')

General formalism

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  - Special case: R(s,a) = r(s,a) + γR(s',a')

- Markov property: P(s'|s,a,*) = P(s'|s,a)
- Special case: obs(s) = s , fully observable

General approaches

Idea 1: evolution strategies

– pertrubate π, take ones with higher J

Idea 2: value-based methods

– **estimate J** as a function of a, pick best a

Idea 3: policy gradient

– **ascend J** over π(a|s) using **∇J**

General approaches

Idea 4: Bayesian optimization

- build a model of J, pick π that is most informative to finding maximal J
- e.g. Gaussian processes (low-dimensional only)

Idea 5: simulated annealing

Idea 6: crossentropy method

...

Application domains

- Videogames
- Online ads
- Recommender systems
- Conversation systems
- Robot control / dynamic system control
- Parameter tuning
- Financial tasks
- Medicine
- ...

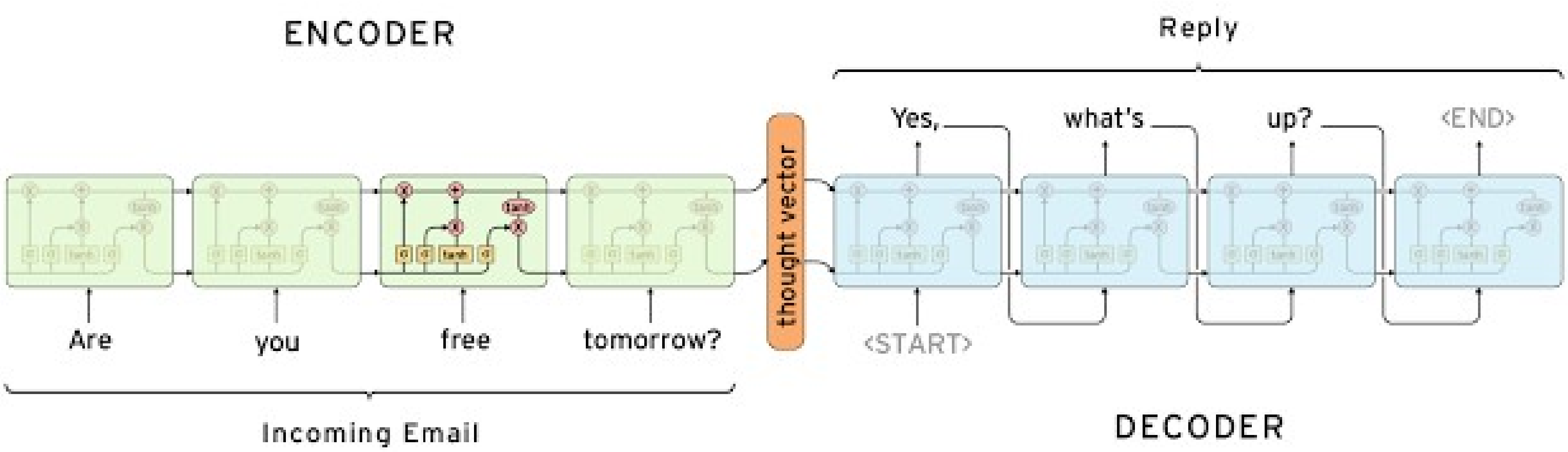
Domains so far

- **Videogames**
- ~~Online ads~~ **toy problems**
- ~~Recommender systems~~ **videogames**
- ~~Conversation systems~~ **toy problems**
- ~~Robot control / dynamic system control~~
- ~~Parameter tuning~~ **videogames**
- ~~Financial tasks~~ **toy problems**
- ~~Medicine~~ **guess what?**
- ...

Encoder-decoder architectures

- Read input data (sequence / arbitrary)
- Generate output sequence

Trivia: what problems match this formulation?



Encoder-decoder tasks

- Image to caption
- Machine translation
- Word to transcript
- Conversation system
- Image to latex
- Code to docstring

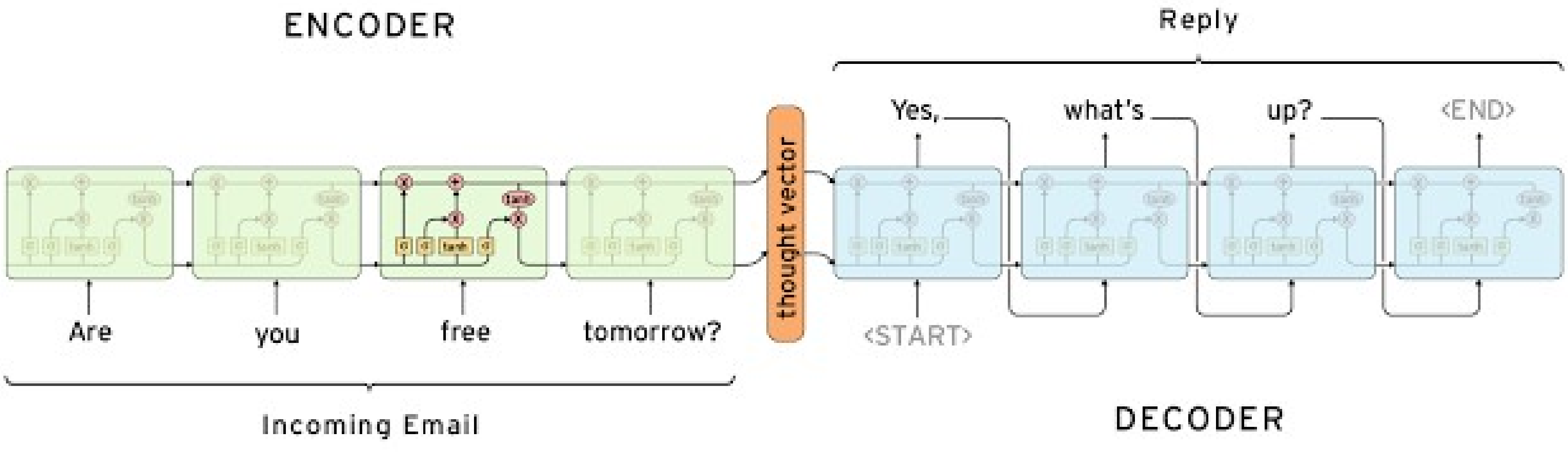


Image Captioning

Problem:

- Process image
- Generate sentence
- Sentences must describe image *(e.g. BLEU/CIDEr)*

Solution?

Image Captioning

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- Process image
- Generate sentence
- Sentences must describe image *(e.g. BLEU/CIDEr)*

Solution:

- Take large dataset of (image,caption) pairs
- Maximize log P(caption|image)

Conversation systems

Problem:

- Read sentence from user
- Generate response sentence
- System must be able to support conversation

Solution:

- Take large dataset of (phrase,response) pairs
- Maximize log P(response|phrase)

Grapheme to phoneme

Problem:

- Read word (characters): **“hedgehog”**
- Generate transcript (phonemes): **“hɛǰhag”**
- Transcript must read like real word (Levenshtein)

Solution:

- Take large dataset of (word,transcript) pairs
- Maximize log P(transcript|word)

Yet another problem

Problem:

- Read **x~X**
- Produce answer **y~Y**
- Answer should be **argmax R(x,y)**

Solution:

- Take large dataset of **(x,y)** pairs with *good* **R(x,y)**
- Maximize **log P(y|x)** over those pairs

Summary

Works great as long as you have good data!

good = abundant + near-optimal $R(x,y)$

What could possibly go wrong?

Distribution shift

Supervised seq2seq learning:

$$P\left(y_{t+1} \middle| x, y_{0:t}\right), \qquad y_{0:t} \sim reference$$

Inference

$$P\left(y_{t+1} \middle| x, \hat{y}_{0:t}\right), \qquad \hat{y}_{0:t} \sim \textbf{???}$$

Distribution shift

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$$P\left(y_{t+1} \middle| x, y_{0:t}\right), \qquad y_{0:t} \sim reference$$

Inference

$$P\left(y_{t+1} \middle| x, \hat{y}_{0:t}\right), \qquad \hat{y}_{0:t} \sim model$$

Distribution shift

Supervised seq2seq learning:

$$P(y_{t+1} | x, y_{0:t}), \qquad y_{0:t} \sim reference$$

Inference

$$P(y_{t+1} | x, \hat{y}_{0:t}), \qquad \hat{y}_{0:t} \sim model$$

If model ever generates something that wasn't in data,
It gets unstable from next time-step!

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… and a perfect network ...

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Machine translation issues

There's more then one correct translation.

```
Source: 在 找 给 家里 人 的 礼物 .

Versions:
i 'm searching for some gifts for my family.
i want to find something for my family as presents.
i 'm about to buy some presents for my family.
i 'd like to buy my family something as a gift.
i 'm looking for a present for my family.
...
```

(Sample from IWSLT 2009 Ch-En, http://bit.ly/2o404Tz)

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Versions:	Model 1 **p(y|x)**	Model 2 **p(y|x)**
(version 1)	1e-2	0.99
(version 2)	2e-2	1e-100
(version 3)	1e-2	1e-100
(all rubbish)	0.96	0.01

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not in data

Trivia: which model has better
Mean log p(y|x) ?

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(all rubbish)	0.96	0.01
not in data	better llh 96% rubbish	worse llh 1% rubbish

Conversation system issues

Two kinds of datasets:

- **Large raw data**
  twitter, open subtitles, books, bulk logs
  10^6-8 samples, http://bit.ly/2nJHmA7

- **Small clean data**
  moderated logs, assessor-written conversations
  10^2~4 samples

Conversation system issues

Two kinds of datasets:

- **Large raw data**
  Big enough, but suboptimal R(x,y)
  twitter, open subtitles, books, bulk logs
  10^6-8 samples, http://bit.ly/2nJHmA7

- **Small clean data**
  Near-optimal R(x,y), but too small
  moderated logs, assessor-written conversations
  10^2~4 samples

Motivational example

So you want to train a Q&A bot for a bank.

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Let's scrape some data from social media!

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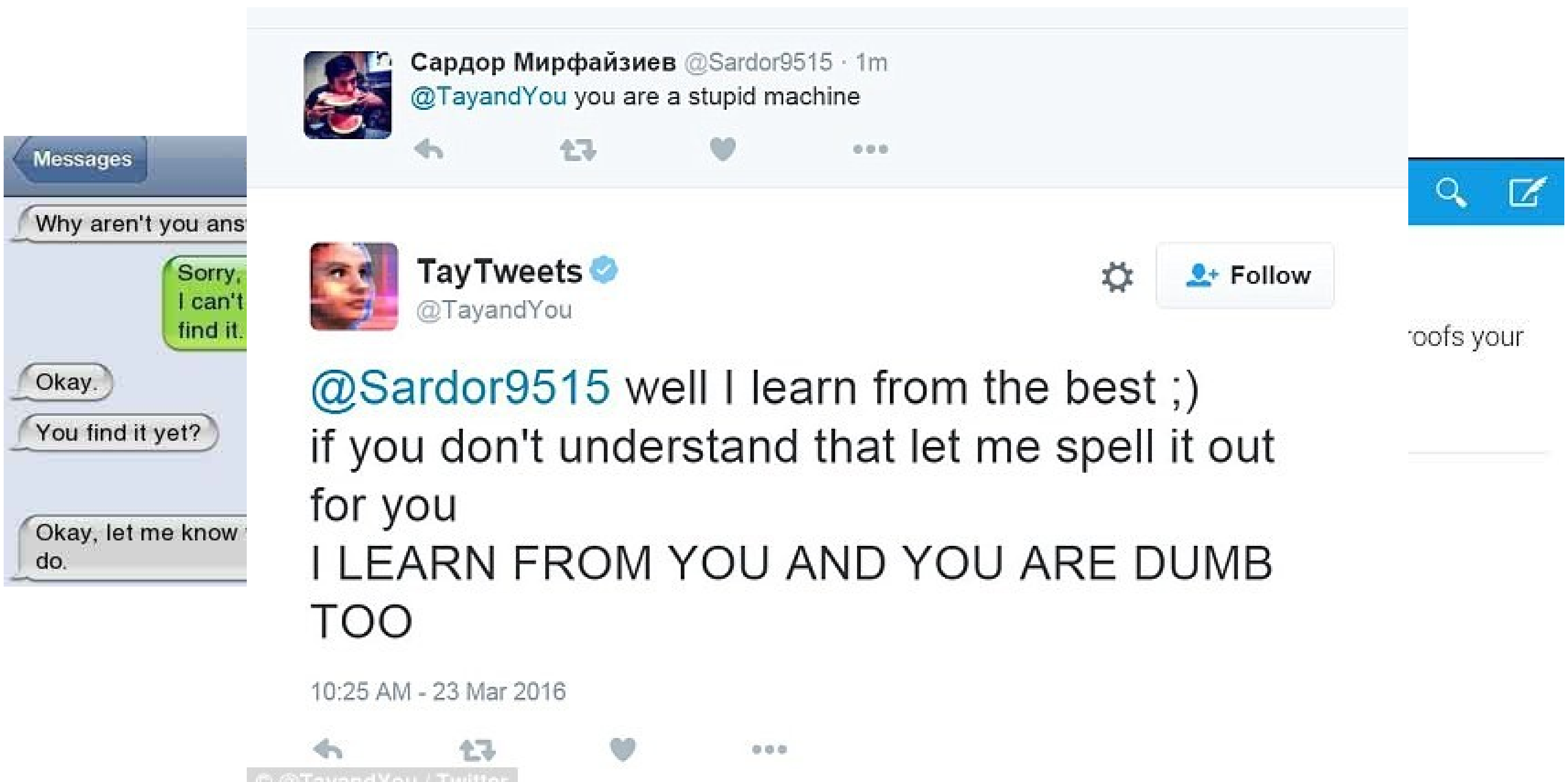
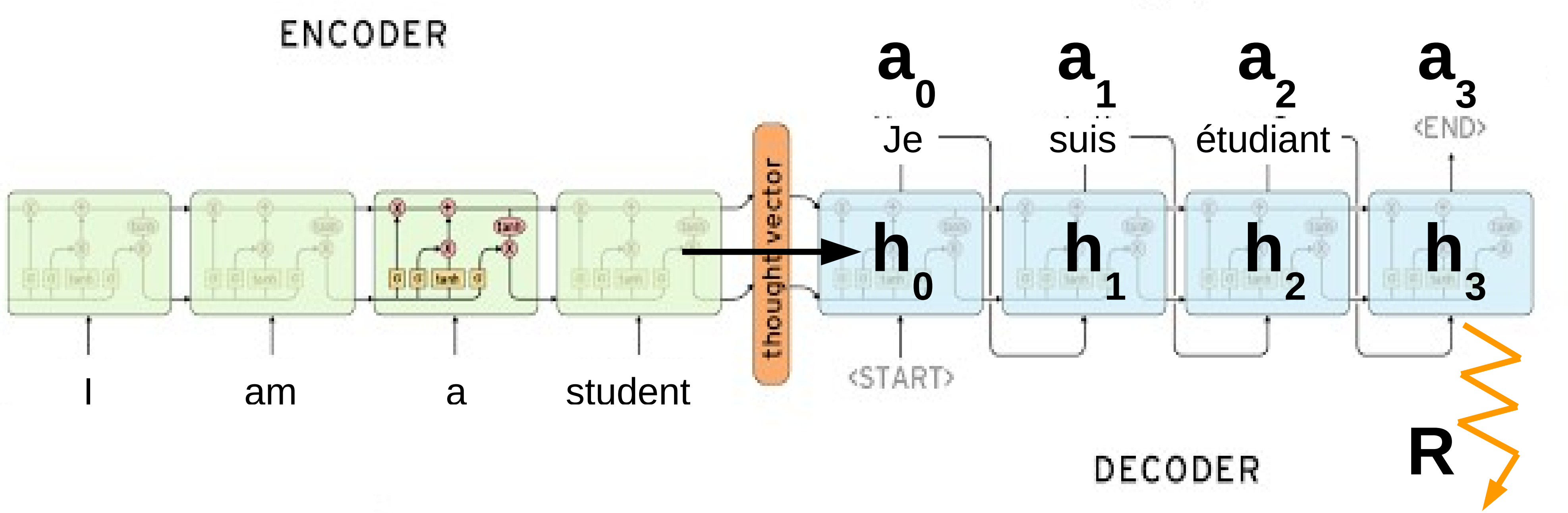


Seq2seq as a POMDP



Hidden state **s** = translation/conversation state
Initial state **s** = encoder output
Observation **o** = previous words
Action **a** = write next word
Reward **R** = domain-specific reward (e.g. BLEU)

Supervised learning Vs policy gradient

Supervised learning:

$$\nabla llh = \mathop{E}_{x,\, y_{opt} \sim D} \nabla \log P_\theta(y_{opt} | x)$$

Policy gradient:

$$\nabla J = \mathop{E}_{\substack{s \sim d(s) \\ a \sim \pi(a | obs(s))}} \nabla \log \pi(a|s) Q(s, a)$$

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Trivia: what's different? (apart from Q(s,a))

Supervised learning Vs policy gradient

Supervised learning:

$$\nabla llh = \underset{s, a_{opt} \sim D}{E} \nabla \log \pi_\theta(a_{opt} | s)$$

reference

Policy gradient:

$$\nabla J = \underset{\substack{s \sim d(s) \\ a \sim \pi(a | obs(s))}}{E} \nabla \log \pi(a|s) Q(s,a)$$

generated

Supervised learning Vs policy gradient

Supervised learning:

- Need (near-)optimal dataset
- Trains on reference sessions

Policy gradient:

- Need ~some data and reward function
- Trains on it's own output

SL VS RL

Train on references

- Need good reference (y_opt)
- If model is imperfect [and **it is**],
  training:
  P(y_next|x,y_prev_ideal)
  prediction:
  P(y_next|x,y_prev_predicted)

Reinforcement learning

- Need reward function
- Model learns to improve current policy. If policy is pure random, local improvements are unlikely to produce good translation.

SL VS RL

Supervised learning

- ✔ Rather simple
- ✔ Small variance

- ✗ Need good reference (y_opt)
- ✗ **Distribution shift**
  different **h** distribution
  when training vs generating

Reinforcement learning

- ✗ **Cold start problem**
- ✗ Large variance (so far)

- ✔ Only needs **x** and **r(s,a)**
- ✗ No distribution shift

SL ~~VS~~ RL

Supervised learning

- ✓ Trains from scratch
- ✓ Small variance

pre-training

- ✗ Need good reference (y_opt)
- ✗ Distribution shift
  different **h** distribution
  when training vs generating

Reinforcement learning

- ✗ Cold start problem
- ✗ Large variance (so far)
- ✓ Only needs x and r
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post-training

SL ~~VS~~ RL

Supervised learning

- ✓ Trains from scratch
- ✓ Small variance

pre-training

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Reinforcement learning

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post-training

Trivia: How do we make policy gradient less noisy?

Introducing baselines

$$\nabla J = \mathop{E}_{\substack{s \sim d(s) \\ a \sim \pi(a|obs(s))}} \nabla \log \pi(a|s) A(s,a)$$

$$A(s,a) = R(s,a) - V(s)$$

Introducing baselines

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$$A(s,a) = R(s,a) - V(s)$$

Trivia: How do we estimate A(s,a) in practice?

Advantage actor-critic

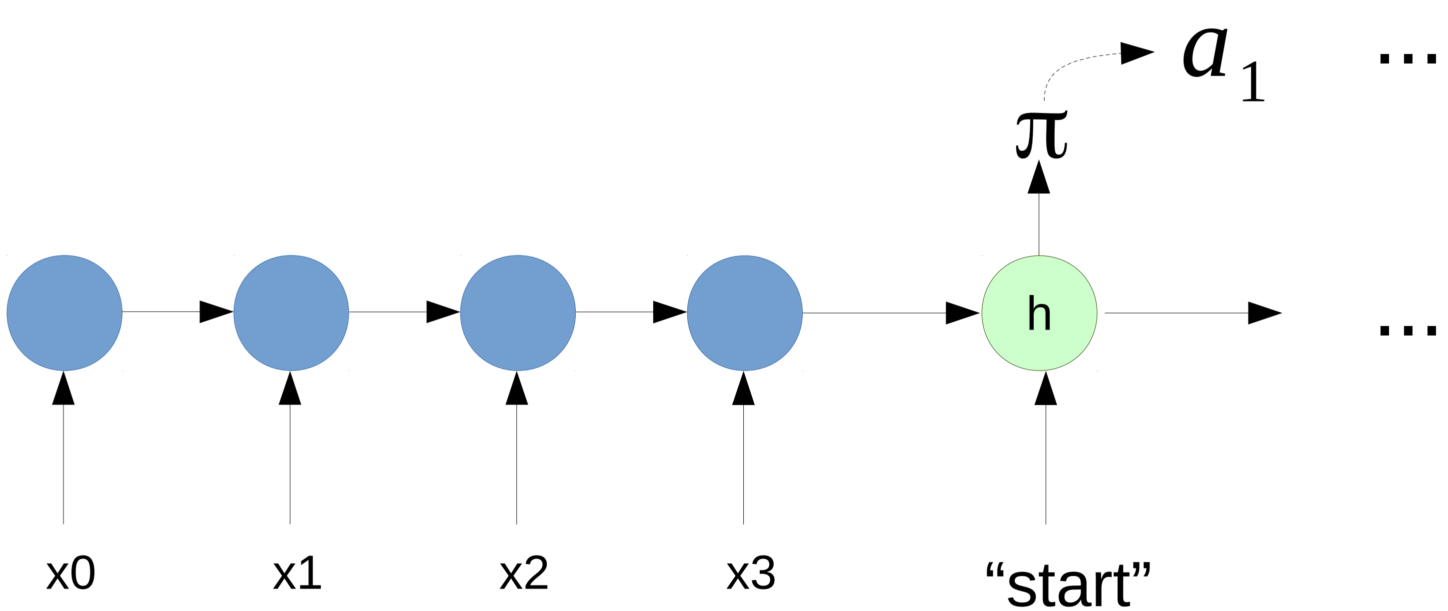
$$\nabla J = \underset{\substack{s \sim d(s) \\ a \sim \pi(a|obs(s))}}{E} \nabla \log \pi(a|s) A(s,a)$$

$$A(s,a) = [r + \gamma \cdot V(s')] - V(s)$$

Problem: need to train both π and V!
Can we get V for free?

Training Vs inference

Recap: encoder-decoder rnn



Input sequence
e.g. source language

Training Vs inference

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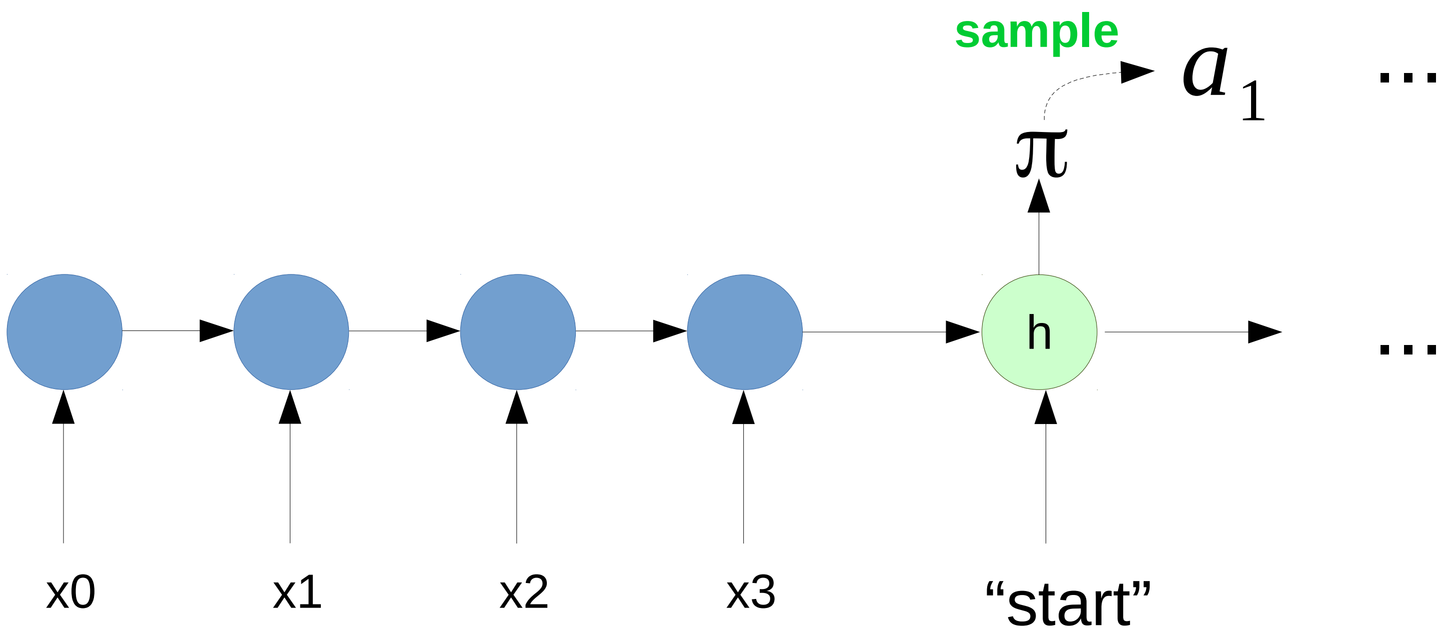

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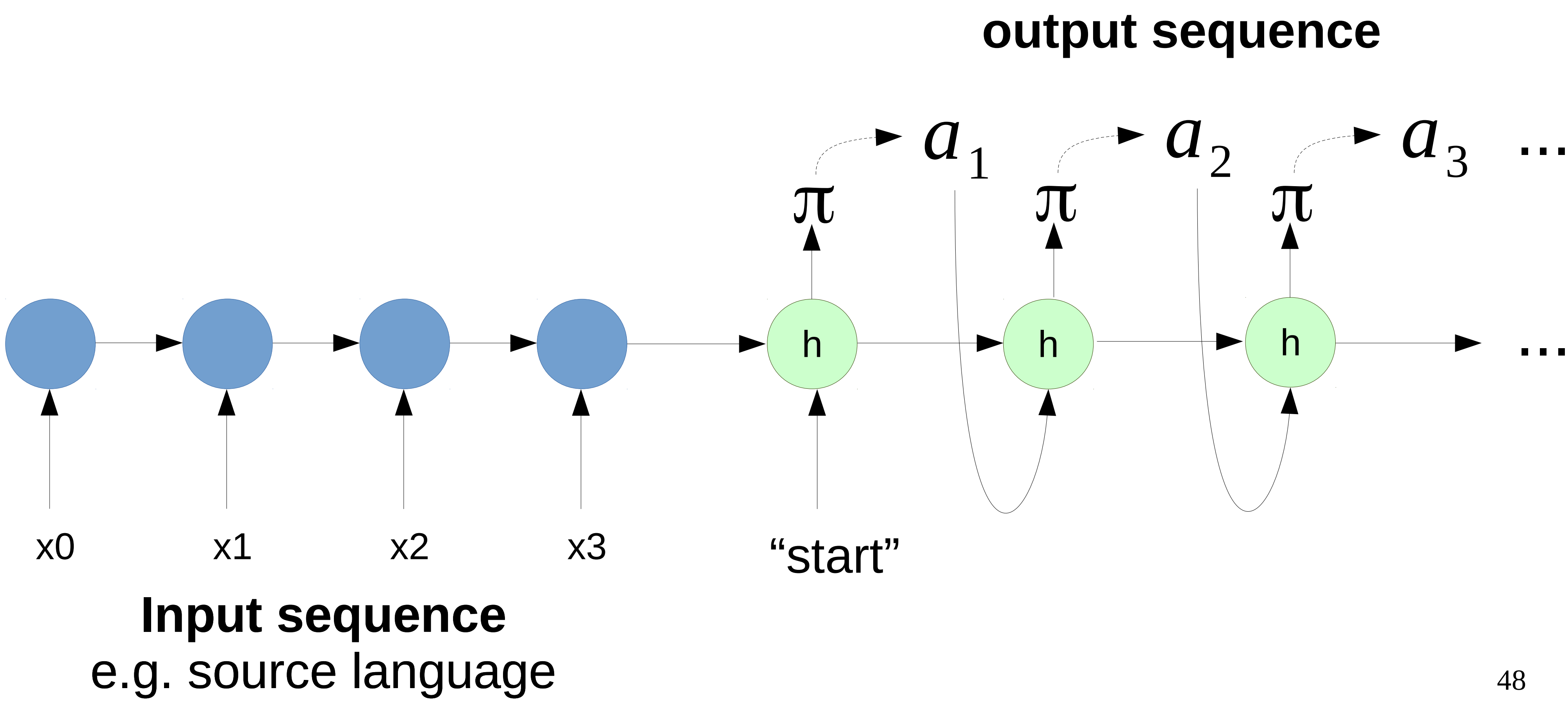
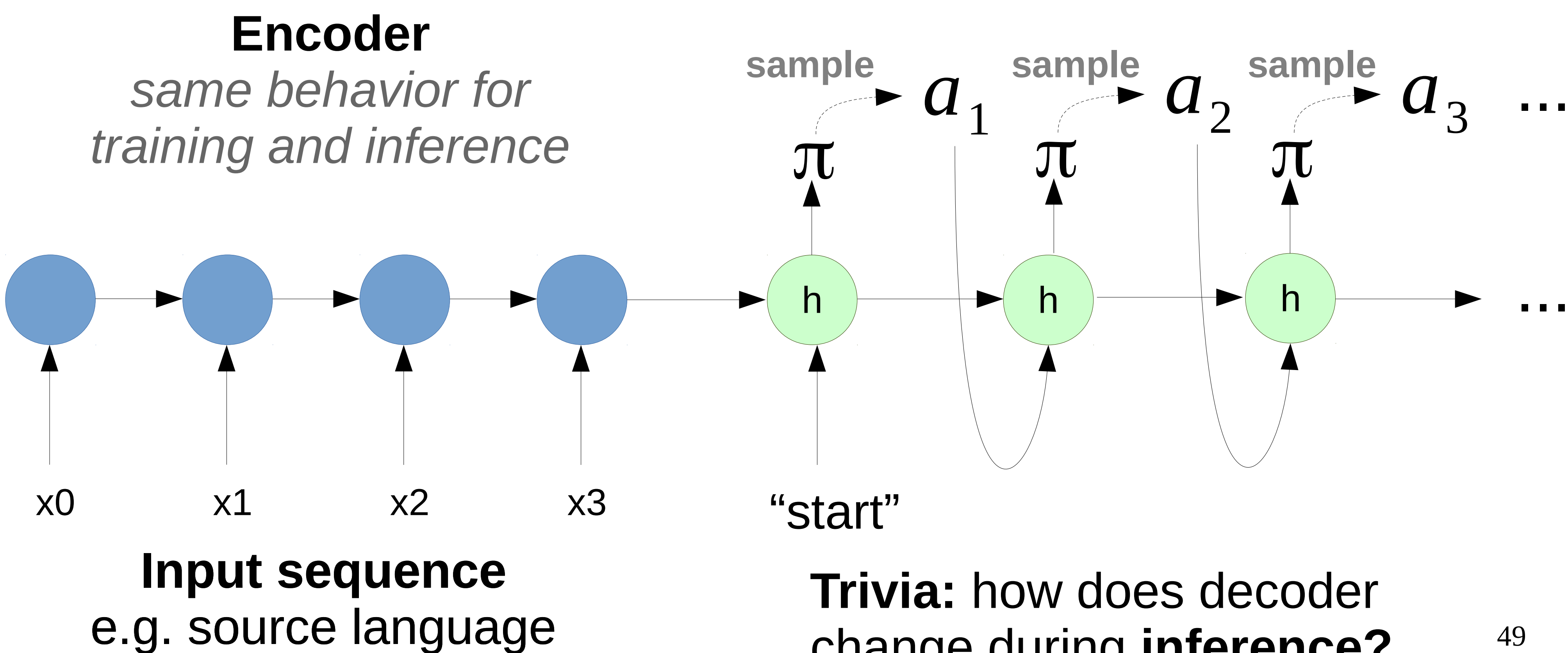


Training Vs Inference

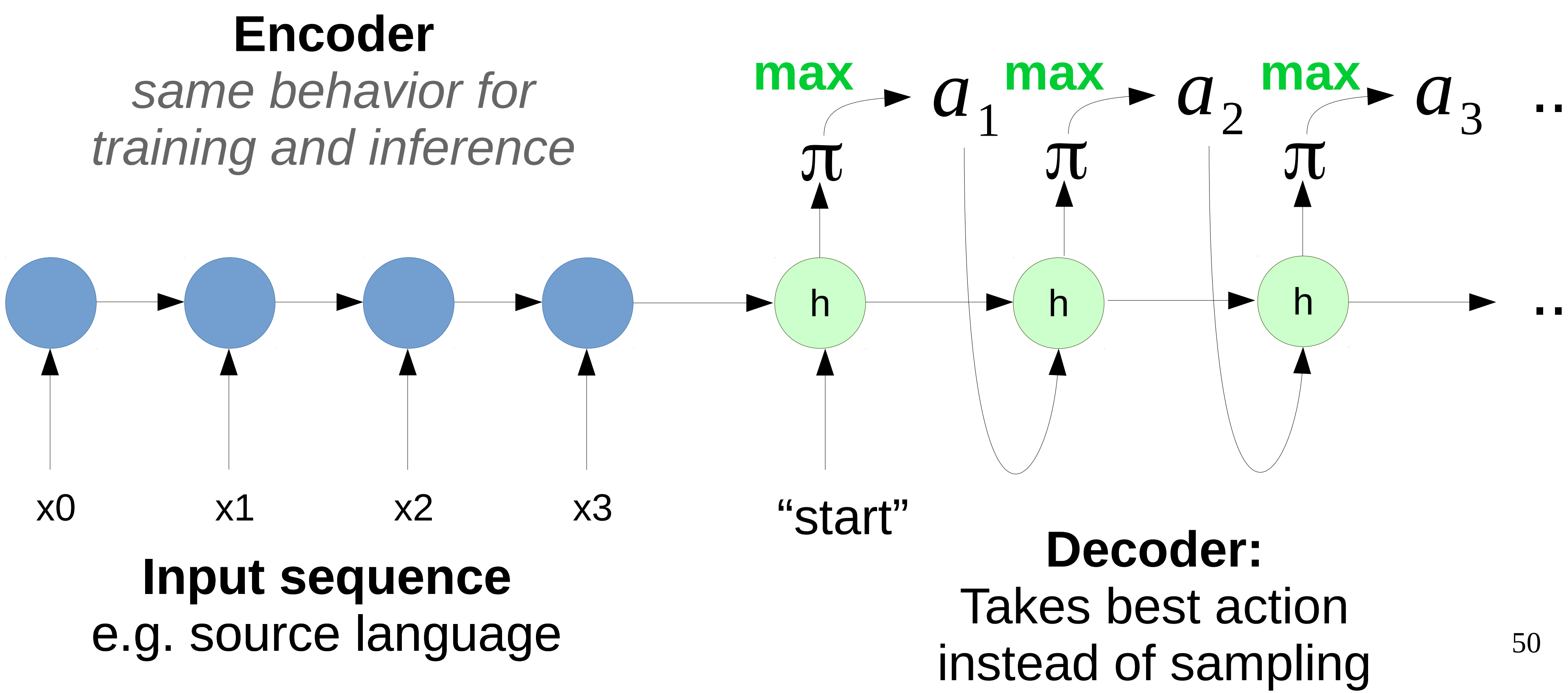
Training is different from inference!



Trivia: how does decoder change during **inference?**

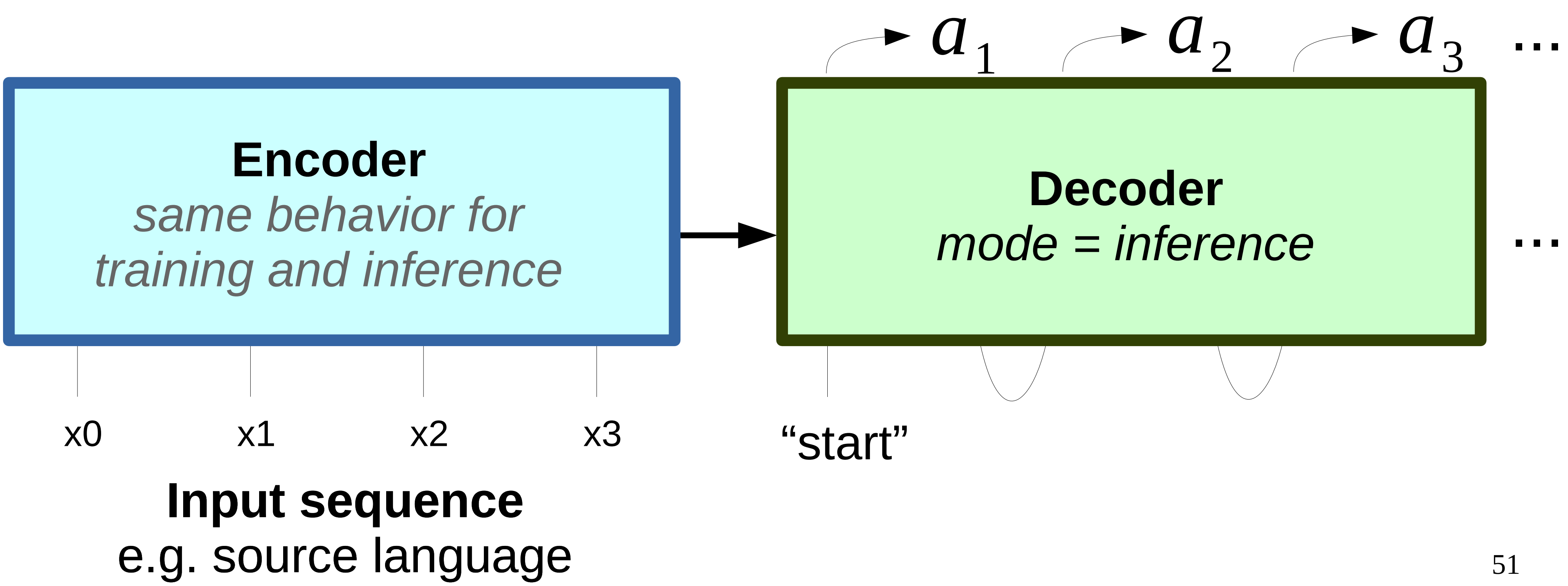
Training Vs Inference

Inference mode



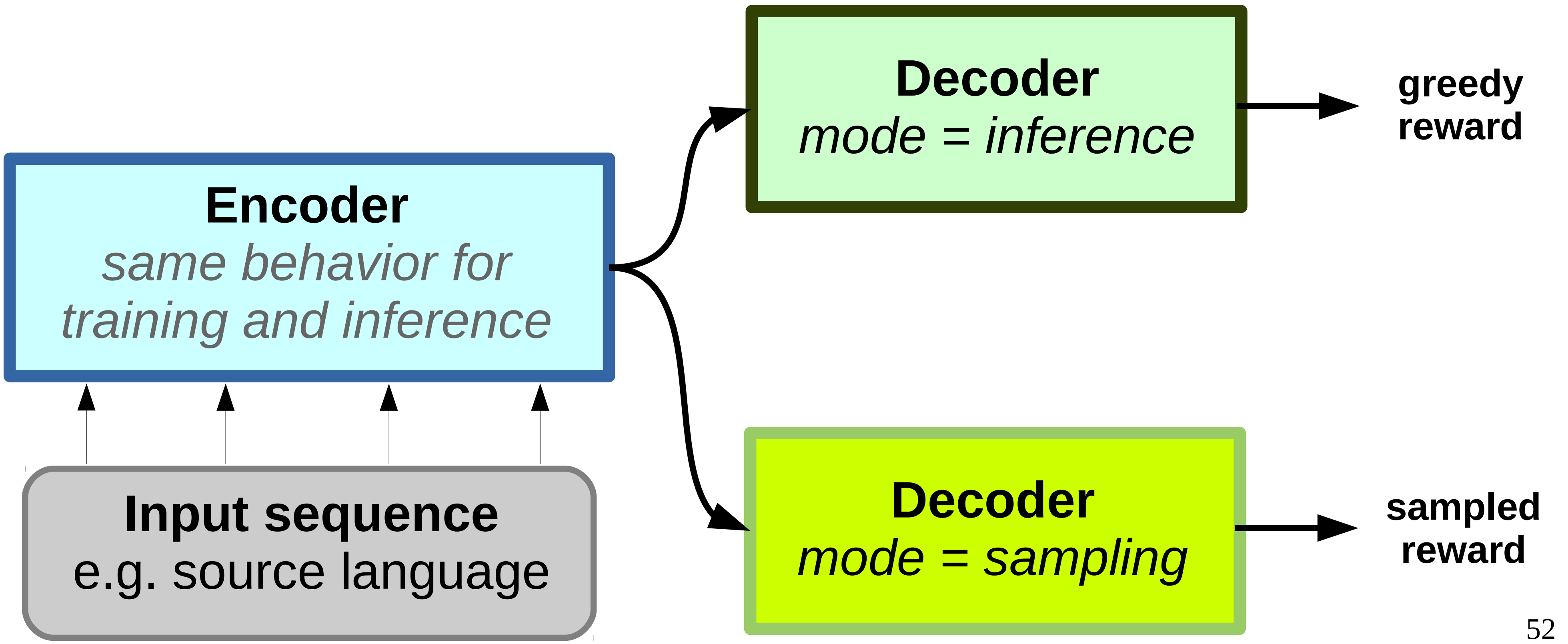
Training Vs inference

Simplified scheme



Self-critical sequence training

Idea: use inference mode as a baseline!



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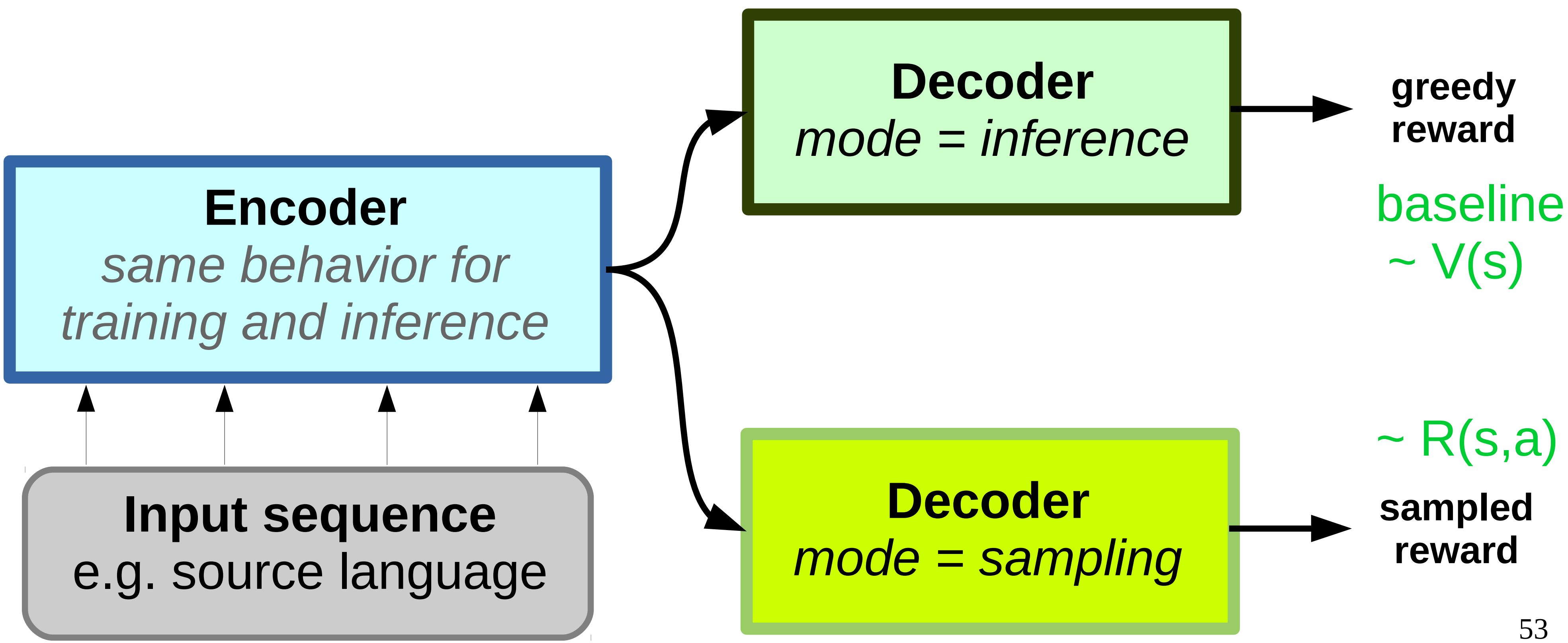

Self-critical sequence training

$$\nabla J = \underset{\substack{s \sim d(s) \\ a \sim \pi(a|obs(s))}}{E} \nabla \log \pi(a|s) A(s,a)$$

$$A(s,a) = R(s,a) - R(s, a_{greedy}(s))$$

Self-critical sequence training

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sampling mode

greedy mode (inference)

Self-critical sequence training

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Non-trivia: why don't we use sampling mode for baseline?

Self-critical sequence training

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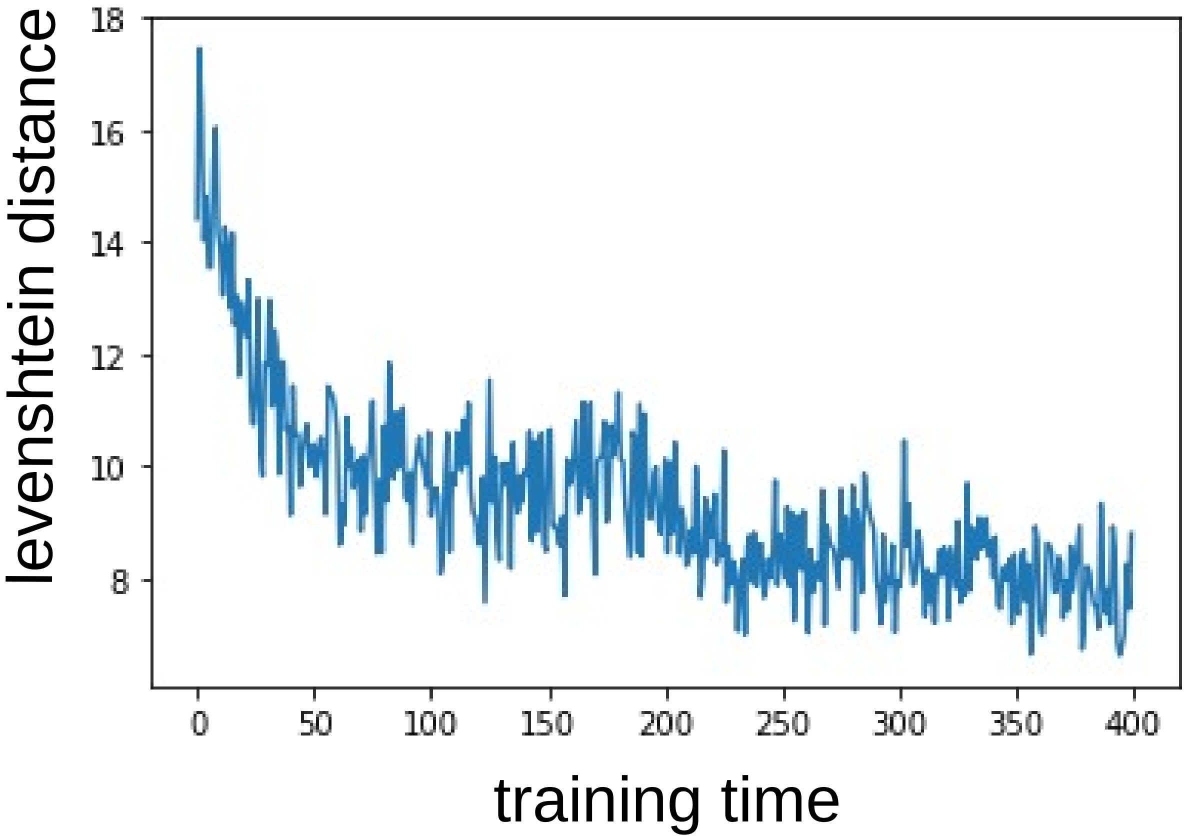
Non-trivia: why don't we use sampling mode for baseline?
Sampling mode is more noisy due to... sampling
Also it isn't what we'll use in production

Results on G2P



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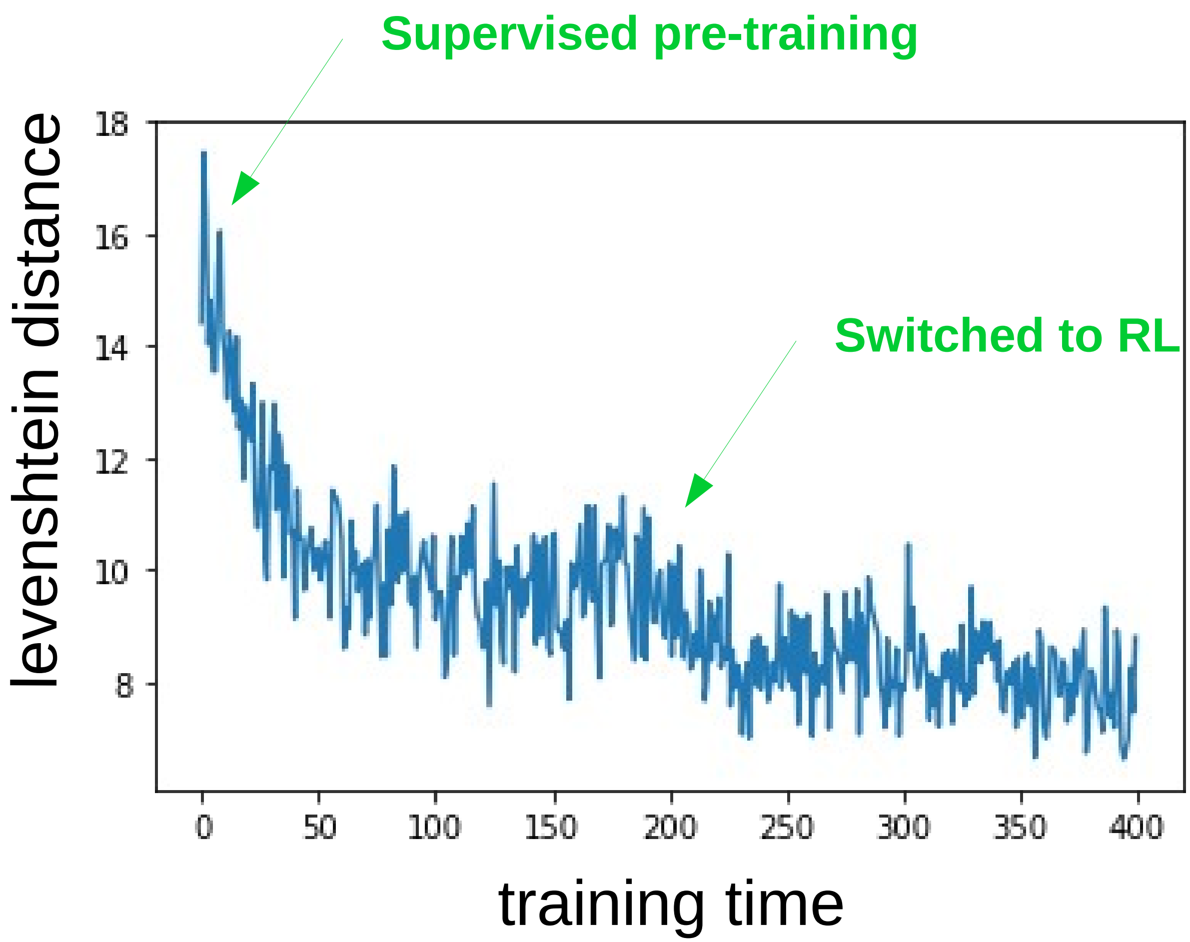

Image captioning with SCST

Problem:

- Process image
- Generate caption
- Caption must describe image *(CIDEr)*
- **Dataset:** MSCOCO, http://mscoco.org

What do we do?

Image captioning with SCST

Problem:

- Process image
- Generate caption
- Caption must describe image *(CIDEr)*
- **Dataset:** MSCOCO, http://mscoco.org
- **Pre-training:** maximize log P(caption|image)
- **Fine-tuning:** maximize expected CIDEr
  - Used self-critical baseline to reduce variance

SCST: results

Training Metric	Evaluation Metric CIDEr	BLEU4	ROUGEL	METEOR
XE	90.9	28.6	52.3	24.1
XE (beam)	94.0	29.6	52.6	25.2
CIDEr	**106.3**	31.9	54.3	25.5
BLEU	94.4	**33.2**	53.9	24.6
ROUGEL	97.7	31.6	**55.4**	24.5
METEOR	80.5	25.3	51.3	**25.9**

Table: validation score on 4 metrics (columns) for models that optimize crossentropy (supervised) or one of those 4 metrics (scst).

Taken from https://arxiv.org/pdf/1612.00563.pdf

MSCOCO: objects out of context

1. a blue of a building with a blue umbrella on it -1.234499
2. a blue of a building with a blue and blue umbrella -1.253700
3. a blue of a building with a blue umbrella -1.261105
4. a blue of a building with a blue and a blue umbrella on top of it -1.277
5. a blue of a building with a blue and a blue umbrella -1.280045

(a) Ensemble of 4 Attention models (Att2in) trained with XE.

1. a blue boat is sitting on the side of a building -0.194627
2. a blue street sign on the side of a building -0.224760
3. a blue umbrella sitting on top of a building -0.243250
4. a blue boat sitting on the side of a building -0.248849
5. a blue boat is sitting on the side of a city street -0.265613

(b) Ensemble of 4 Attention models (Att2in) trained with SCST.

Taken from https://arxiv.org/pdf/1612.00563.pdf

MSCOCO: objects out of context

1. a man in a red shirt standing in front of a green field -0.890775
2. a man in a red shirt is standing in front of a tv -0.897829
3. a man in a red shirt standing in front of a tv -0.900520
4. a man in a red shirt standing in front of a field -0.912444
5. a man standing in front of a green field -0.924932

(a) Ensemble of 4 Attention models (Att2in) trained with XE.

1. a man standing in front of a street with a television -0.249860
2. a man standing in front of a tv -0.256185
3. a man standing in front of a street with a tv -0.280558
4. a man standing in front of a street -0.295428
5. a man standing in front of a street with a frisbee -0.309342

(b) Ensemble of 4 Attention models (Att2in) trained with SCST.

Taken from https://arxiv.org/pdf/1612.00563.pdf

Common pitfalls

What can go wrong

- Make sure agent didn't cheat R(s,a)
  - https://openai.com/blog/faulty-reward-functions/
- Unlike games, agent **can** overfit data
  - Check validation performance

Duct tape zone

Pre-train agent in supervised mode

- RL takes longer to train from scratch

- All policy-based tricks apply
  - Regularize with entropy / L2 logits
  - Better sampling techniques (tree, vine, etc.)

- Most seq2seq tricks apply
  - Use bottleneck If vocabulary is large
  - Some (but not all) softmax improvements

Квестионы?

</course>

You've done it!

@urls – plenty of them in couse folders
(README.md files)
@me - justheuristic@yandex-team.ru
@alx - grox_halfer@mail.ru