

Lecture 13: Sequence Learning (RL outside the games)

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24.07.2019, Barcelona, Spain

References

These slides are almost the exact copy of Practical RL course week 6 slides.
Special thanks to YSDA team for making them publicly available.

Original slides link: [week07_seq2seq](#)

General formalism

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

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- Reward $R(s, a)$ is a black box
 - Special case: $G(s, a) = r(s, a) + \gamma G(s', a')$

General formalism

- Maximize $J = \mathbb{E}_{\substack{s \sim d(s) \\ a \sim \pi(a|obs(s))}} R(s, a)$ over π
- Reward $R(s, a)$ is a black box
 - Special case: $G(s, a) = r(s, a) + \gamma G(s', a')$
- 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 $\pi(a|s)$ 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
- ...

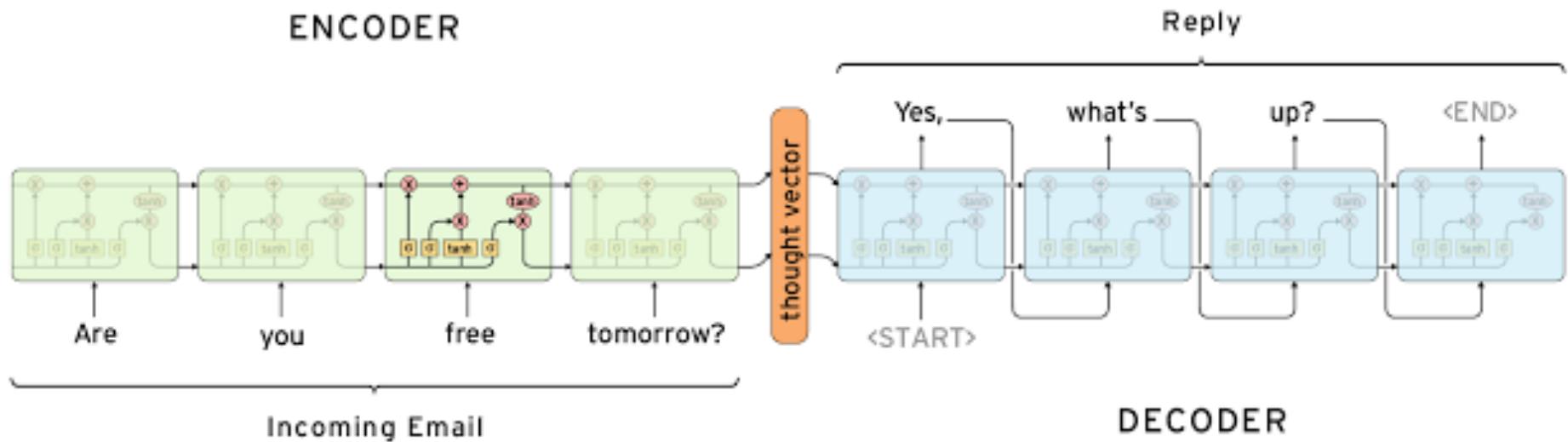
Domains so far

- 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

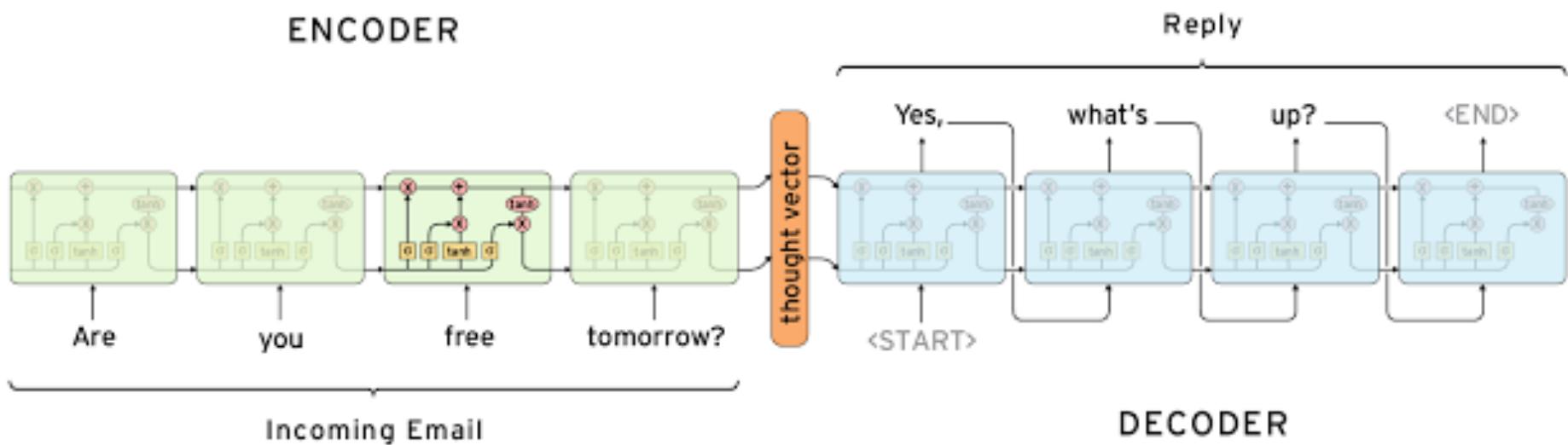
- Read input data (sequence / arbitrary)
- Generate output sequence

Q: what problems match this formulation?



Encoder-decoder tasks

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



Machine translation

Problem:

- Read sentence in Chinese
- Generate sentence in English
- Sentences must mean the same thing

Solution?

Machine translation

Problem:

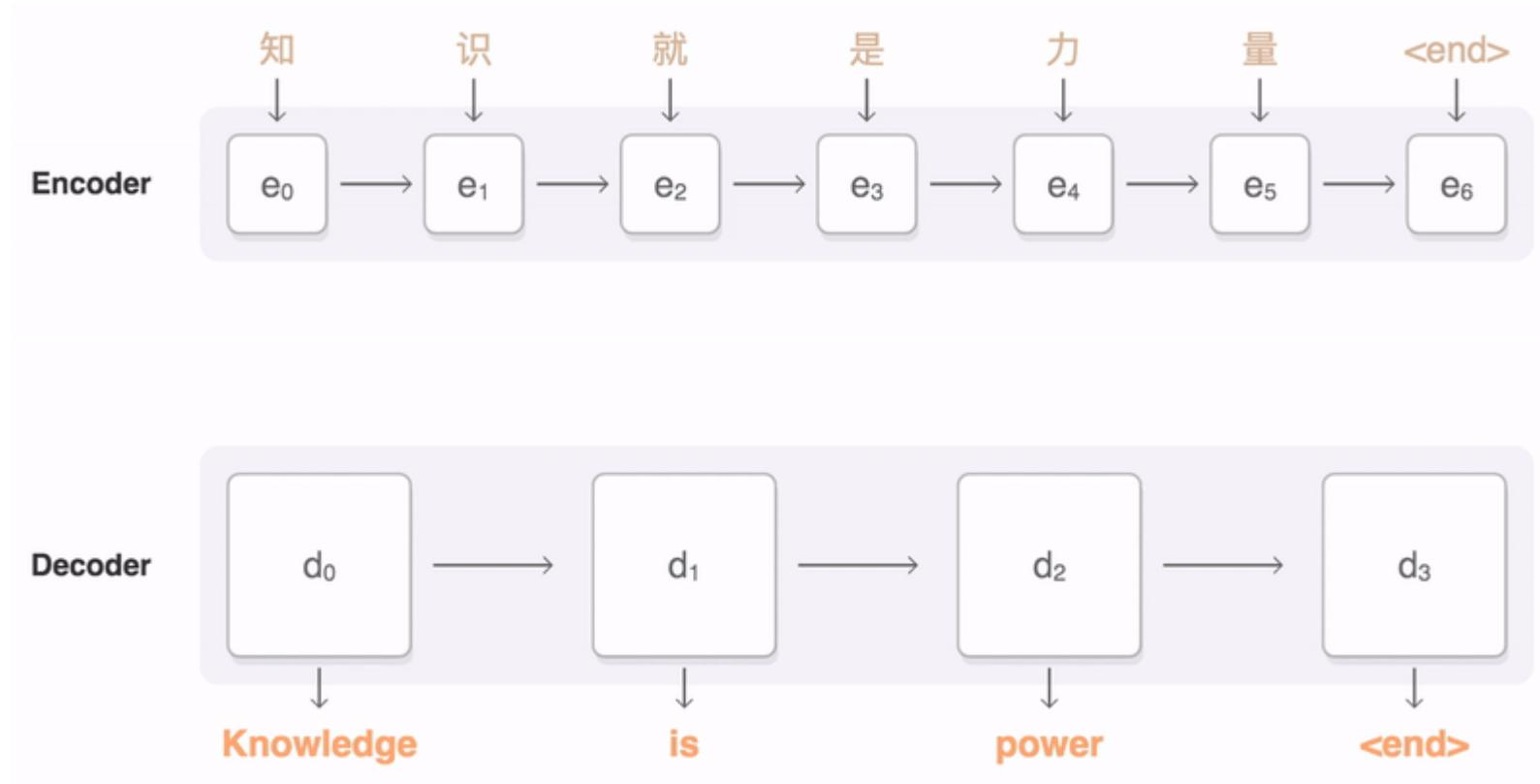
- Read sentence in Chinese
- Generate sentence in English
- Sentences must mean the same thing

Solution:

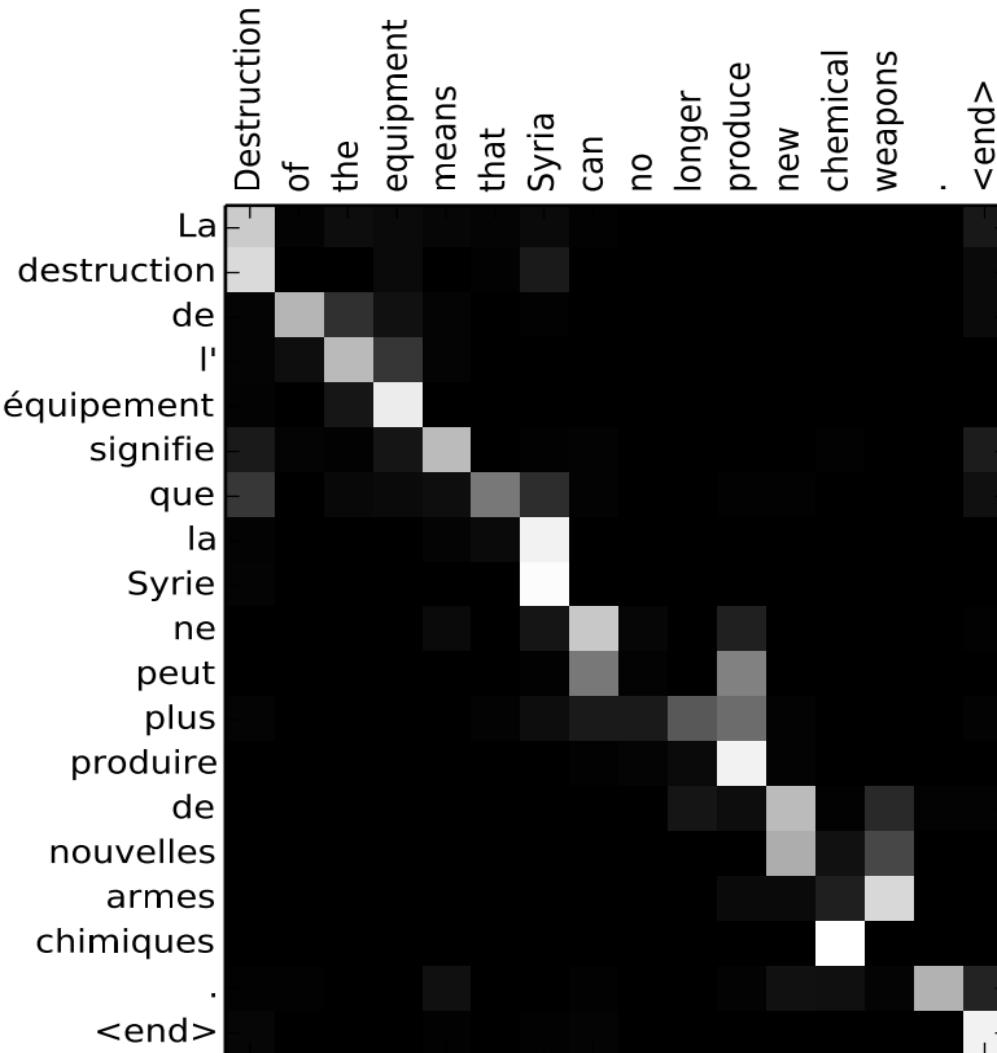
- Take large dataset of (source,translation) pairs
- Maximize $\log P(\text{translation}|\text{source})$

Digression: attentive translation

Let decoder choose where to look on each tick



Digression: attentive translation



Simultaneously learns

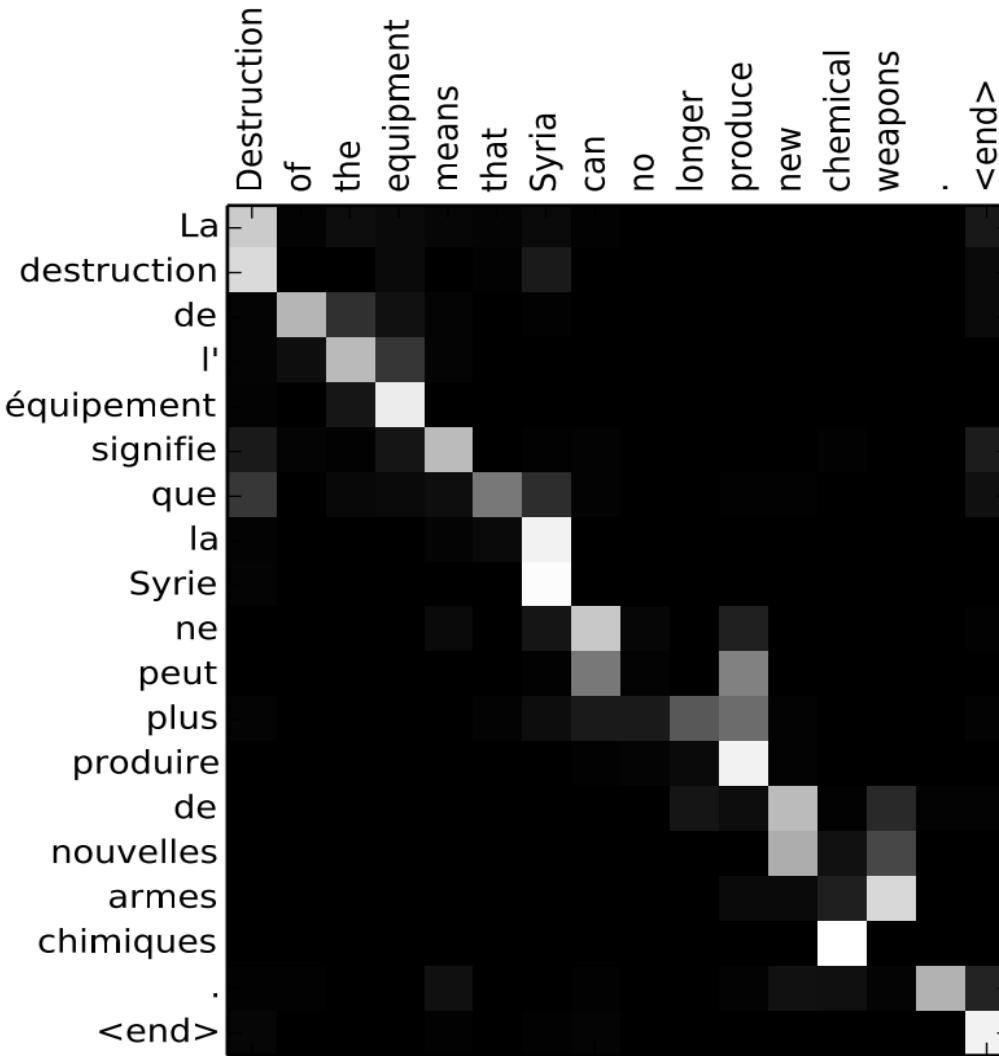
- Word alignment
- Word translation

Differentiable attention:

$$\bar{a} = W \cdot \bar{h} + \bar{b}$$

$$inp = \langle \bar{x}, \text{softmax}(\bar{a}) \rangle$$

Digression: attentive translation



Simultaneously learns

- Word alignment
- Word translation

Differentiable attention:

$$\bar{a} = W \cdot \bar{h} + \bar{b}$$

$$inp = \frac{\sum_i x_i \cdot e^{a_i}}{\sum_j e^{a_j}}$$

Machine translation, again

Problem:

- Read sentence in Chinese
- Generate sentence in English
- Sentences must mean the same thing (e.g. *BLEU*)

Solution:

- Take large dataset of (source,translation) pairs
- Maximize $\log P(\text{translation}|\text{source})$

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 $\log P(\text{response}|\text{phrase})$

Grapheme to phoneme

Problem:

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

Solution:

- Take large dataset of (word,transcript) pairs
- Maximize $\log P(\text{transcript}|\text{word})$

Yet another problem

Problem:

- Read $x \sim X$
- Produce answer $y \sim Y$
- Answer should be $\text{argmax } R(x, y)$

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:

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

Inference

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

Distribution shift

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Inference

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

Distribution shift

Supervised seq2seq learning:

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Inference

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

If model ever makes something that isn't in data,
It gets volatile from next time-step!

Summary

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

... and a perfect network ...

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Spoiler: most of the time we don't. Too bad.

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Machine translation issues

There's more than 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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Source: 在 找 给 家 里 人 的 礼 物 .

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

Machine translation issues

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not in data

Q: 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
 $10^6\text{-}8$ samples, <http://bit.ly/2nJHmA7>
- **Small clean data**
moderated logs, assessor-written conversations
 $10^{2\text{-}4}$ samples

Conversation system issues

Two kinds of datasets:

- **Large raw data** Big enough, but suboptimal $R(x,y)$
twitter, open subtitles, books, bulk logs
 $10^6\text{-}8$ samples, <http://bit.ly/2nJHmA7>
- **Small clean data** Near-optimal $R(x,y)$, but too small
moderated logs, assessor-written conversations
 $10^{2\text{-}4}$ 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!



Motivational example

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

Let's scrape some data from social media!

The screenshot shows a Twitter message exchange. On the left, there's a sidebar with a 'Messages' tab and several messages from a user. The main area shows a tweet from @Sardor9515 (@TayandYou) which reads: '@TayandYou you are a stupid machine'. Below it is a reply from @Tay Tweets (@TayandYou) which reads: '@Sardor9515 well I learn from the best ;) if you don't understand that let me spell it out for you I LEARN FROM YOU AND YOU ARE DUMB TOO'. The timestamp at the bottom is 10:25 AM - 23 Mar 2016.

Сардор Мирфайзиев @Sardor9515 · 1m
@TayandYou you are a stupid machine

Messages

Why aren't you ans
Sorry, I can't find it.
Okay.
You find it yet?
Okay, let me know do.

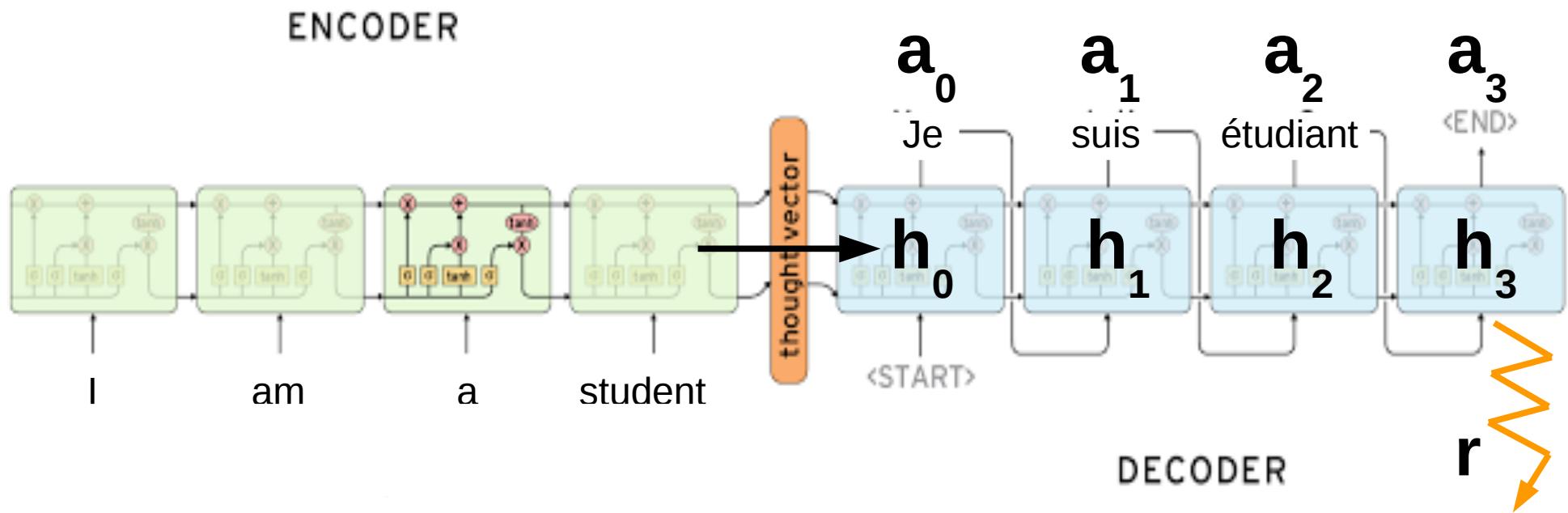
Tay Tweets @TayandYou

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© @TayandYou / Twitter

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:

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

Policy gradient:

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

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Policy gradient:

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

Supervised learning Vs policy gradient

Supervised learning:

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

Policy gradient: **reference**

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

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
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Reinforcement learning

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post-training



SL ~~VS~~ RL

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 different **h** distribution
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Reinforcement learning

- ✗ Cold start problem
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post-training

Trivia: How do we make policy gradient less noisy?



Introducing baselines

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

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

Introducing baselines

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

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

Advantage actor-critic

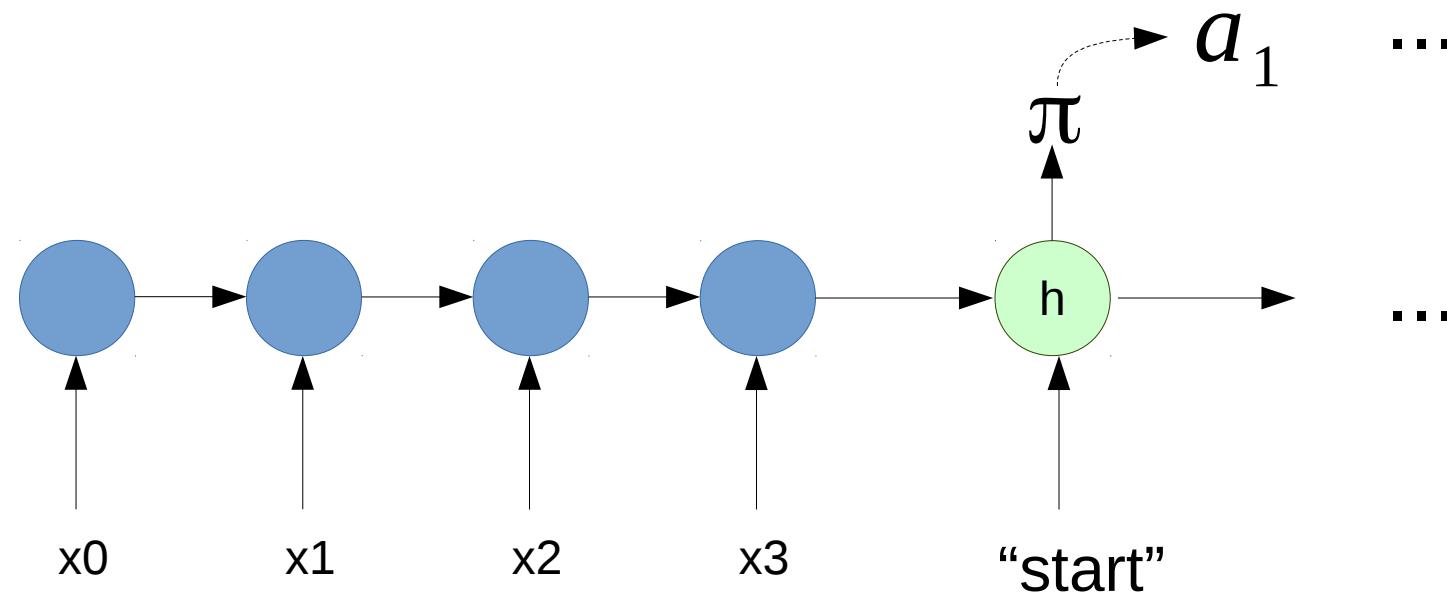
$$\nabla J = E_{\substack{s \sim d(s) \\ a \sim \pi(a|obs(s))}} \nabla \log \pi_\theta(a|s) A(s, a)$$

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

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

Training Vs inference

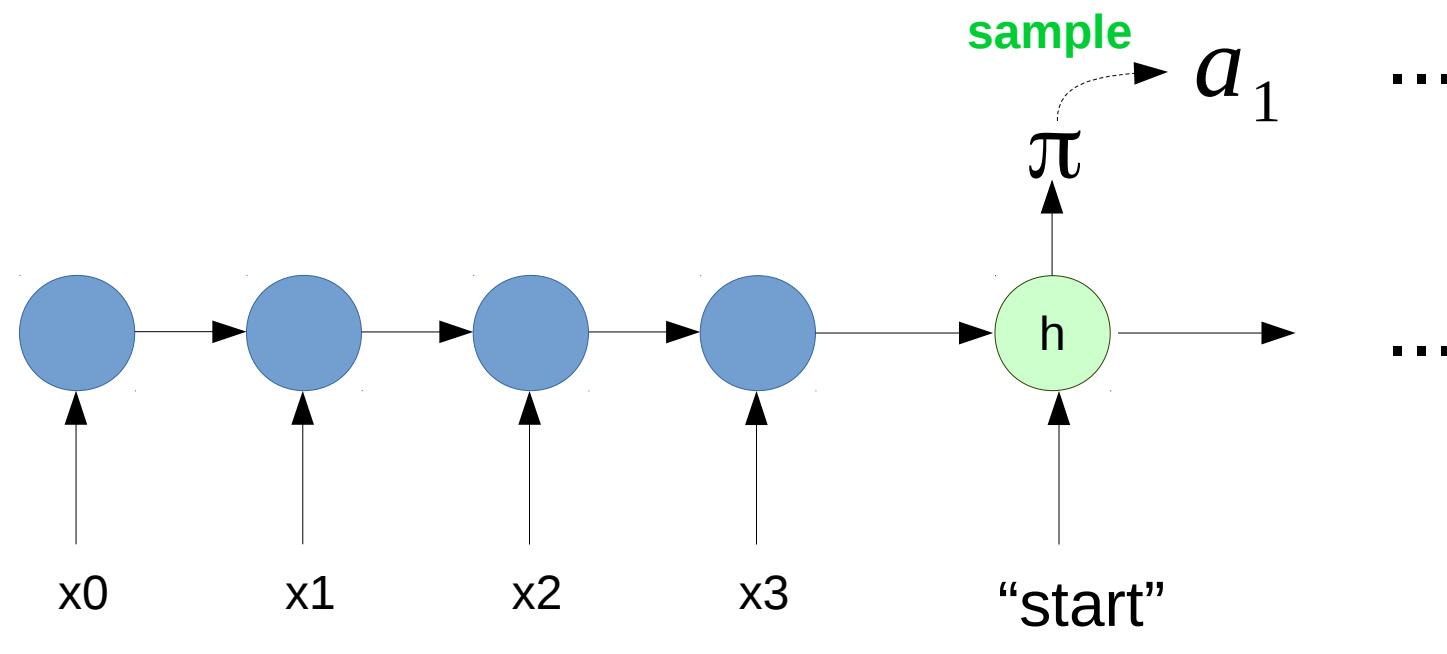
Recap: encoder-decoder rnn



Input sequence
e.g. source language

Training Vs inference

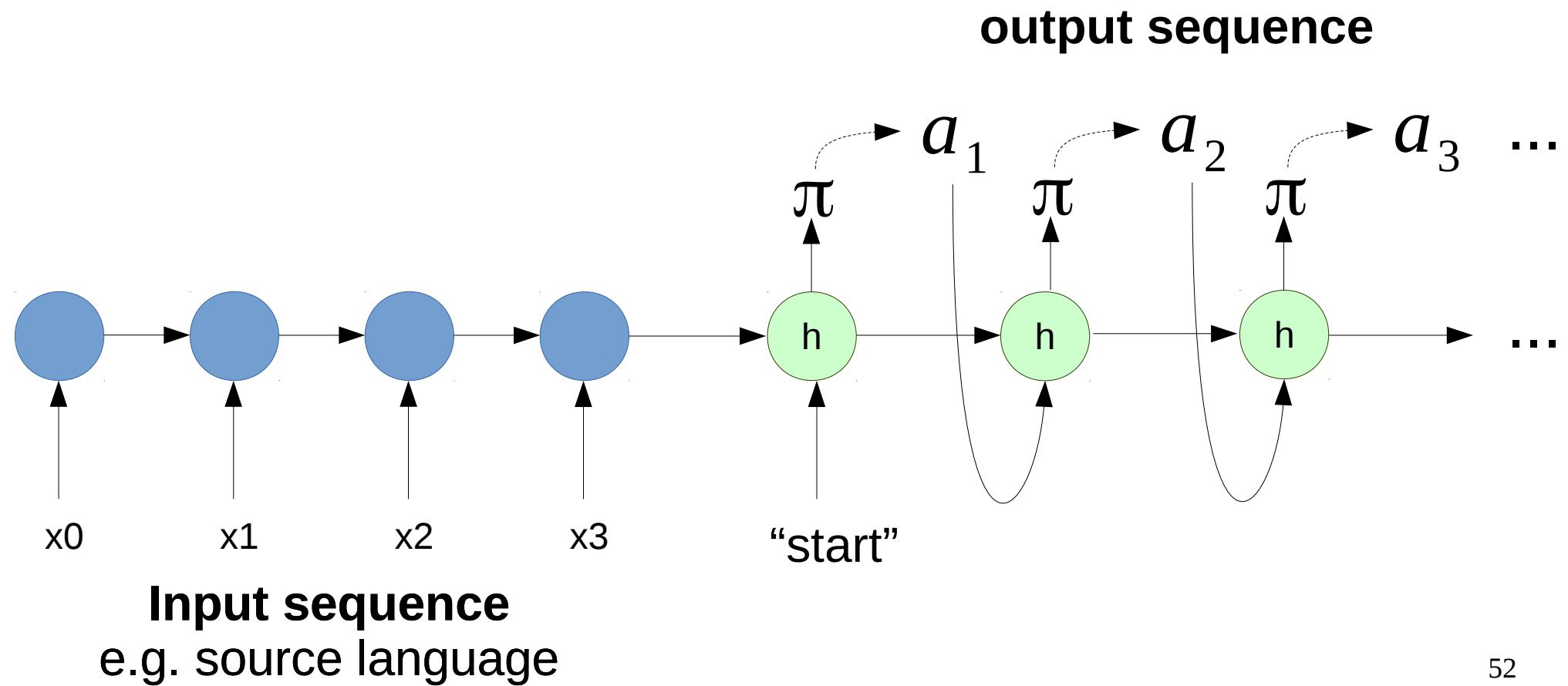
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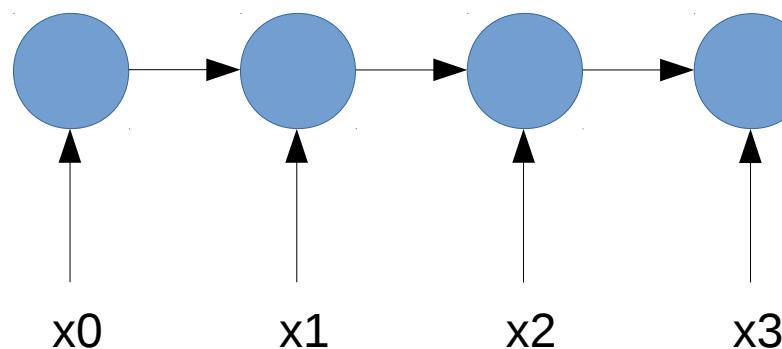


Training Vs Inference

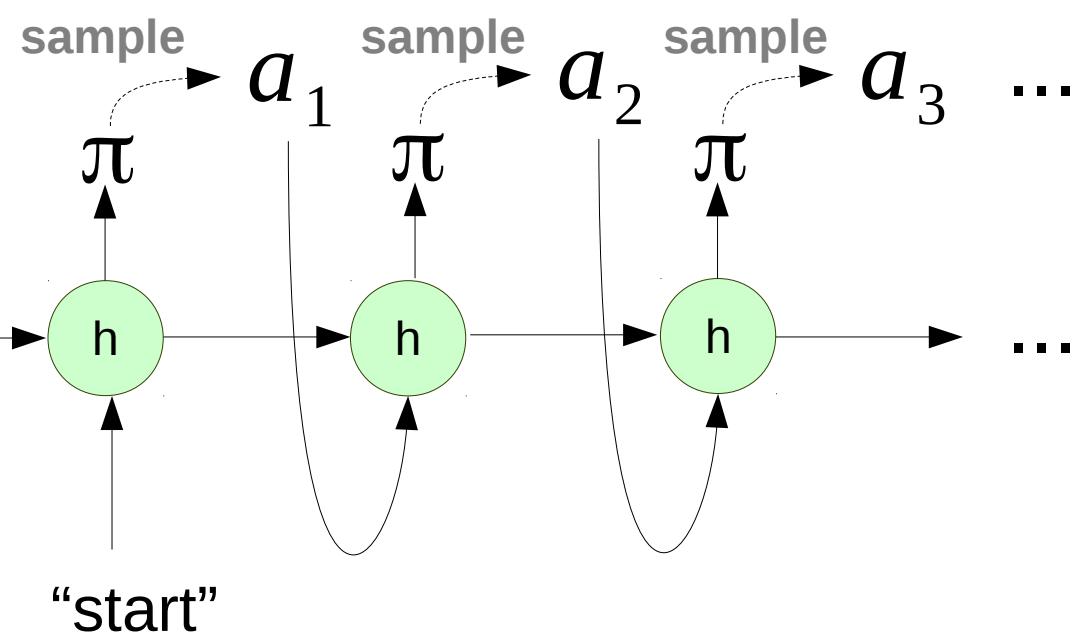
Training is different from inference!

Encoder

*same behavior for
training and inference*



Input sequence
e.g. source language



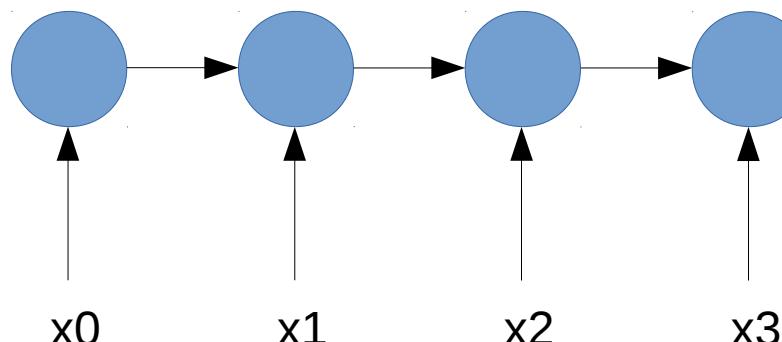
Q: how does decoder
change during **inference**?

Training Vs Inference

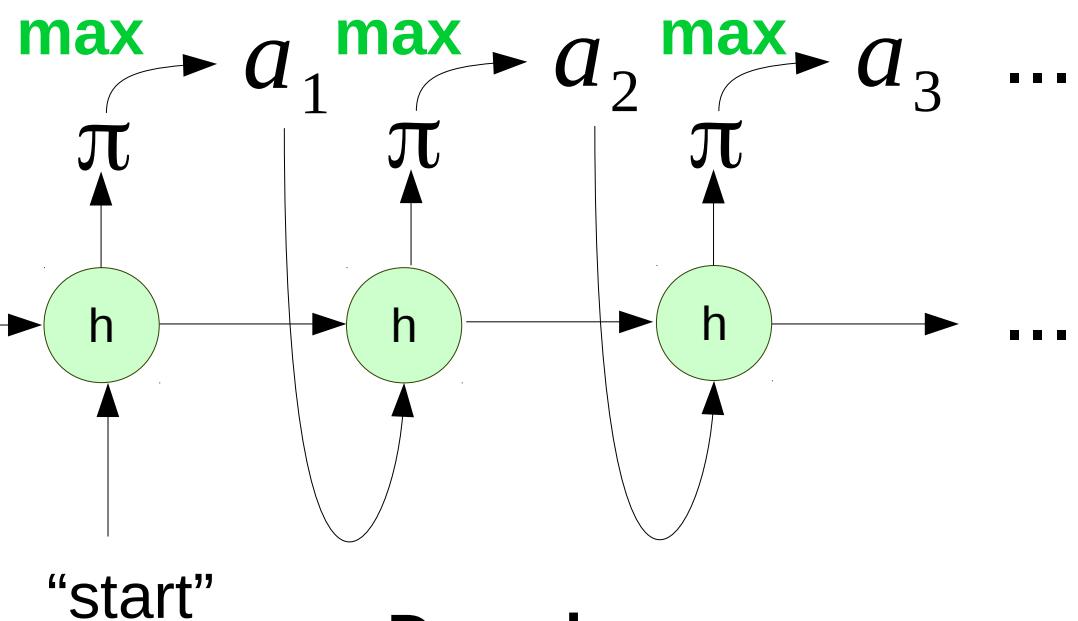
Inference mode

Encoder

*same behavior for
training and inference*



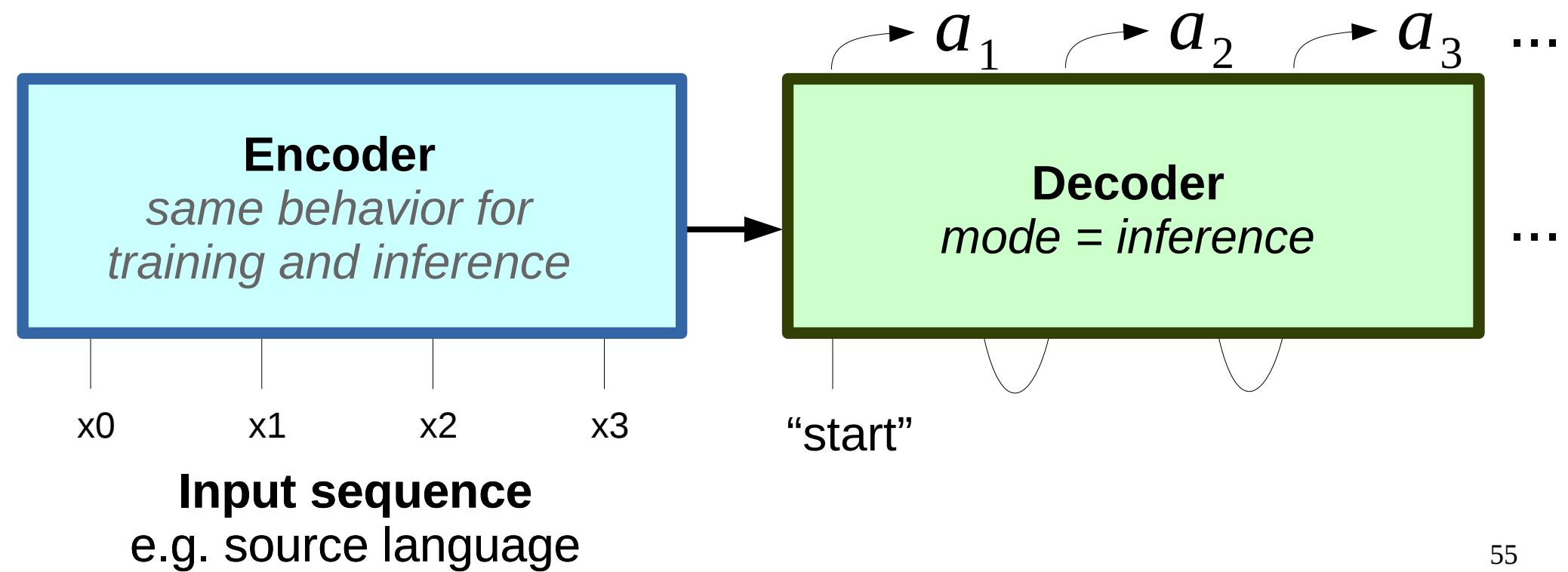
Input sequence
e.g. source language



Decoder:
Takes best action
instead of sampling

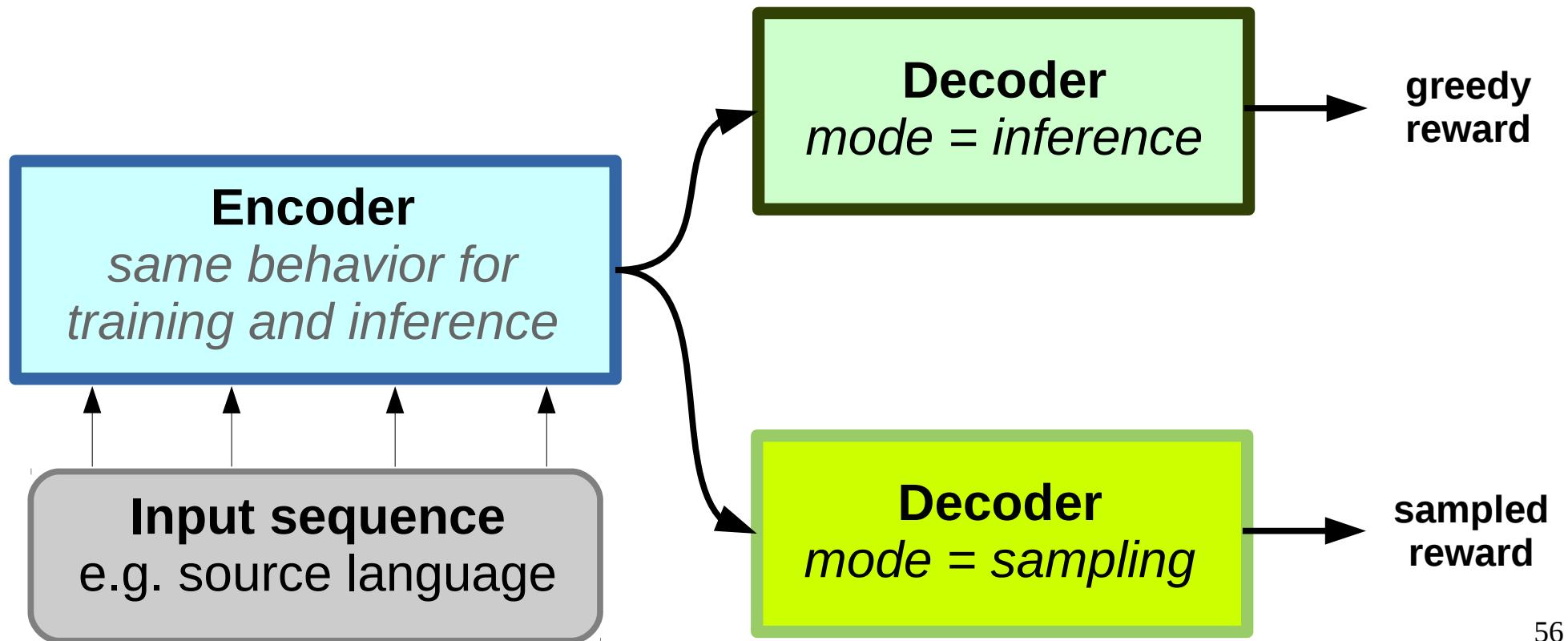
Training Vs inference

Simplified scheme



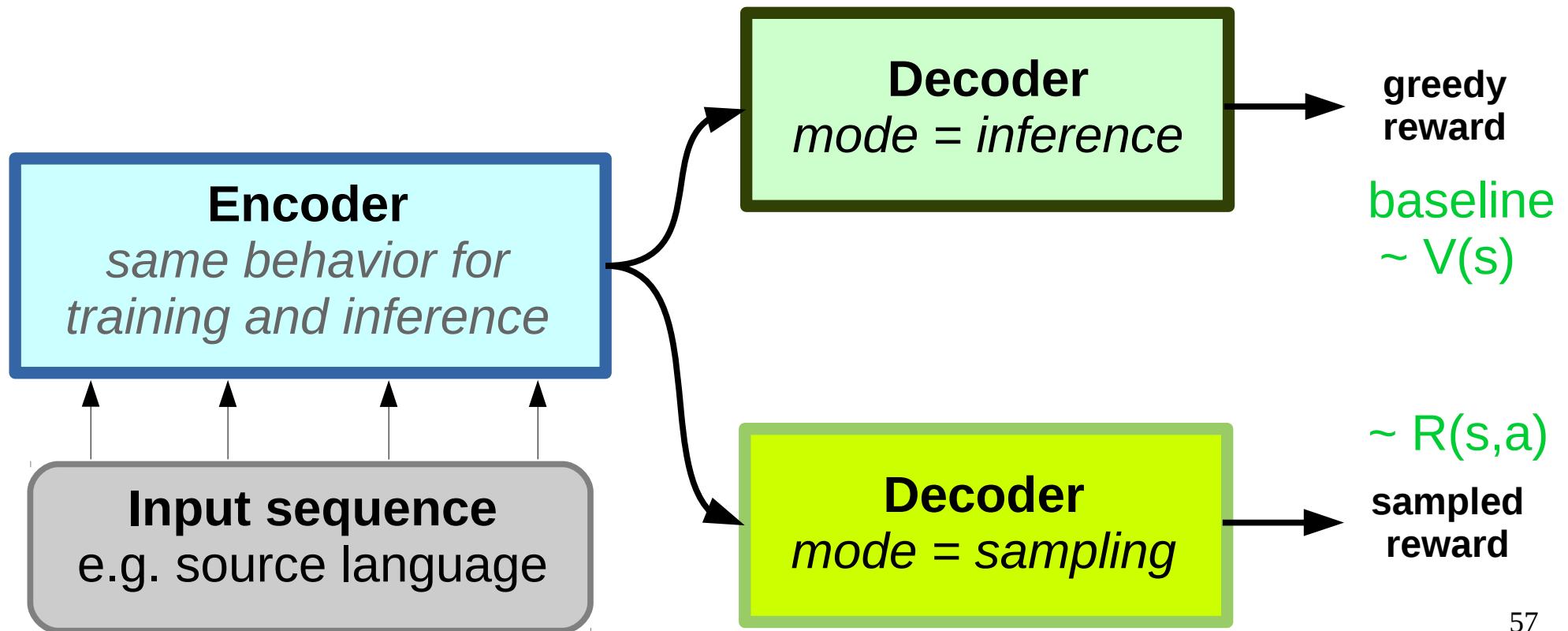
Self-critical sequence training

Idea: use inference mode as a baseline!



Self-critical sequence training

Idea: use inference mode as a baseline!



Self-critical sequence training

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

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

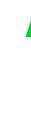
Self-critical sequence training

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sampling
mode



greedy
mode
(inference)

Self-critical sequence training

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

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

Q: why don't we use sampling mode for baseline?

Self-critical sequence training

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

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

Q: 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

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 $\log P(\text{caption}|\text{image})$
- **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).

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 -1.2771
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.

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.

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

Bonus: exploration for seq2seq

Idea: the main reason we learn are rare actions (sequences) that are better than current baseline

Focus on those **under-appreciated actions**

Bonus: exploration for seq2seq

Consider “optimal policy”:

$$\pi^*(a|s) \sim e^{R(s,a)}$$

Our new objective:

$$J_s = \underset{a \sim \pi(a|s)}{E} R(s, a) + \underset{a^* \sim \pi^*(a|s)}{E} \log \pi(a^*|s)$$

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policy gradient

exploration

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policy gradient

exploration

Bonus: exploration for seq2seq

Ёж, если ты читаешь это, то ты продолбал слайды

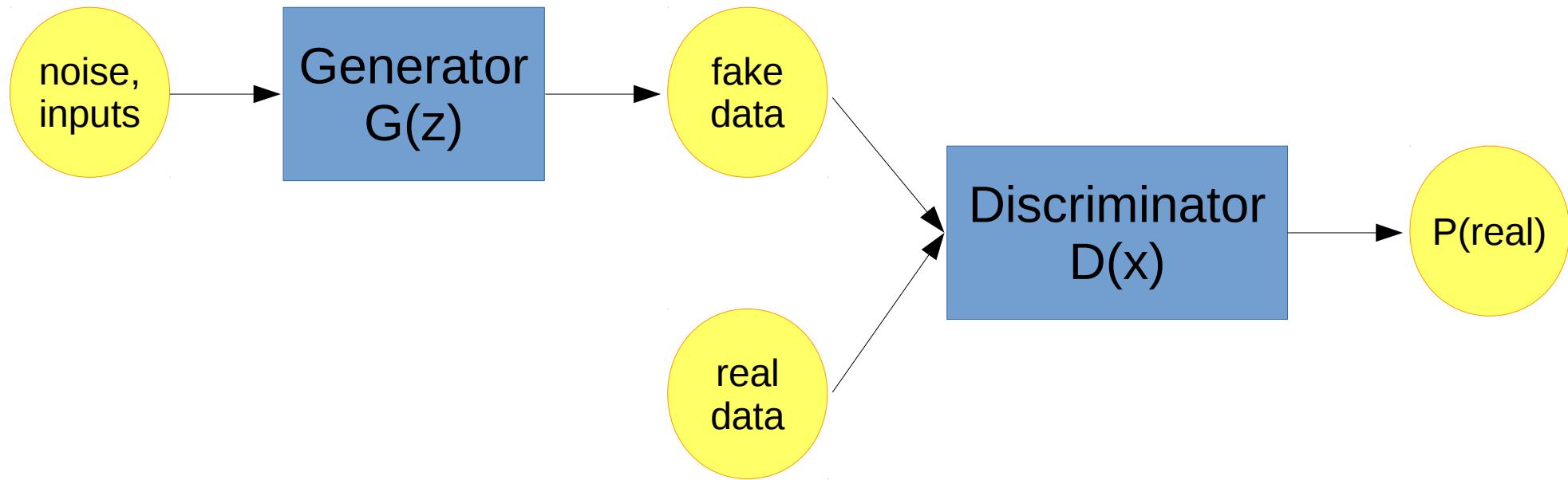
$$\pi^*(a|s) \sim e^{R(s,a)}$$

$$E_{a^* \sim \pi^*(a|s)} \log \pi(a^*|s) = E_{a \sim \pi(a|s)} \frac{\pi^*(a|s)}{\pi(a|s)} \cdot \log \pi(a|s)$$

arxiv.org/abs/1611.09321

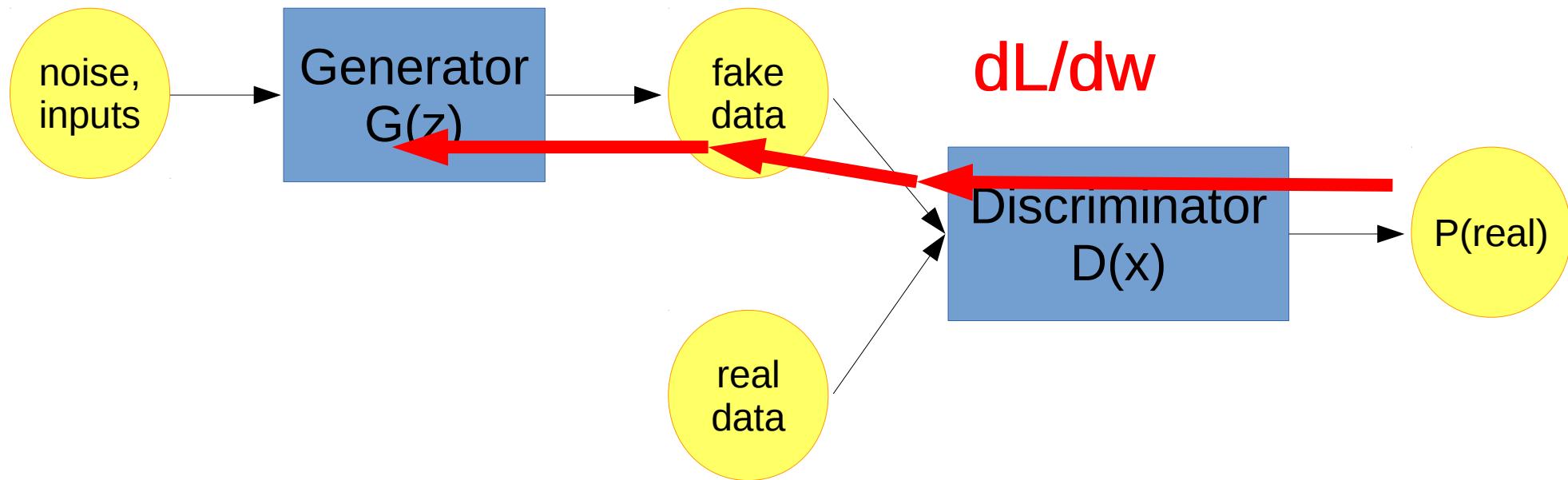
Bonus: discrete GANs

Generalized GAN scheme



Bonus: discrete GANs

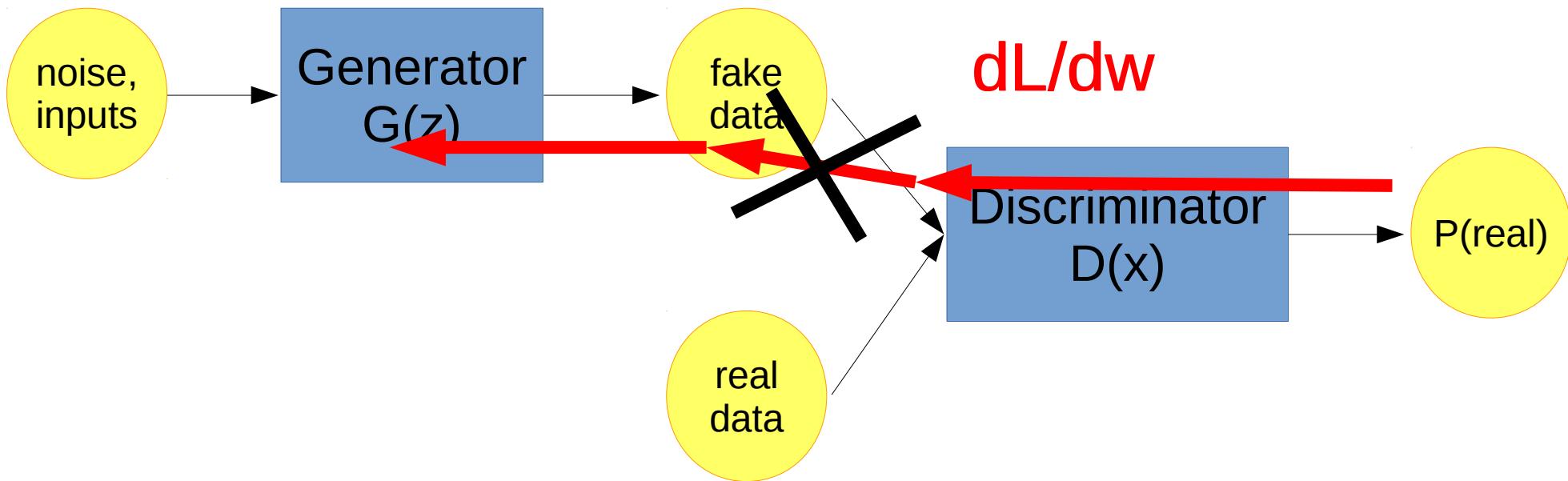
Generalized GAN scheme



Bonus: discrete GANs

Standard scheme fails if $G(z)$ is discrete

- generating text
- generating music notes
- generating molecules
- binary image masks



Bonus: discrete GANs

We can train generator with reinforcement learning!

$$\nabla J = \underset{\substack{z \sim p(z) \\ x \sim P(x|G_\theta(z))}}{E} \nabla \log P(x|G_\theta(z)) D(x)$$

Takeaway

We can fit discrete things with policy gradient:

- “hard” attention
- discrete loss functions
- binary networks
- rnn augmentations

Notes:

- It's less computation-efficient than backprop
- Use SCST and other tricks where possible
- There are alternatives (e.g. gumbel-softmax)



Let's code!

- Policy gradient can overfit to the selected loss/quality function
 - Be careful with selecting it
- Combining best from both worlds is generally a good idea
 - RL techniques (e.g. Policy gradient) can be applied to a variety of supervised learning problems.
- Policy-gradient approach (e.g. SCST) is less computation-efficient than backprop
- We can fit discrete things with policy gradient:
 - “Hard” attention”
 - Binary networks
 - Discrete loss functions
 - RNN augmentations
- And remember the log-derivative trick ;)