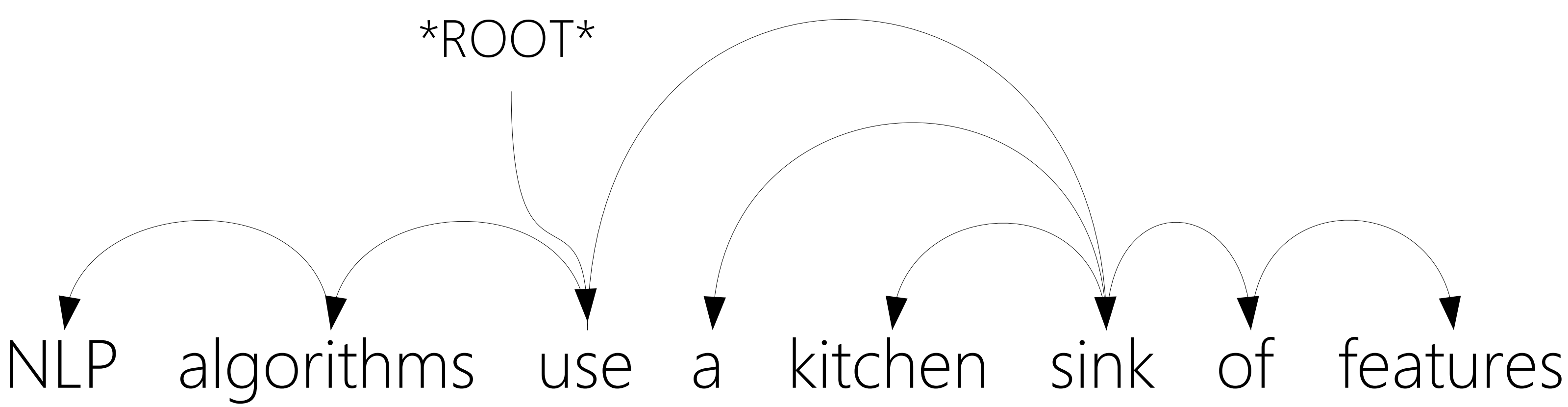
Joint prediction via imitation learning

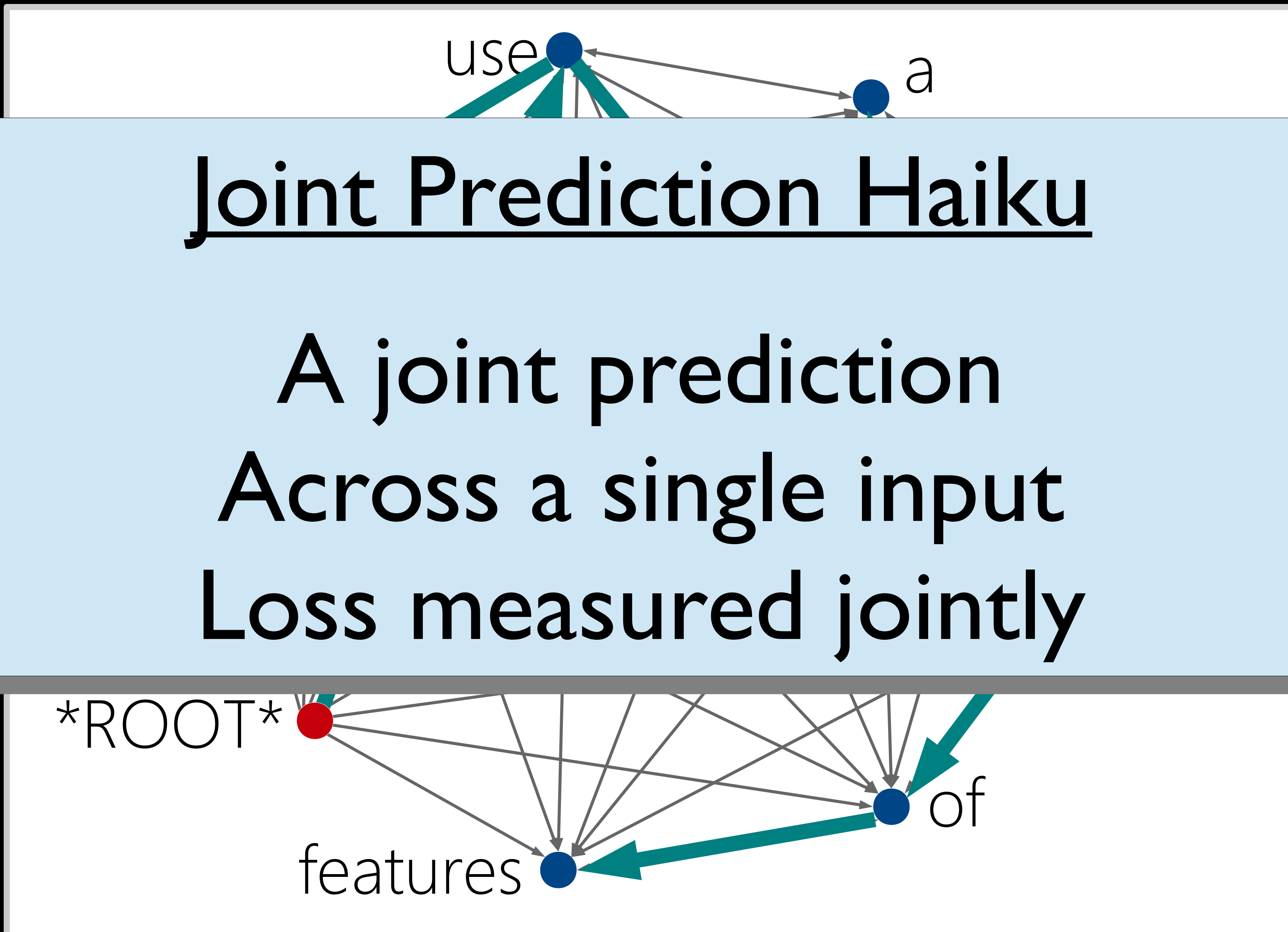
Part of Speech Tagging

NN	NNS	VBP	DT	NN	NN	IN	NNS
NLP	algorithms	use	a	kitchen	sink	of	features

Dependency Parsing



Joint prediction via imitation learning



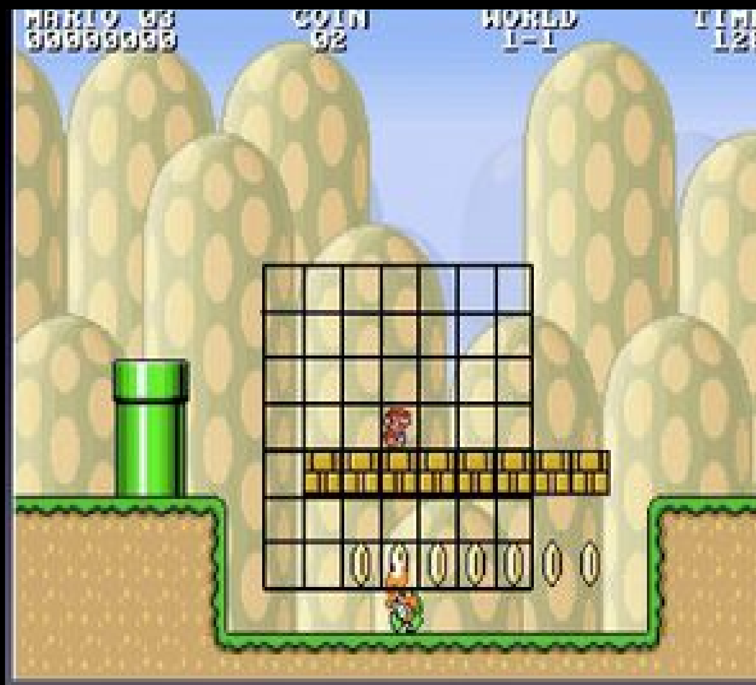
Joint Prediction Haiku

A joint prediction
Across a single input
Loss measured jointly

An analogy from playing Mario

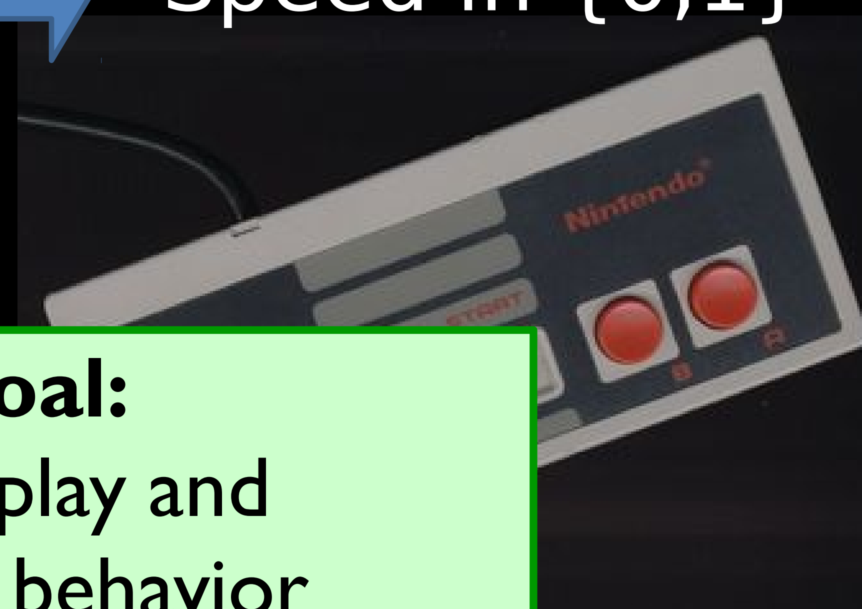
From Mario AI competition 2009

Input:



Output:

Jump in {0,1}
Right in {0,1}
Left in {0,1}
Speed in {0,1}

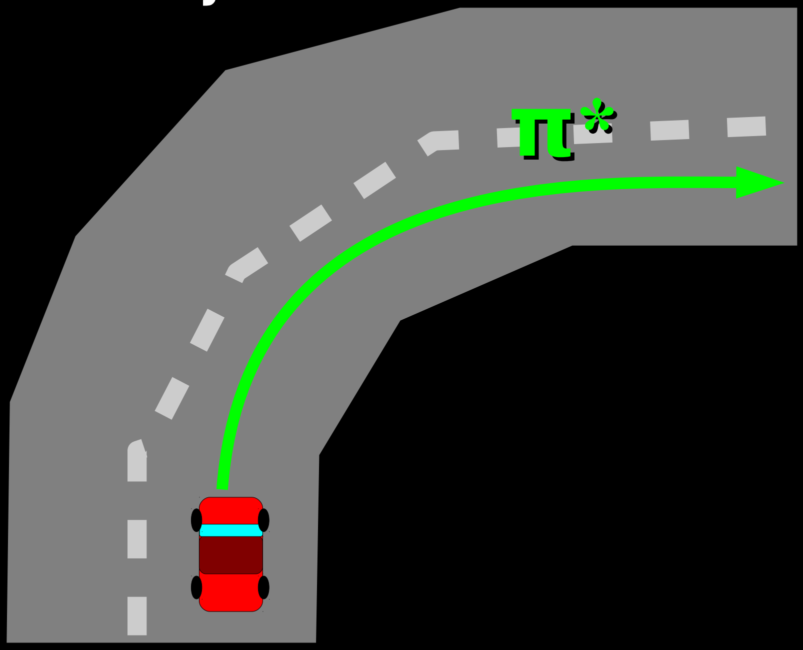


High level goal:
Watch an expert play and
learn to mimic her behavior

Vanilla supervised learning

1. Collect trajectories from expert **π***
   - Trajectory = sequence of state/action pairs over time
   - States are represented as feature vectors
     - Incorporates current "observations" …
     - … and *any* past decisions
2. Store as dataset **D** = { (s, **π***(s)) | s ~ **π*** }
3. Train classifier **π** on **D**

- **Let π play the game!**



Training (expert)

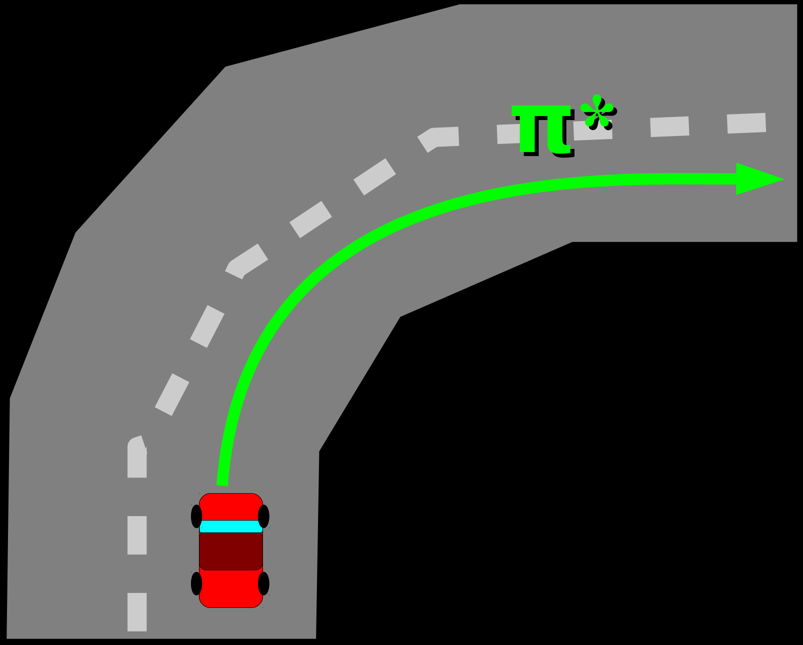
Video credit: Stéphane Ross, Geoff Gordon and Drew Bagnell

Test-time execution (classifier)

Video credit: Stéphane Ross, Geoff Gordon and Drew Bagnell

What's the (biggest) failure mode?

- The expert never gets stuck next to pipes
- => Classifier doesn't learn to recover!



Imitation learning: DAgger

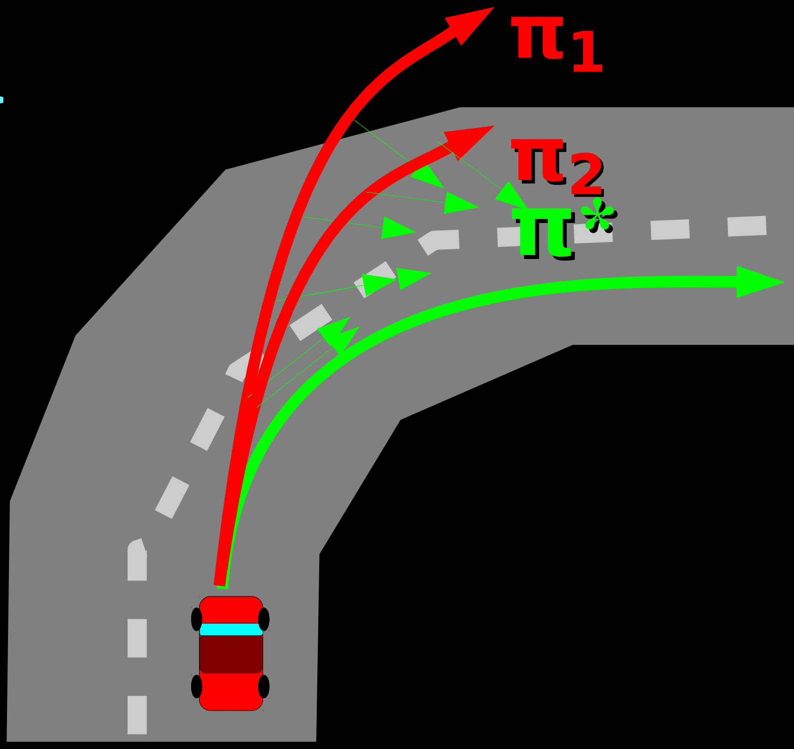
1. Collect trajectories from expert π^*
2. Dataset $D_0 = \{ (s, \pi^*(s)) \mid s \sim \pi^* \}$
3. Train π_1 on D_0
4. Collect new trajectories from π_1
   - But let the *expert* steer!
5. Dataset $D_1 = \{ (s, \pi^*(s)) \mid s \sim \pi_1 \}$
6. Train π_2 on $D_0 \cup D_1$

- In general:
  - $D_n = \{ (s, \pi^*(s)) \mid s \sim \pi_n \}$
  - Train π_n on $\bigcup_{i<n} D_i$

If $N = T \log T$,

$$\mathbf{L(\pi_n) < T\,\epsilon_N + O(1)}$$

for some n

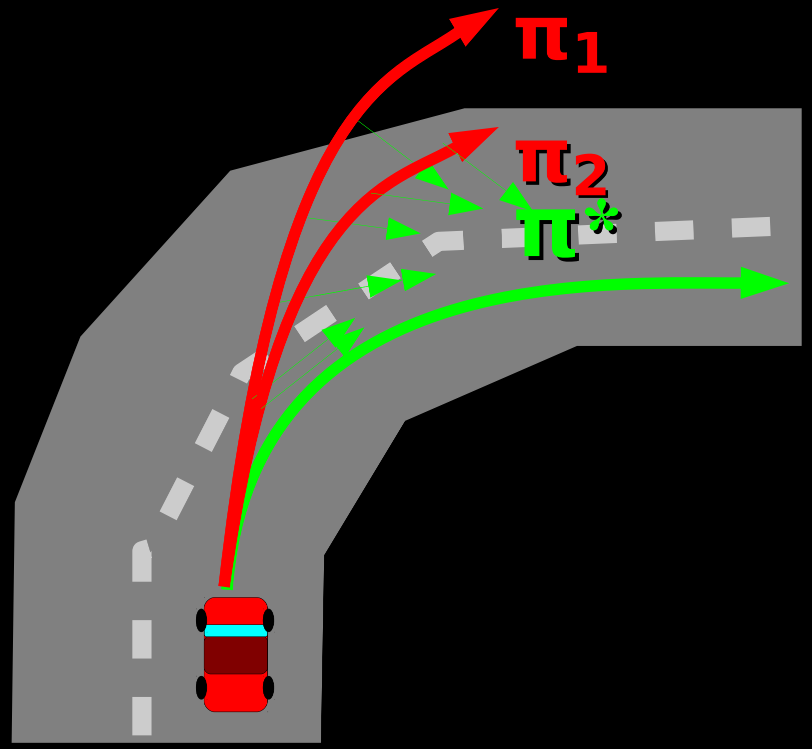


Test-time execution (DAgger)

Video credit: Stéphane Ross, Geoff Gordon and Drew Bagnell

What's the biggest failure mode?

- Classifier only sees "right" versus "not-right"
  - No notion of "better" or "worse"
  - No "partial credit"
  - Must have a single "target" answer



Joint prediction via learning to search

Part of Speech Tagging

NN	NNS	VBP	DT	NN	NN	IN	NNS
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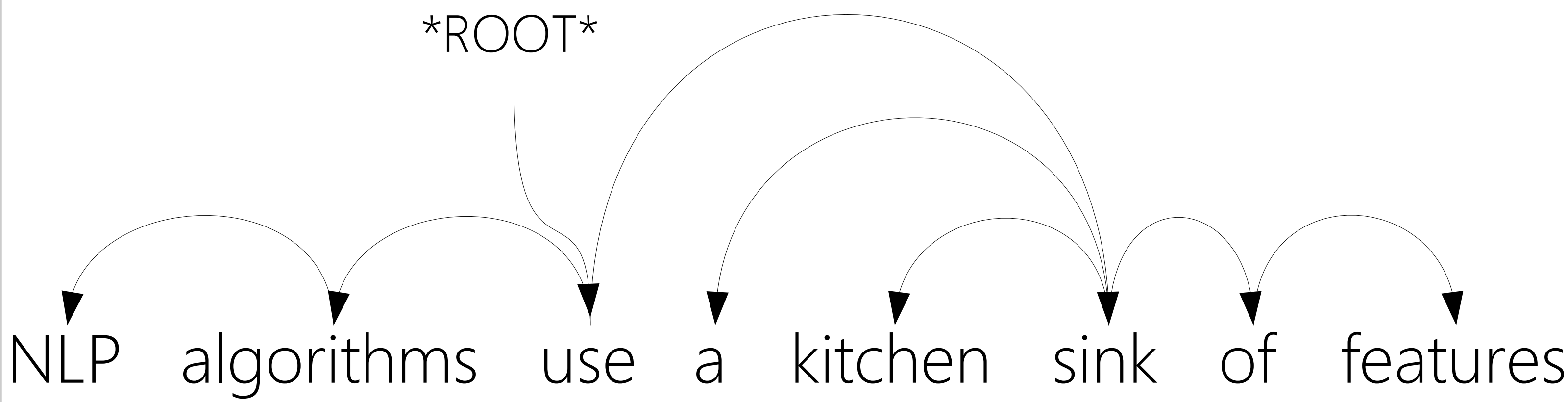
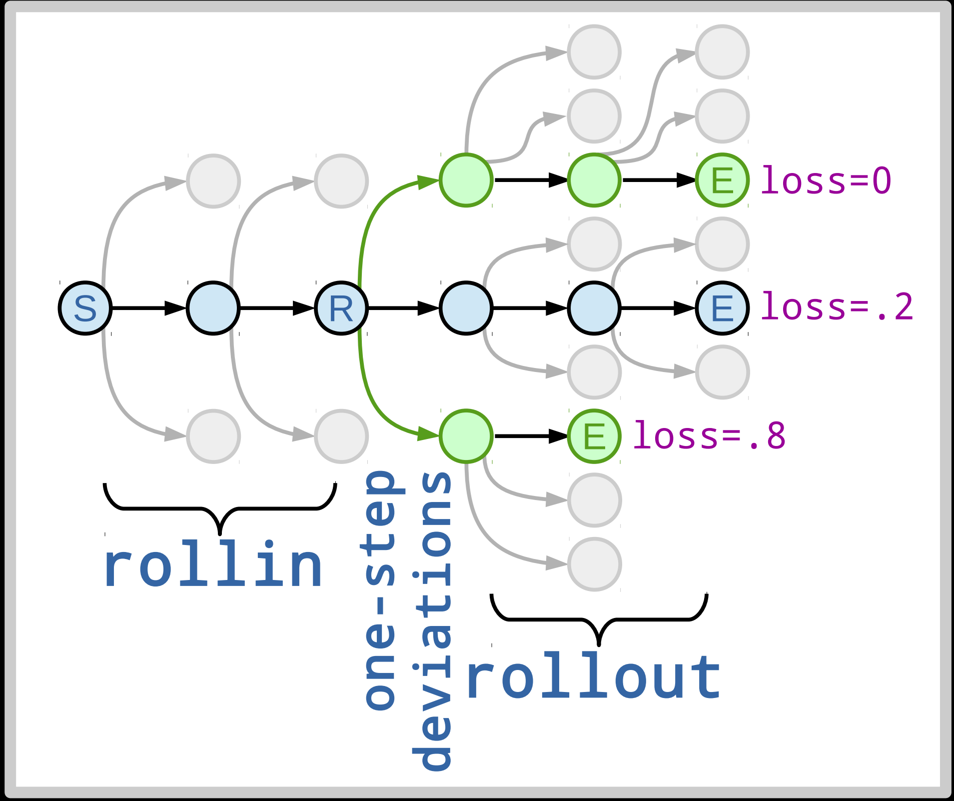
Dependency Parsing



Learning to search



1. Generate an initial trajectory using a *rollin policy*
2. Foreach state R on that trajectory:
   a) Foreach possible action *a* (one-step deviations)
      i. Take that action
      ii. Complete this trajectory using a rollout policy
      iii. Obtain a final loss

   b) Generate a cost-sensitive classification example:

   $$(\Phi(R), \langle c_a \rangle_{a \in A})$$

Choosing the rollin/rollo

Note: if the reference policy is *optimal* then: In=Learn & Out=Ref is also a good choice

- Three basic options:
  - The currently learned policy (“lear
  - The reference/expert policy (“ref
  - A stochastic mixture of these ix”)

Out / In	Ref	ix	Learn
Ref	Inconsistent One-step fai	nconsistent	Inconsistent
Learn	One-step fail	**Good**	Really hard

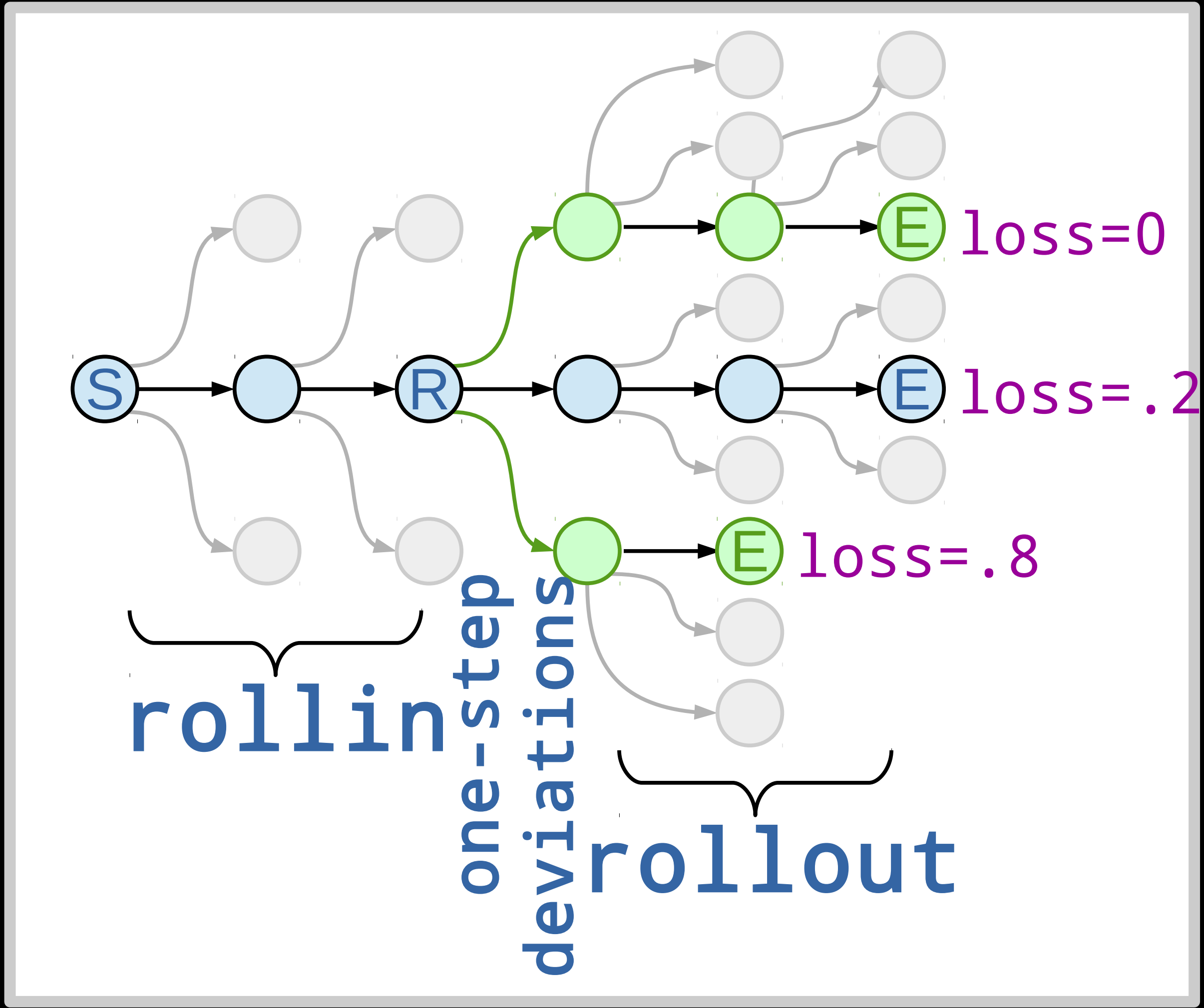
Sanity check: which of these is closest to DAgger?

From Mario back to POS tagging

```
def _run(self, sentence):
  out = []
  for n in range(len(sentence)):
    pos,word = sentence[n]
    ex   = example({'w': [word]})
    pred = predict(ex, pos)
    out.append( pred )
  loss( # of pred != pos )
  return out
```

- The oracle (reference) policy gives the true label for the corresponding word
- Sanity check: why/when is this optimal?

Optimal policies



- Given:
  - Training input *x*
  - State R
  - Loss function
- Return the action a that:
  - (If all future actions are taken optimally)
  - Minimizes the corresponding loss

Optimal policies for harder problems

- **Consider word-based machine translation**

- You want to write
- But what does the optimal policy do?

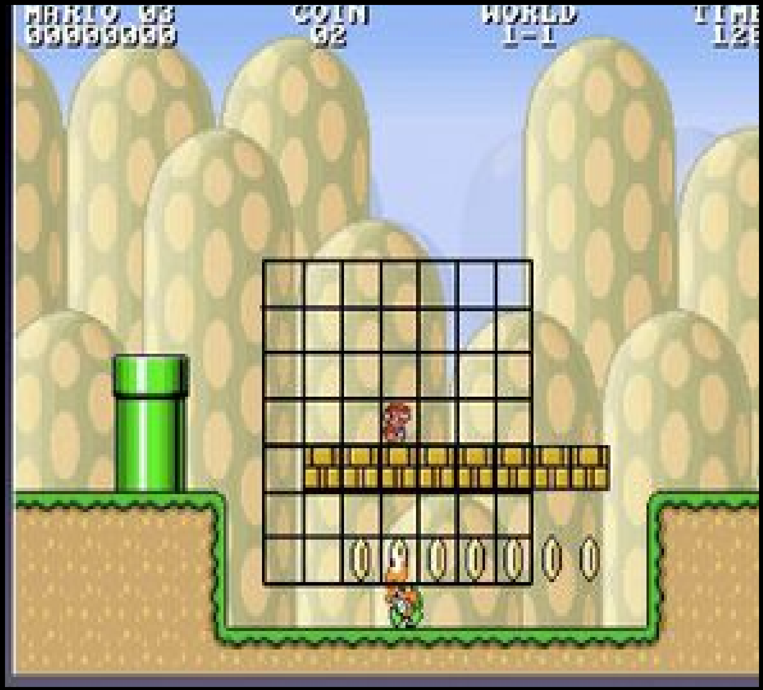
```
F,ref = input
E = [ <s> ]
i = 1
cov = {}
while |cov| != |F|:
   a = predict(cov, ???)
   e = predict(F_a, ???)
   cov[a] = true
   E.push(e)
   i += 1
loss( 1-BLEU(E, ref) )
return E
```

F: Marie programme l' ordinateur
E: Mary programs the computer

State R: Mary ______
State R': The computer ______
State R'': Aardvarks ______

How can you do this for Mario?

Input:



Output:

Jump in {0,1}
Right in {0,1}
Left in {0,1}
Speed in {0,1}

Reference policy is constructed on-the-fly:

At each state, execute a depth-4 BFS

At each of the 64k leaves, evaluate

Choose initial action that leads to local optimum

Key concepts and commentary

- Rollin / rollout / one-step deviations
- Reference policy / optimal policy
- Joint loss

- Tips:
  - Defining a good reference can be tricky:
    - If optimal, do: in=learn, out=ref|none
    - If suboptimal, do: in=learn, out=mix
  - Can only learn to avoid compounding errors given the right features

Coming up next....

- Instantiating these ideas in vw
- During the break, please:

```
git clone git@github.com:JohnLangford/vowpal_wabbit.git
make
make python
cd python
python test.py
python test_search.py
```

- And ask us any questions you might have!
- When we return, we'll build some predictors!

A short reading list

- DAgger (imitation learning from oracle):
  A reduction of imitation learning and structured prediction to no-regret online learning
  Ross, Gordon & Bagnell, AIStats 2011

- AggreVaTe (roughly "DAgger with rollouts")
  Reinforcement and imitation learning via interactive no-regret learning
  Ross & Bagnell, arXiv:1406.5979

- LOLS (analysis of rollin/rollout, lower bounds, suboptimal reference)
  Learning to search better than your teacher
  Chang, Krishnamurthy, Agarwal, Daumé III & Langford, ICML 2015

- Imperative learning to search (programming framework, sequence labeling results)
  Efficient programmable learning to search
  Chang, Daumé III, Langford & Ross, arXiv:1406.1837

- State of the art dependency parsing in ~300 lines of code
  Learning to search for dependencies
  Chang, He, Daumé III & Langford, arXiv:1503.05615

- Efficiently computing an optimal policy for shift-reduce dependency parsing
  A tabular method for dynamic oracles in transition-based parsing
  Goldberg, Sartorio & Satta, TACL 2014