Incremental structured prediction

L101: Machine Learning for Language Processing

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Structured prediction reminder

Given an input **x** (e.g. a sentence) predict **y** (e.g. a PoS tag sequence, cf lecture 6):

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} score(x, y)$$

Where $\boldsymbol{Y}$ is rather large and often depends on the input (e.g. $L^{|\boldsymbol{x}|}$ in PoS tagging)

Various approaches:

- Linear models (structured perceptron)
- Probabilistic linear models (conditional random fields)
- Non-linear models

Decoding

Assuming we have a trained model, decode/predict/solve the argmax/inference:

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} score(x, y; \theta)$$

Dynamic programming to the rescue?

Yes! But we need to make assumptions on the structure:

- 1st order Markov assumption (linear chains), rarely more than 2nd
- The scoring function must decompose over the output structure

What if we need greater flexibility?

Incremental structured prediction

A classifier $\mathbf{f}$ predicting actions to construct the output:

$$\hat{\mathbf{y}} = output\left(\begin{aligned} \hat{\alpha}_1 &= \arg\max_{\alpha \in \mathcal{A}} f(\alpha, \mathbf{x}), \\ \hat{\alpha}_2 &= \arg\max_{\alpha \in \mathcal{A}} f(\alpha, \mathbf{x}, \hat{\alpha}_1), \cdots \\ \hat{\alpha}_N &= \arg\max_{\alpha \in \mathcal{A}} f(\alpha, \mathbf{x}, \hat{\alpha}_1 \ldots \hat{\alpha}_{N-1}) \end{aligned}\right)$$

Examples:

- Predicting the PoS tags word-by-word (MEMM without Viterbi)
- Building a syntax tree by shifting items to and reducing a stack
- Generating a sentence word-by-word

Incremental structured prediction

Pros:

✓ No need to enumerate all possible outputs

✓ No modelling restrictions on features

Cons:

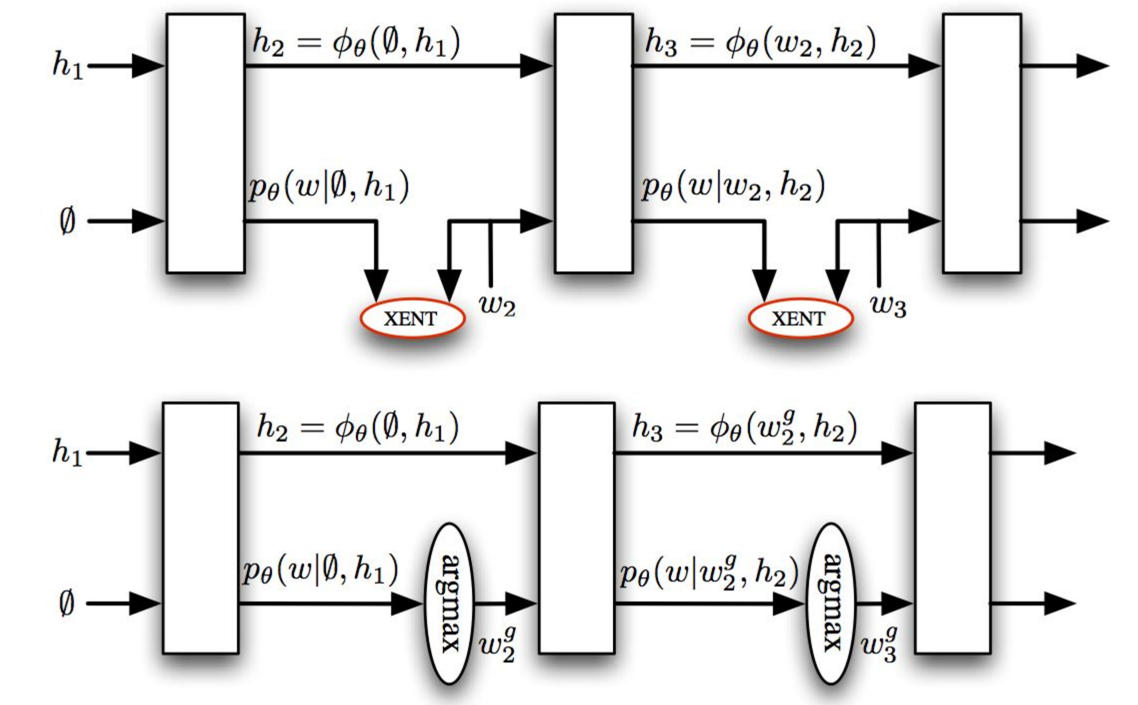
x Prone to error propagation

x Classifier not trained w.r.t. task-level loss

Error propagation

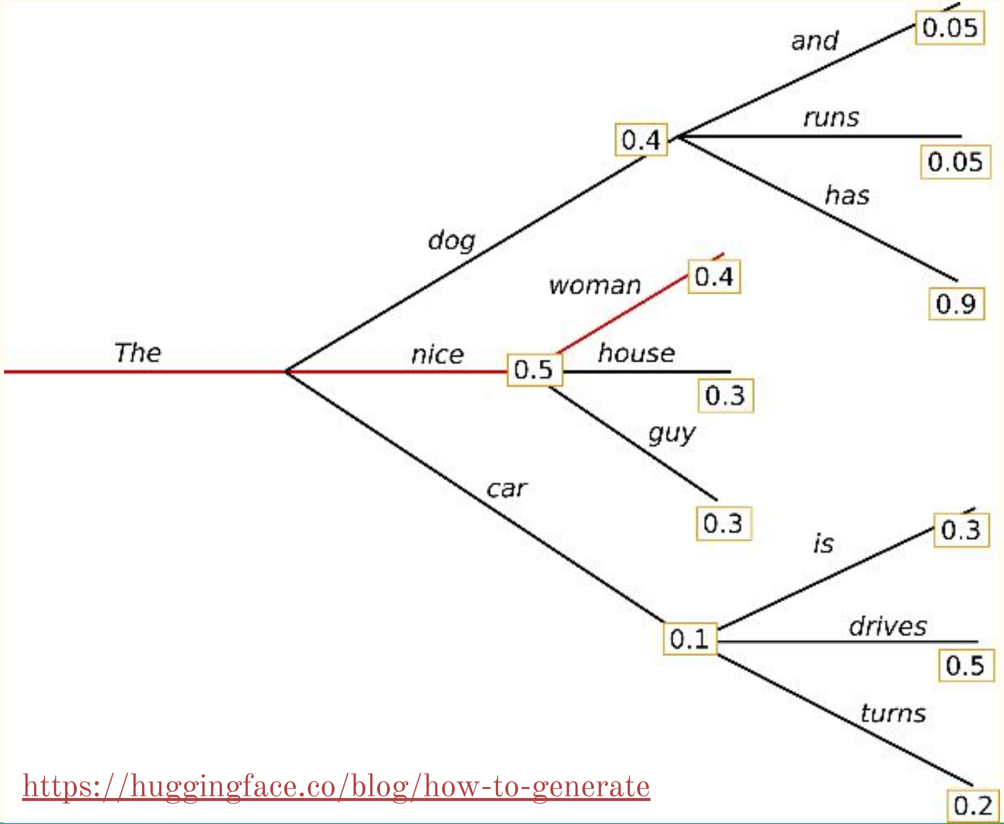
We do not score complete outputs:

- early predictions do not know what follows
- cannot be undone if purely incremental/monotonic (doesn't need to be)
- we are training with gold standard predictions for previous predictions, but test with predicted ones (**exposure bias**)



Ranzato et al. (ICLR2016)

Incremental basics: Greedy and Beam search



https://huggingface.co/blog/how-to-generate

Greedy: pick the most likely action ("the nice woman")

Beam: keep the top-k paths alive ("the dog has" with k=2)

Overcome locally optimal decisions that are not globally optimal **according to the model**

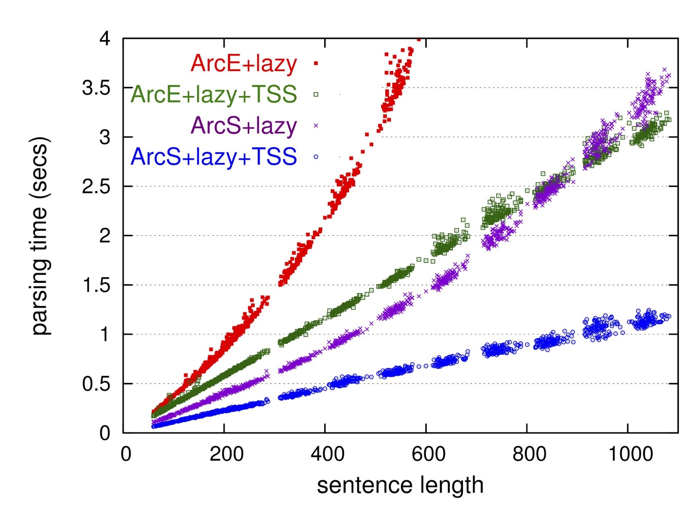
Beam search algorithm

Input: word sequence $x = [x_1, \ldots, x_N]$, tags $\mathcal{Y}$, parameters θ
Initialize beam $B = \{y_{temp} = ([START], score = 0)\}$, size k
for $n = 1 \ldots N$ **do**
    $B' = \{\}$
    for $b \in B$ **do**
        for $y \in \mathcal{Y}$ **do**
            $s = score(\mathbf{x}, [b.y_{temp}; y]); \theta)$
            $B' = B' \cup ([b.\mathbf{y_{temp}}; y], s)$
        end for
    end for
    $B = B'[1 : k]$
end for
return $B[1]$

Beam search in practice

- It works, but implementation matters
  - Feature decomposability is key to reuse previously computed scores
  - Sanity check: on small/toy instances large enough beam should find the exact argmax

- Take care of bias due to action types with different score ranges: picking among all English words is not comparable with picking among PoS tags



Beam search extensions

Reranking:

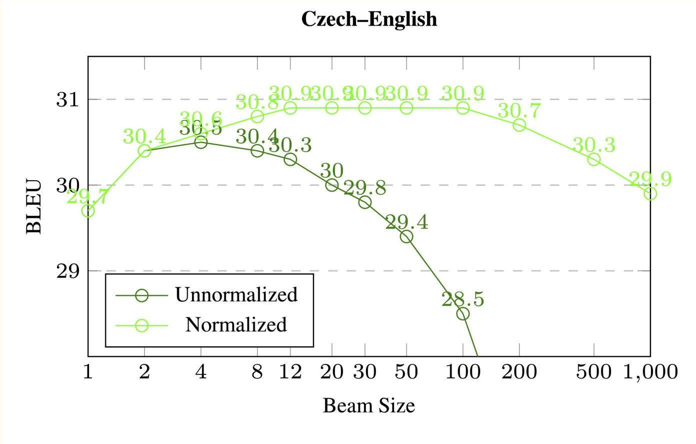
- Adjust probabilities to normalise for sentence length
- Model to pick outputs that are likely to have better global score (e.g. BLEU)

We still rely on beam search to generate good hypotheses

Training decoders for beam search:

- Penalize the model when the correct hypothesis falls of the beam (beam search optimization)
- Train a greedy decoder to approximate beam search to maximize a sentence-level score

Being less exact helps?



Search	BLEU	Ratio	#Search errors	#Empty
Greedy	29.3	1.02	73.6%	0.0%
Beam-10	30.3	1.00	57.7%	0.0%
Exact	2.1	0.06	0.0%	51.8%

Table 1: NMT with exact inference. In the absence of search errors, NMT often prefers the empty translation, causing a dramatic drop in length ratio and BLEU.

- In Neural Machine Translation performance degrades with larger beams…
- Search errors save us from model errors!
- Part of the problem at least is that we train word-level models but the task makes sense at the sentence-level really…

Training for incremental structured prediction

In supervised training we assume a loss function e.g. negative log likelihood against gold labels in classification with logistic regression/ feedforward NNs.

In incremental structured prediction, what do we train our classifier to do?

Predict the action leading the correct output. Losses over **structured outputs**:

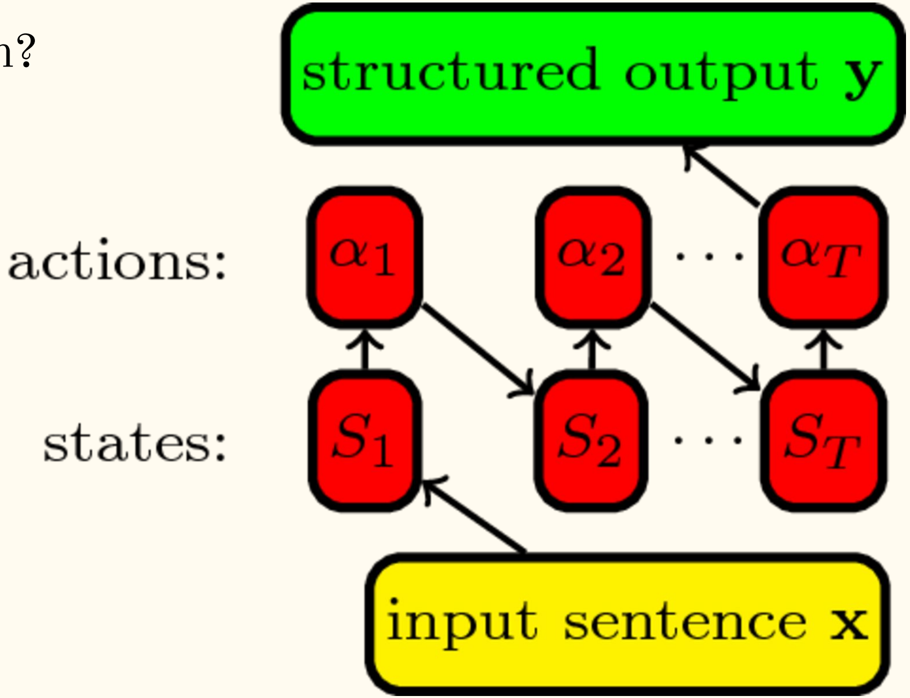
- Hamming loss: number of incorrect part of speech tags in a sentence
- False positives and false negatives: e.g. named entity recognition
- Reduction in BLEU score (n-gram overlap) in generation tasks, e.g. machine translation

Loss and decomposability

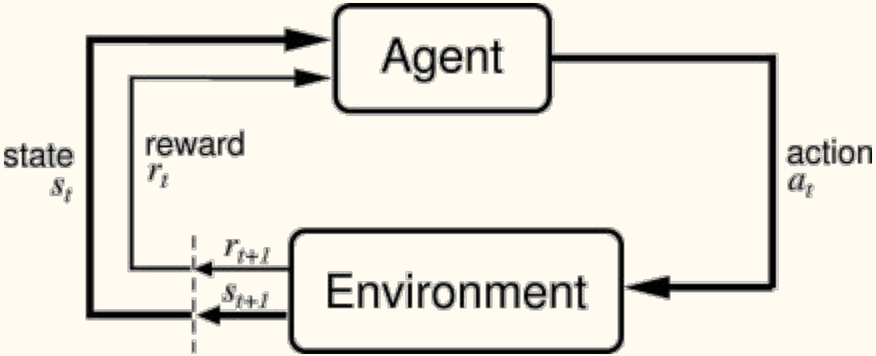
Can we assess the goodness of each action?

- In PoS tagging, predicting a tag at a time with Hamming loss?
  - **YES**
- In machine translation predicting a word at a time with BLEU score?
  - **NO**

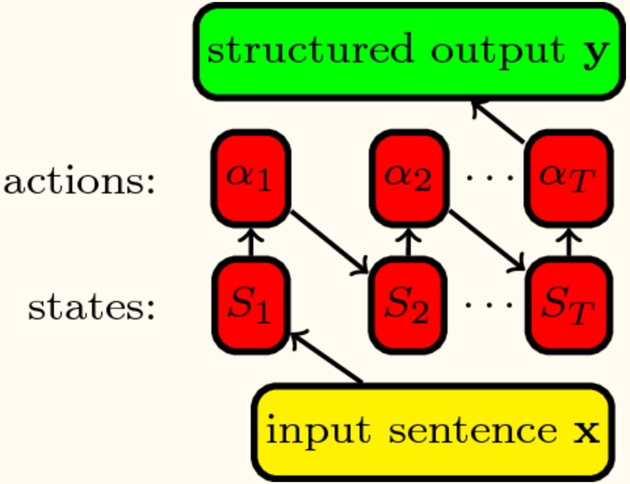
BLEU score doesn't decompose over the actions defined by the transition system



Reinforcement learning



[Sutton and Barto (2018)]



Incremental structured prediction can be viewed as (degenerate) RL:

- No environment dynamics
- No need to worry about physical costs (e.g. robots damaged)

Policy gradient

Learn the parameters $\boldsymbol{\theta}$ of policy/classifier $\boldsymbol{\pi}$ that optimize rewards/task loss v:

$$
\begin{aligned}
J(\theta) &= \sum_{s \in S} d^{\pi_\theta}(s) v^{\pi_\theta}(s) \\
&= \sum_{s \in \mathcal{S}} d^{\pi_\theta}(s) \sum_{\alpha \in \mathcal{A}} \pi_\theta(\alpha|s) Q^{\pi_\theta}(s, \alpha)
\end{aligned}
$$

- on-policy learning: the policy affects the distributions of states visited d
- the reward from reaching a state s is its expectation according to the policy

We can now do our stochastic gradient (ascent) updates:

$$\theta_{t+1} = \theta + \alpha \nabla J(\theta_t)$$

What could go wrong?

Reinforcement learning is hard…

To obtain training signal we need complete trajectories

- Can sample (REINFORCE) but inefficient in large search spaces
- High variance when many actions are needed to reach the end (credit assignment problem)
- Can learn Q to evaluate the outcome of the action (actor-critic)

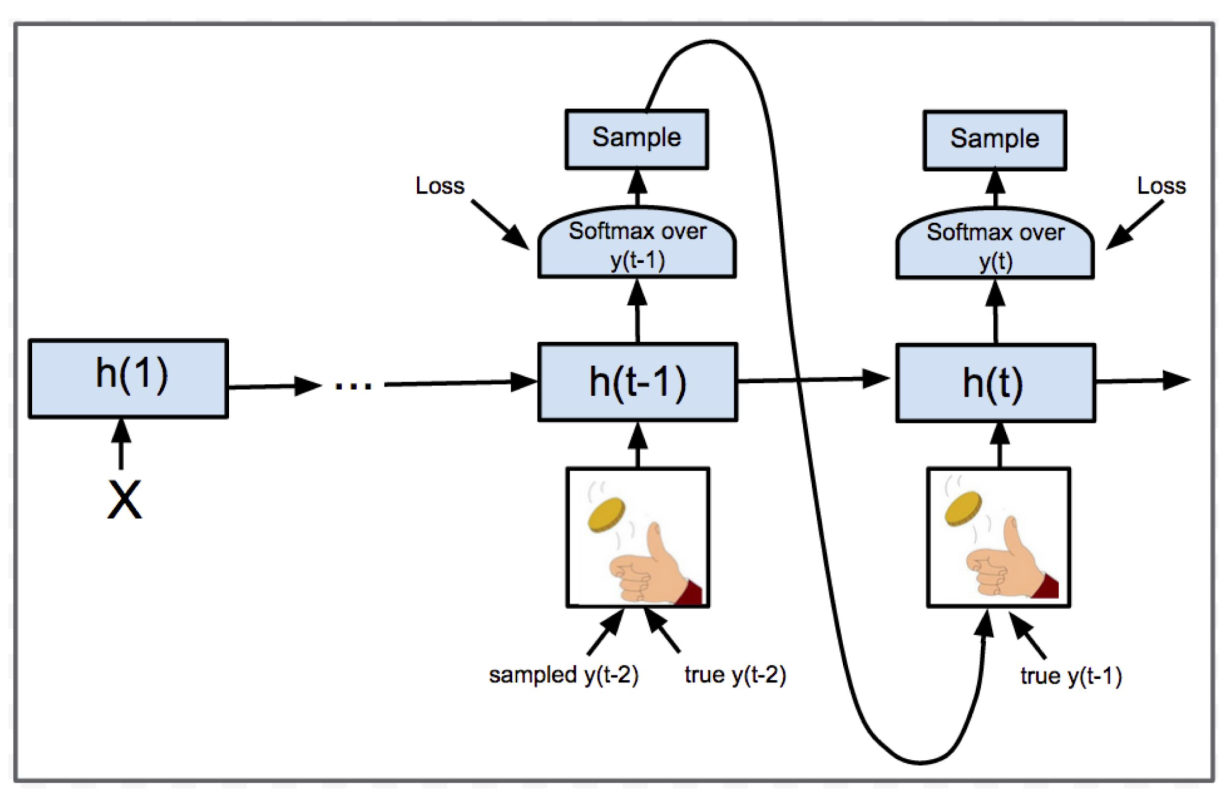
In NLP, often the models are trained initially in the standard supervised way and then fine-tuned with RL (e.g. for summarization)

- Hard to tune the balance between the two
- Constrains the benefits of RL

Imitation learning

- Both reinforcement and imitation learning learn a classifier/policy to maximize reward
- Learning in imitation learning is facilitated by an **expert**

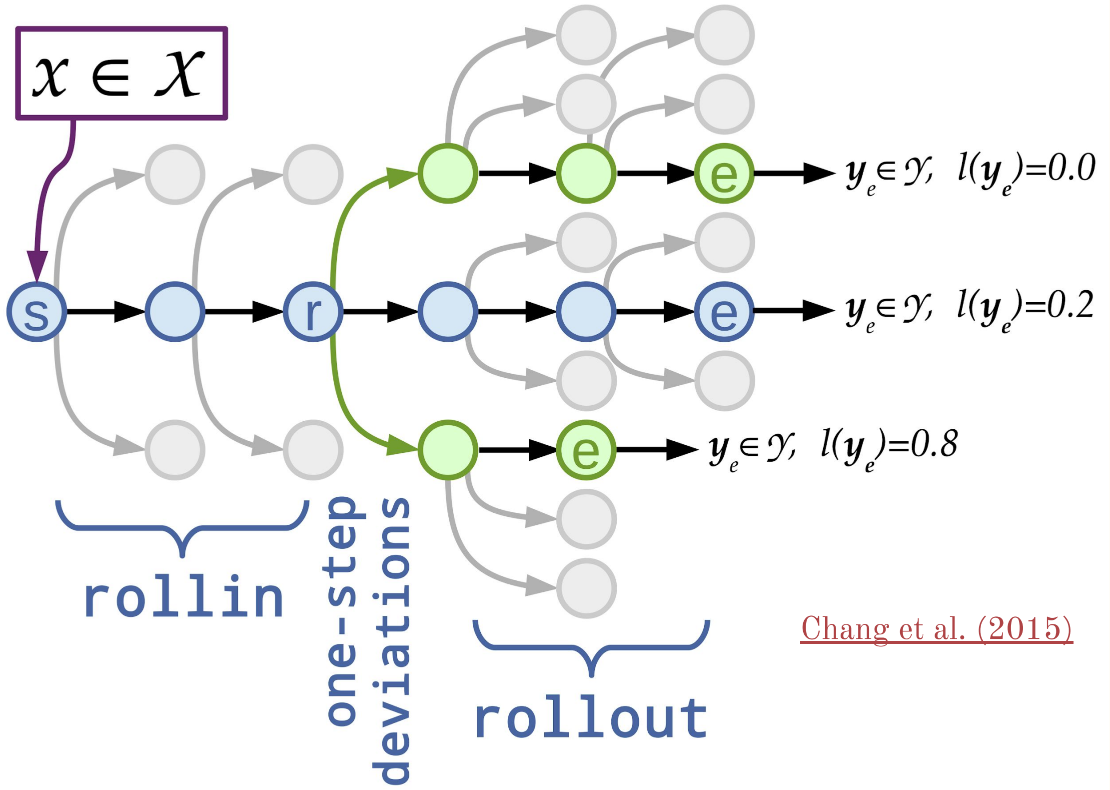
Scheduled sampling



Train without assuming that all previous words are correctly predicted

This idea was first introduced as the DAgger algorithm in robotics

Imitation learning in a nutshell



- Rollins-rollouts mix model and expert predictions
- First iteration trained on expert, later ones increasingly use the trained model
- Exploring one-step deviations from the rollin of the classifier

Imitation learning is hard too!

- Defining a good expert is difficult
  - How to know all possible correct next words to add given a partial translation and a gold standard?
  - Without a better than random expert, we are back to RL

- While expert demonstrations make learning more efficient, it is still difficult to handle large numbers of actions
- The interaction between learning the feature extraction and learning the policy/classifier is not well understood in the context of RNNs

Bibliography

- Kai Zhao's survey
- Noah Smith's book
- Sutton and Barton Reinforcement learning book
- This blog on policy gradient methods
- Imitation learning tutorials:
  - structured prediction
  - natural language generation
  - ML-oriented