

Advances in Structured Prediction



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Slides and more: <http://hunch.net/~l2s>

Examples of structured ~~joint~~ prediction

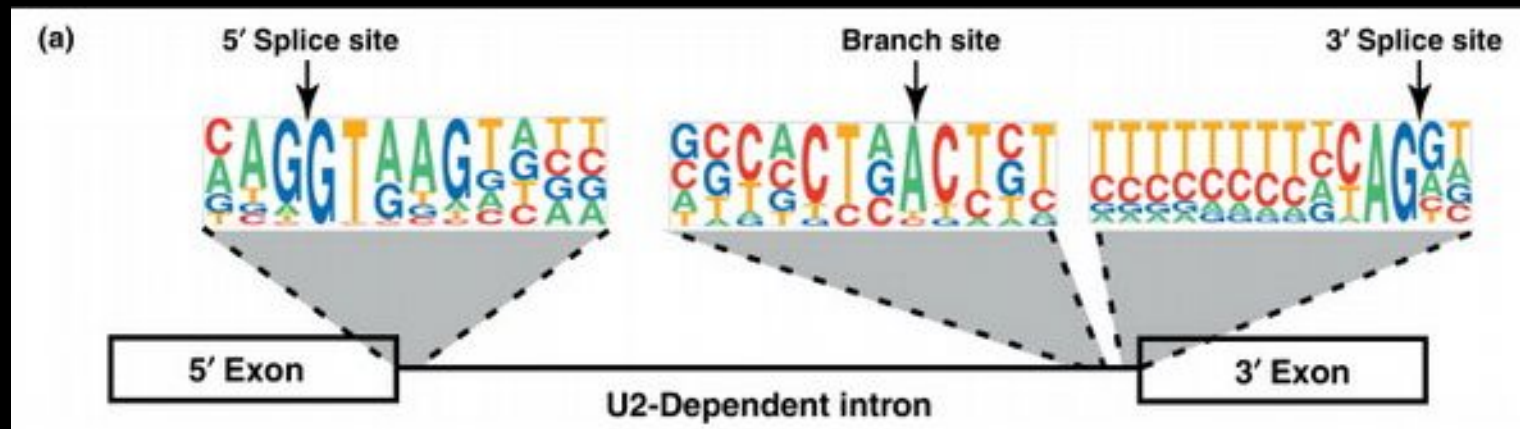
Sequence labeling

x = the monster ate the sandwich

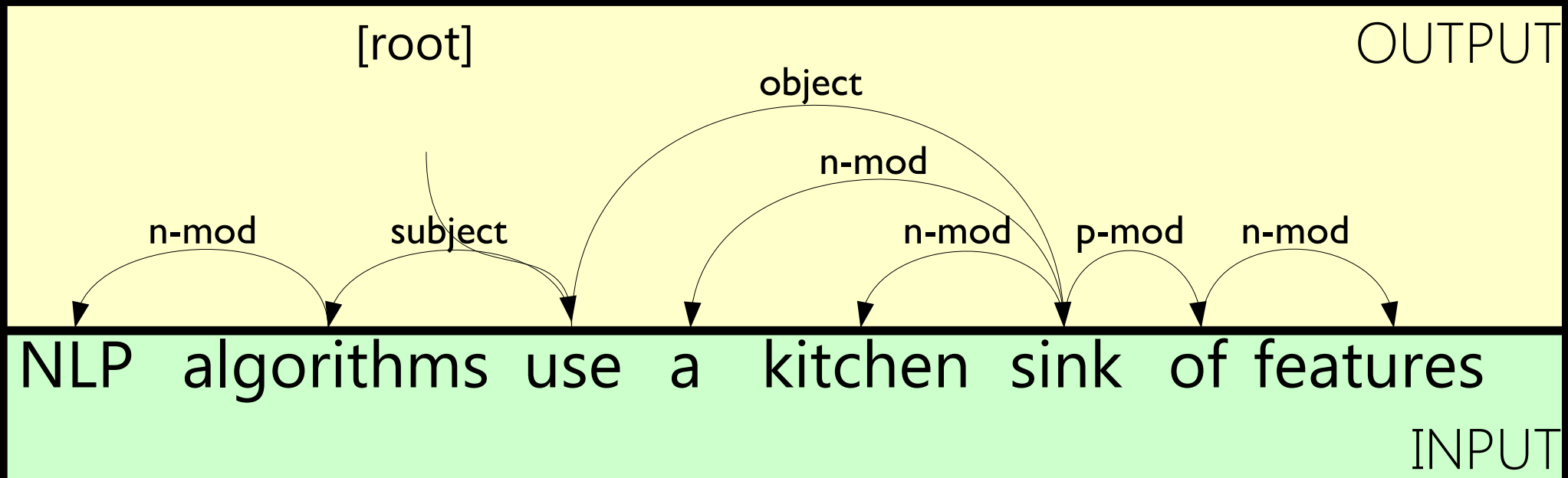
y = Dt Nn Vb Dt Nn

x = Yesterday I traveled to Lille

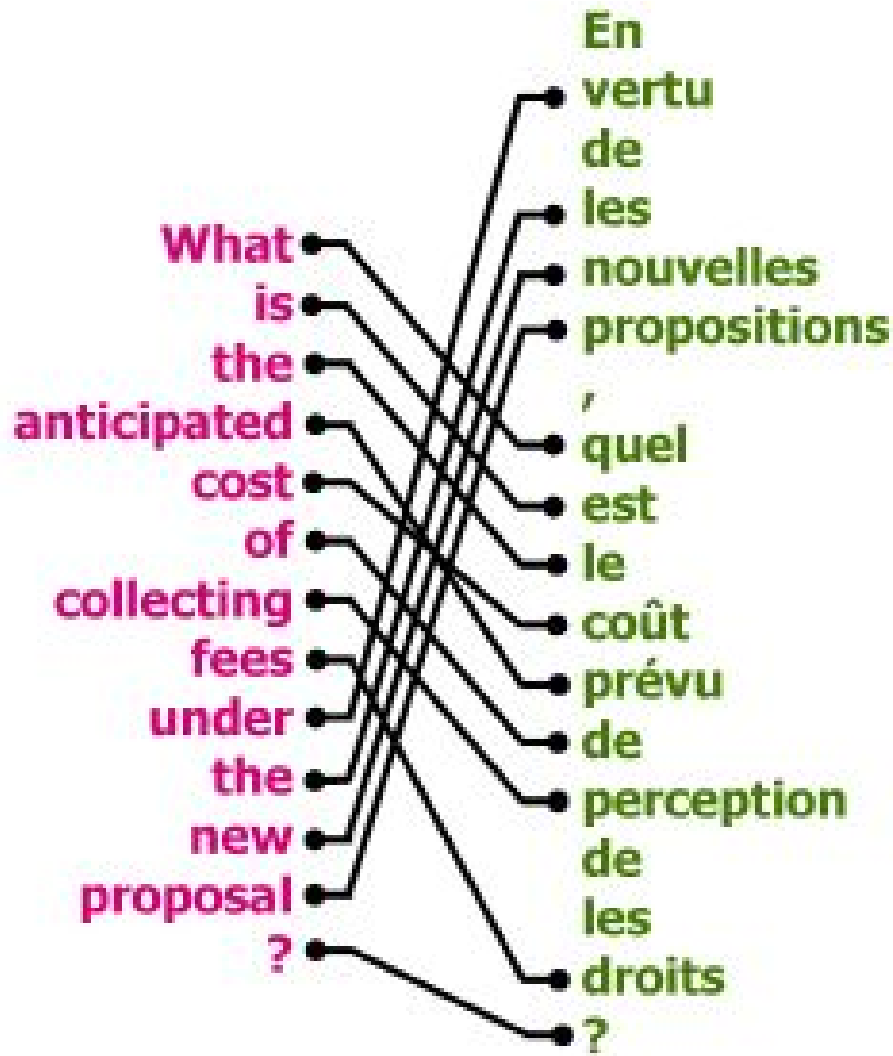
y = - PER - - LOC



Natural language parsing



(Bipartite) matching



Machine translation

 Translate

This text has been [automatically translated](#) from Arabic:

Moscow stressed tone against Iran on its nuclear program. He called Russian Foreign Minister Tehran to take concrete steps to restore confidence with the international community, to cooperate fully with the IAEA. Conversely Tehran expressed its willingness

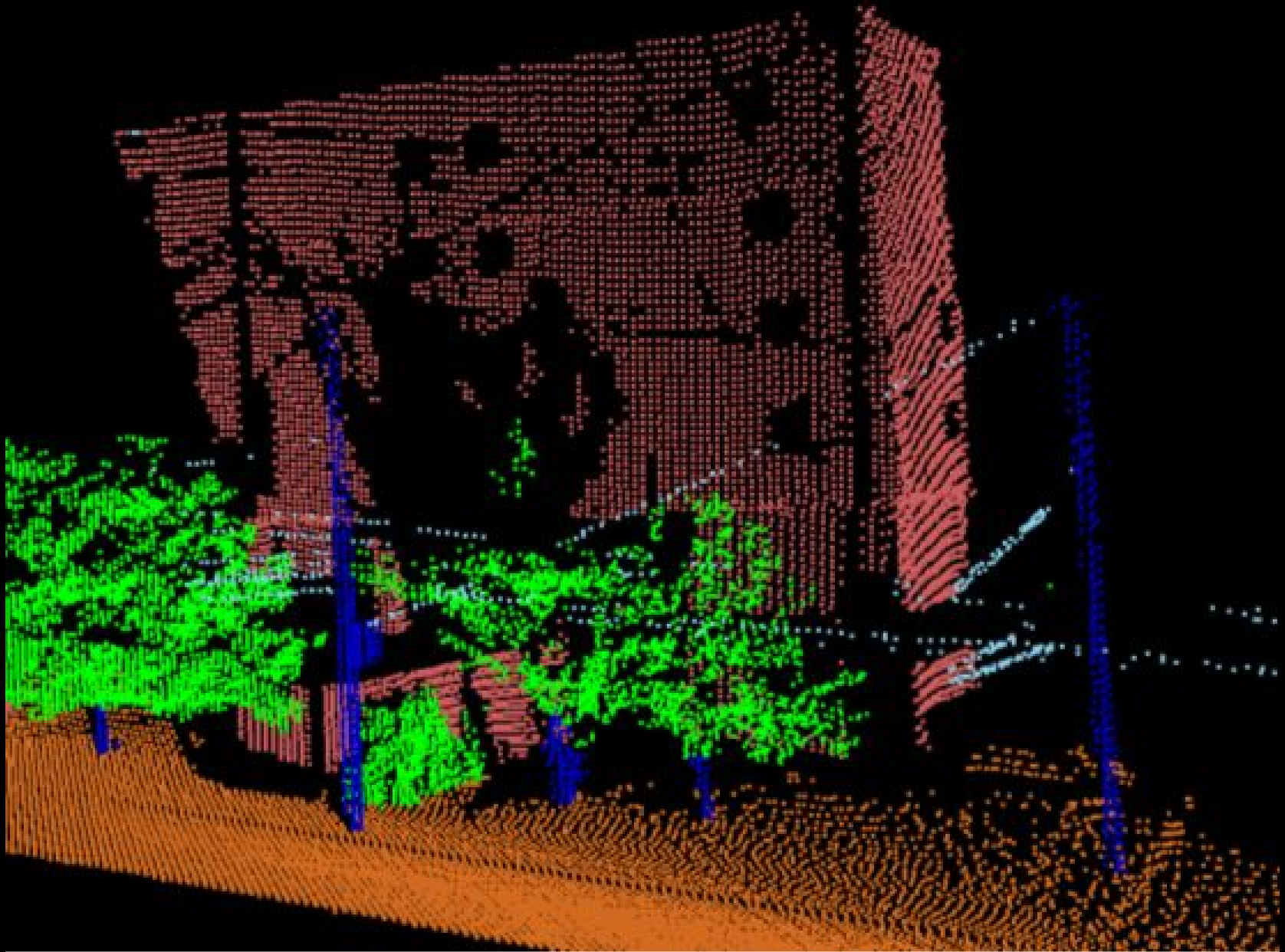
Translate text

شدت موسكو لهجتها ضد إيران بشأن برنامجها النووي. ودعا وزير الخارجية الروسي طهران إلى اتخاذ خطوات ملموسة لاستعادة الثقة مع المجتمع الدولي والتعاون الكامل مع الوكالة الذرية. بالمقابل أبدت طهران استعدادها لاستئناف السماح بعمليات التفتيش المفاجئة بشرط إسقاط مجلس الأمن ملفها النووي.

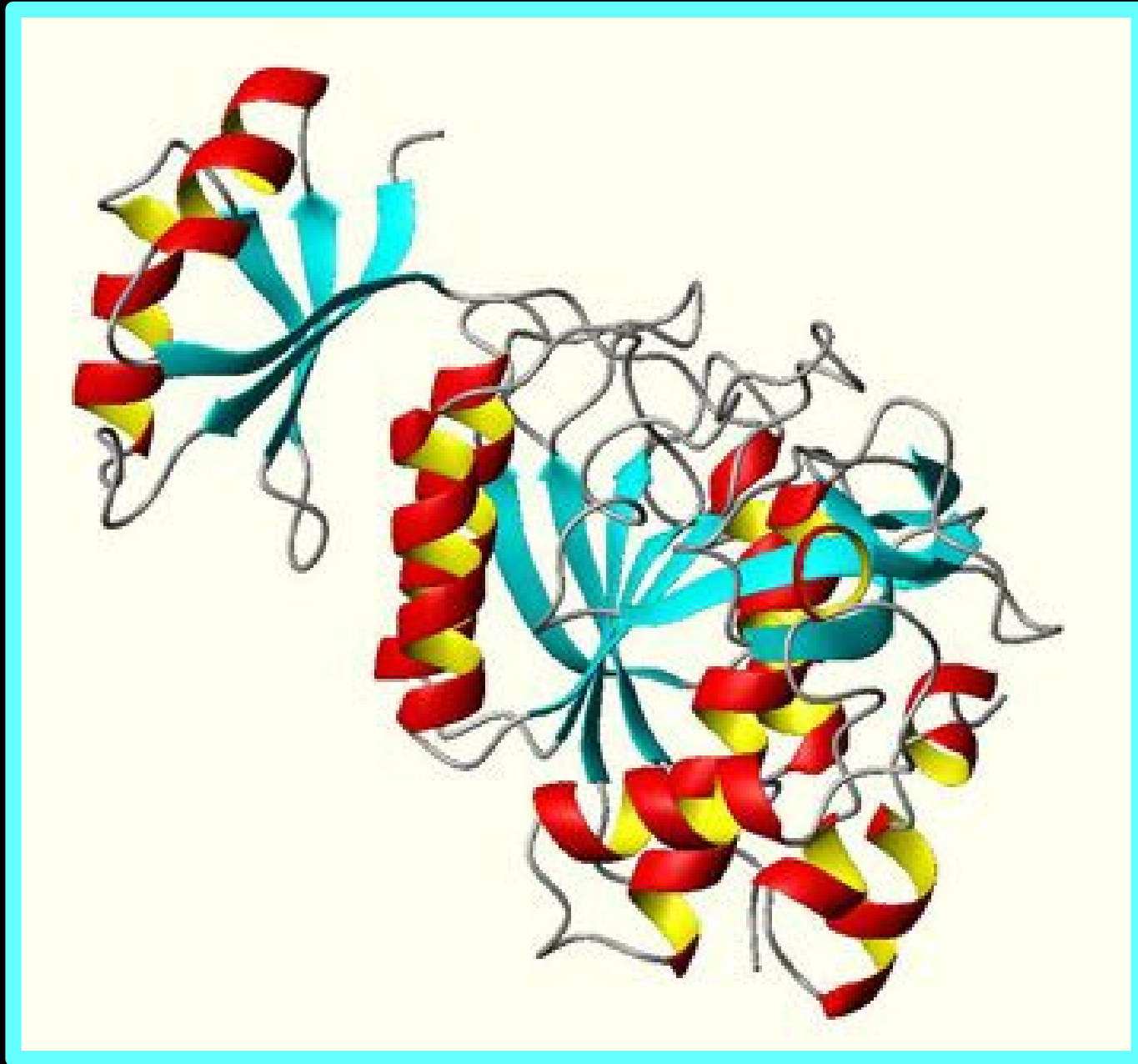
from Arabic to English BETA

Translate

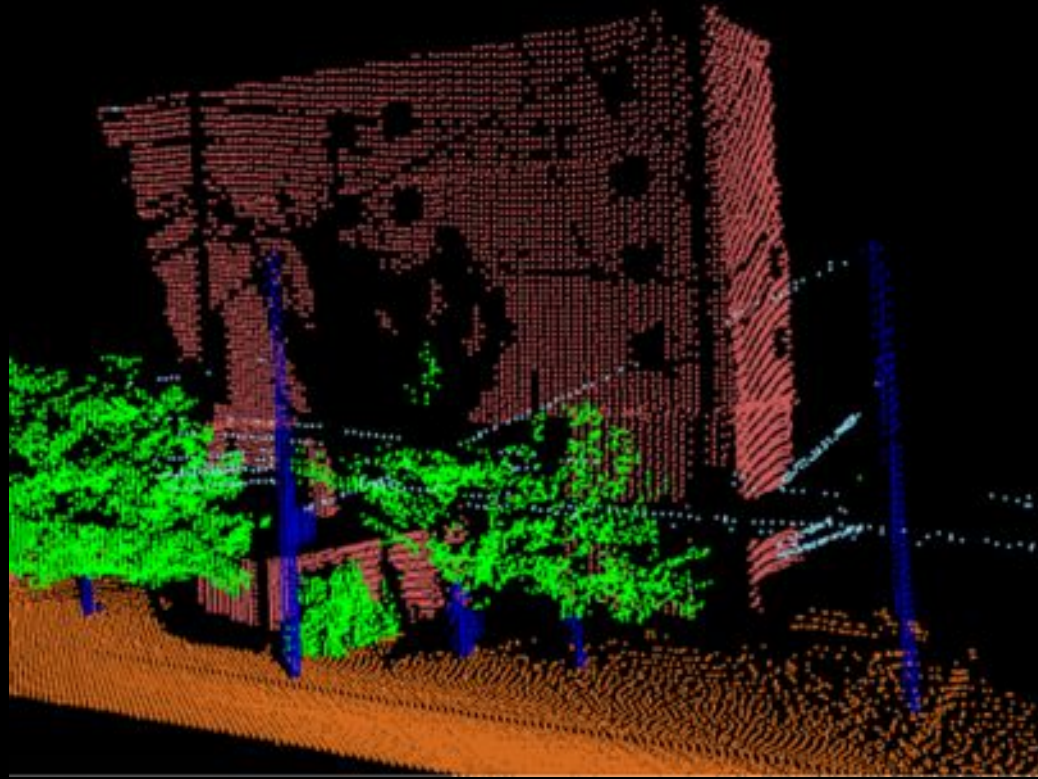
Image segmentation



Protein secondary structure prediction

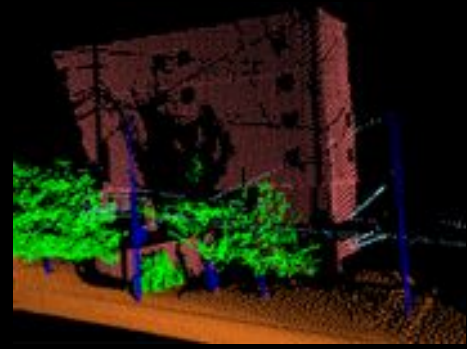


Standard solution methods



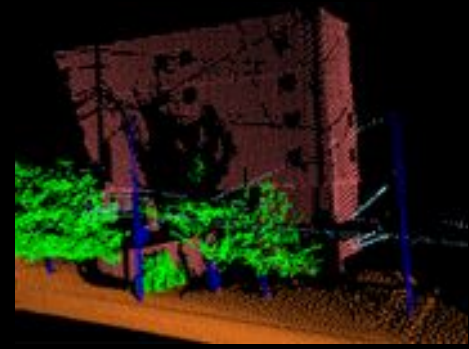
1. Each prediction is independent
2. Shared parameters via “multitask learning”
3. Assume tractable graphical model; optimize
4. Hand-crafted

Predicting independently



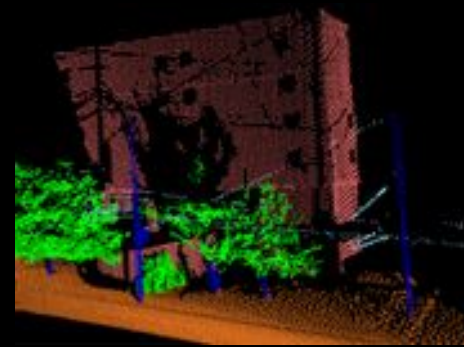
- h : features of nearby voxels \rightarrow class
- Ensure output is coherent at test time
- ✓ Very simple to implement, often efficient
- ✗ Cannot capture correlations between predictions
- ✗ Cannot optimize a joint loss

Prediction with multitask bias



- $h : \text{features} \rightarrow (\text{hidden representation}) \rightarrow \text{yes/no}$
- Share (hidden representation) across all classes
- ✓ All advantages of predicting independently
- ✓ May implicitly capture correlations
- × Learning may be hard (... or not?)
- × Still not optimizing a joint loss

Optimizing graphical models



- Encode output as a graphical model
- Learn parameters of that model to maximize:
 - $p(\text{true labels} \mid \text{input})$ *or*
 - cvx u.b. on $\text{loss}(\text{true labels}, \text{predicted labels})$

- ✓ Guaranteed consistent outputs
- ✓ Can capture correlations explicitly

- ✗ Assumed independence assumptions may not hold
- ✗ Computationally intractable with too many “edges” or non-decomposable loss function

Back to the original problem...

- How to optimize a discrete, joint loss?

- Input: $x \in X$ 


- Truth: $y \in Y(x)$ 

- Outputs: $Y(x)$ 

- Predicted: $\hat{y} \in Y(x)$

- Loss: $\text{loss}(y, \hat{y})$

- Data: $(x, y) \sim D$



I	can	can	a	can
Pro	Md	Vb	Dt	Nn
Pro	Md	Md	Dt	Vb
Pro	Md	Md	Dt	Nn
Pro	Md	Nn	Dt	Md
Pro	Md	Nn	Dt	Vb
Pro	Md	Nn	Dt	Nn
Pro	Md	Vb	Dt	Md
Pro	Md	Vb	Dt	Vb

Back to the original problem...

- How to optimize a discrete, joint loss?

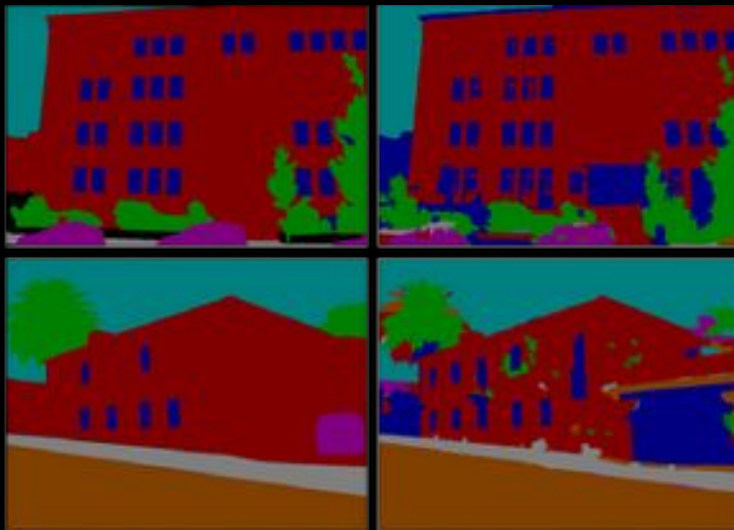
- Input: $\mathbf{x} \in X$
- Truth: $\mathbf{y} \in Y(\mathbf{x})$
- Outputs: $Y(\mathbf{x})$
- Predicted: $\hat{\mathbf{y}} \in Y(\mathbf{x})$
- Loss: $\text{loss}(\mathbf{y}, \hat{\mathbf{y}})$
- Data: $(\mathbf{x}, \mathbf{y}) \sim D$

Goal:

find $h \in H$
such that $h(\mathbf{x}) \in Y(\mathbf{x})$
minimizing
 $E_{(\mathbf{x}, \mathbf{y}) \sim D} [\text{loss}(\mathbf{y}, h(\mathbf{x}))]$
based on N samples
 $(\mathbf{x}_n, \mathbf{y}_n) \sim D$

Challenges

- Output space is too big to exhaustively search:
 - Typically exponential in size of input
 - *implies y must decompose in some way*
(often: x has many pieces to label)
- Loss function has combinatorial structure:
 - Intersection over union
 - Edit Distance



		G	C	A	T	G	C	U	
		0	-1	-2	-3	-4	-5	-6	-7
G		-1	1	0	-1	-2	-3	-4	-5
A		-2	0	0	1	0	-1	-2	-3
T		-3	-1	-1	0	2	1	0	-1
T		-4	-2	-2	-1	1	1	0	-1
A		-5	-3	-3	-1	0	0	0	-1
C		-6	-4	-2	-2	-1	-1	1	0
A		-7	-5	-3	-1	-2	-2	0	0

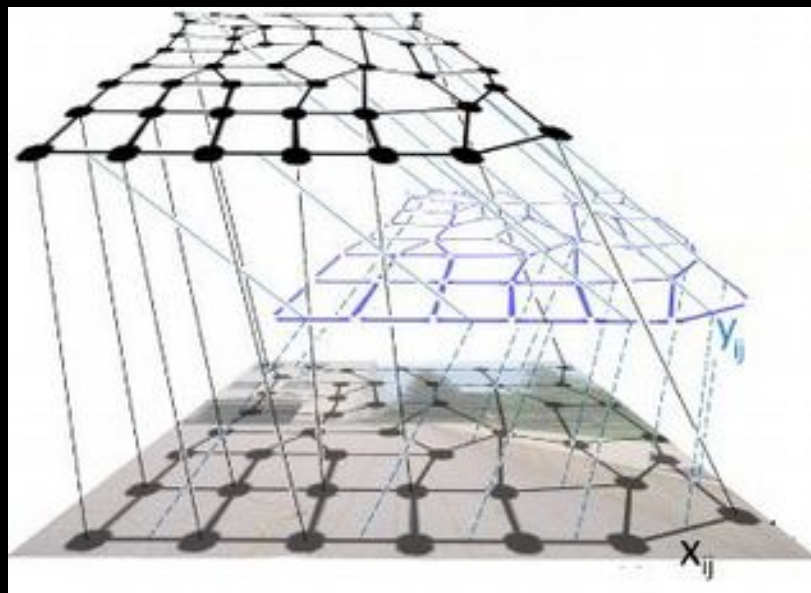
Decomposition of label

- Decomposition of y often implies an ordering

I	can	can	a	can
Pro	Md	Vb	Dt	Nn

		G	C	A	T	G	C	U
	0	-1	-2	-3	-4	-5	-6	-7
G	-1	1	0	-1	-2	-3	-4	-5
A	-2	0	0	1	0	-1	-2	-3
T	-3	-1	-1	0	2	1	0	-1
T	-4	-2	-2	-1	1	1	0	-1
A	-5	-3	-3	-1	0	0	0	-1
C	-6	-4	-2	-2	-1	-1	1	0
A	-7	-5	-3	-1	-2	-2	0	0

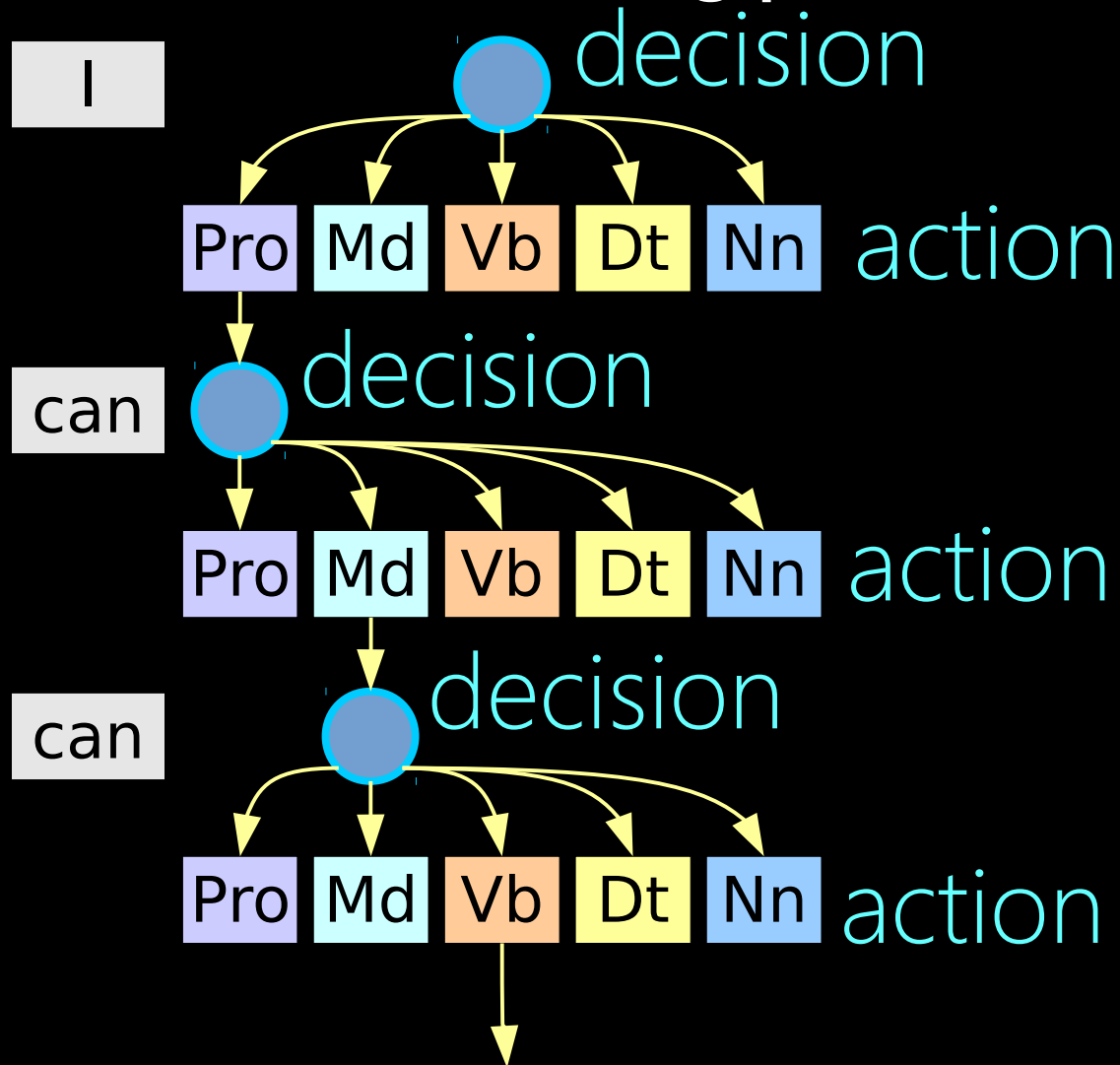
- But sometimes not so obvious....



(we'll come back to this case later...)

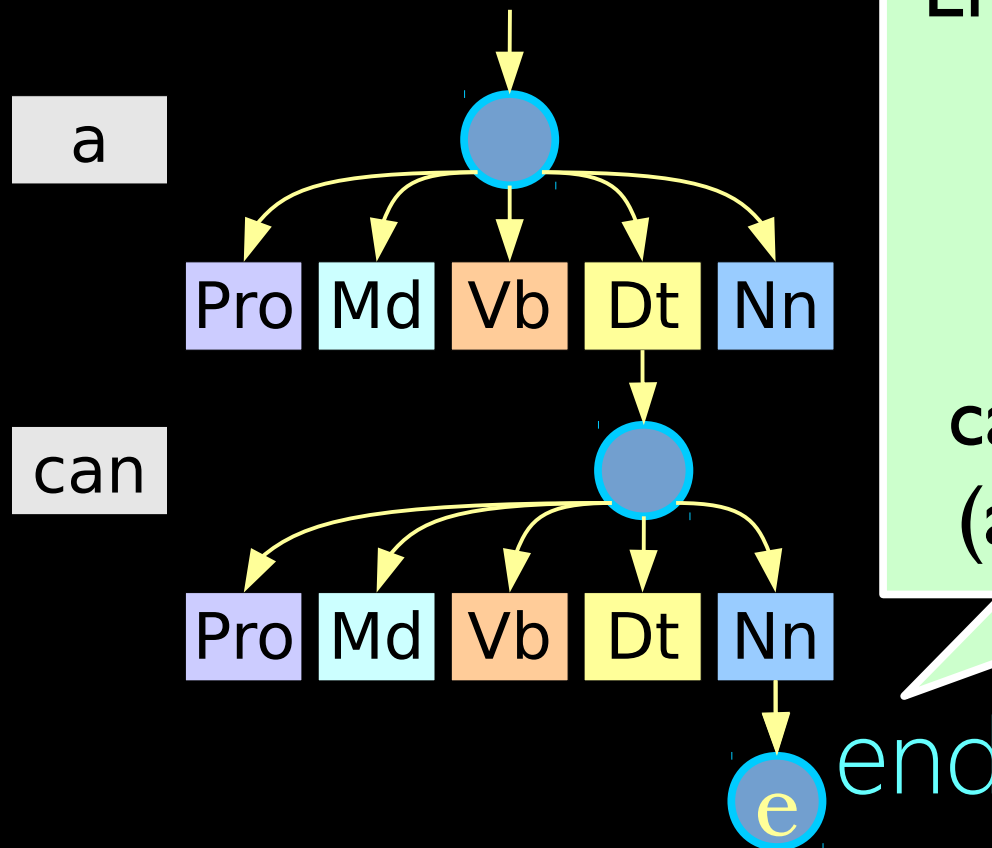
Search spaces

- When **y** decomposes in an ordered manner, a sequential decision making process emerges



Search spaces

- When y decomposes in an ordered manner, a sequential decision making process emerges



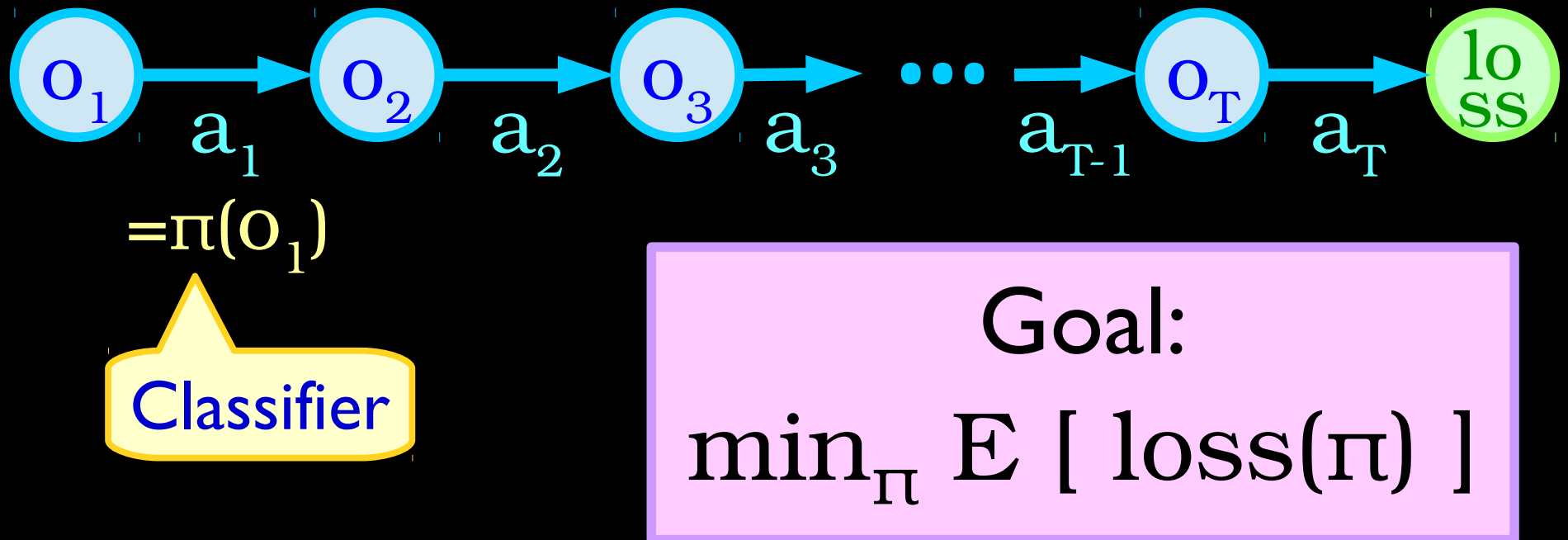
Encodes an output
 $\hat{y} = \hat{y}(e)$
from which
 $\text{loss}(y, \hat{y})$
can be computed
(at training time)

Policies

- A policy maps observations to actions

$$\pi \left(\begin{array}{l} \text{obs.} \\ \text{input: } \mathbf{x} \\ \text{timestep: } t \\ \text{partial traj: } \tau \\ \dots \text{ anything else} \end{array} \right) = a$$

Versus reinforcement learning



In learning to search (L2S):

- *Labeled data* at training time
 \Rightarrow can construct good/optimal policies
- Can “reset” and try the same example many times

Labeled data \rightarrow Reference policy

Given partial traj. $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_{t-1}$ and true label y

The *minimum achievable loss* is:

$$\min_{(\mathbf{a}_t, \mathbf{a}_{t+1}, \dots)} \text{loss}(y, \hat{y}(\vec{\mathbf{a}}))$$

The *optimal action* is the corresponding \mathbf{a}_t

The *optimal policy* is the policy that always selects the optimal action

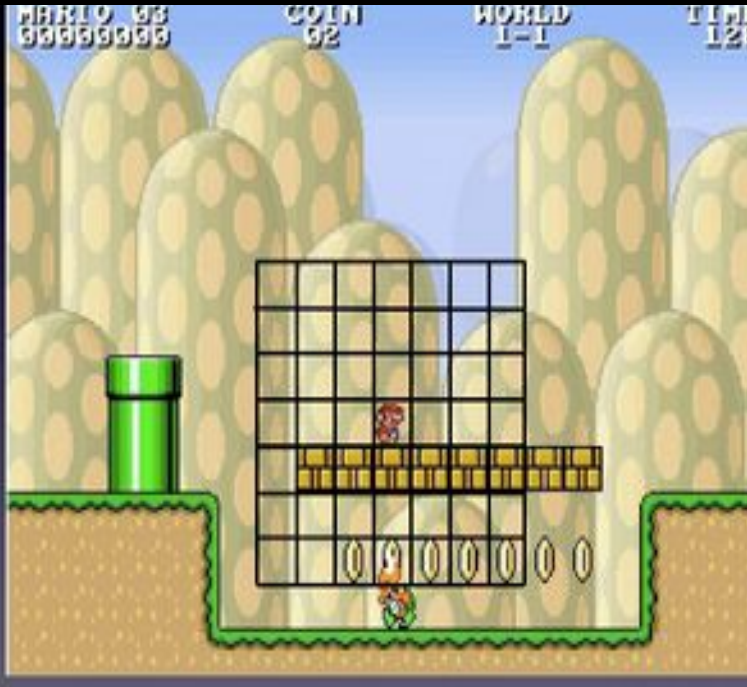
Ingredients for learning to search

- Training data: $(\mathbf{x}_n, y_n) \sim D$
- Output space: $Y(\mathbf{x})$
- Loss function: $\text{loss}(y, \hat{y})$
- Decomposition: $\{o\}, \{a\}, \dots$
- Reference policy: $\pi^{\text{ref}}(o, y)$

An analogy from playing Mario

From Mario AI competition 2009

Input:



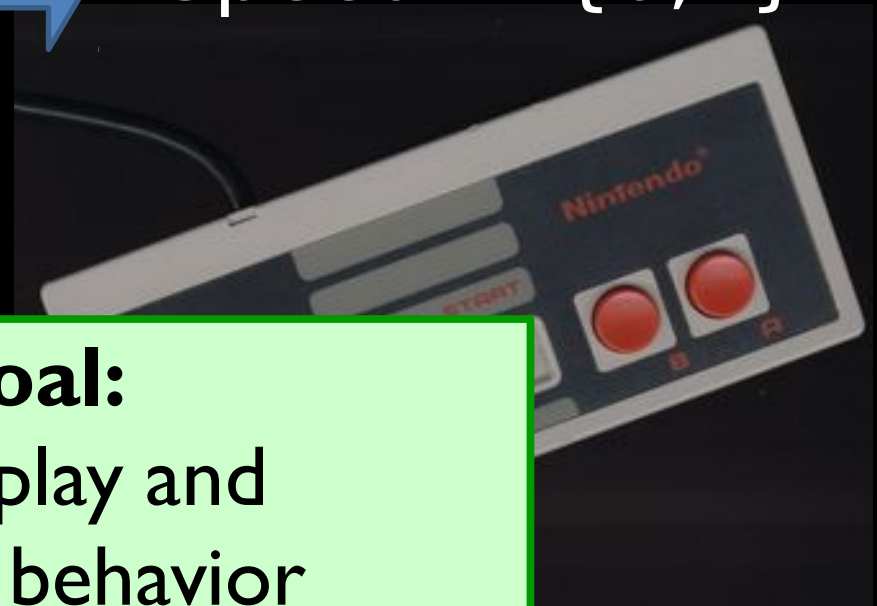
Output:

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

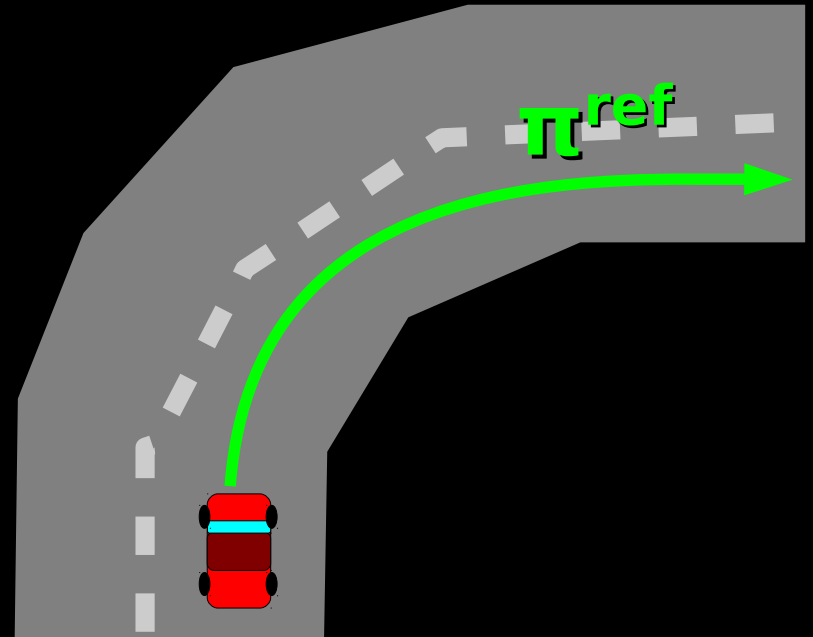


Training (expert)



Warm-up: Supervised learning

1. Collect trajectories from expert π^{ref}
 2. Store as dataset $\mathbf{D} = \{ (o, \pi^{\text{ref}}(o, y)) \mid o \sim \pi^{\text{ref}} \}$
 3. Train classifier π on \mathbf{D}
- Let π play the game!



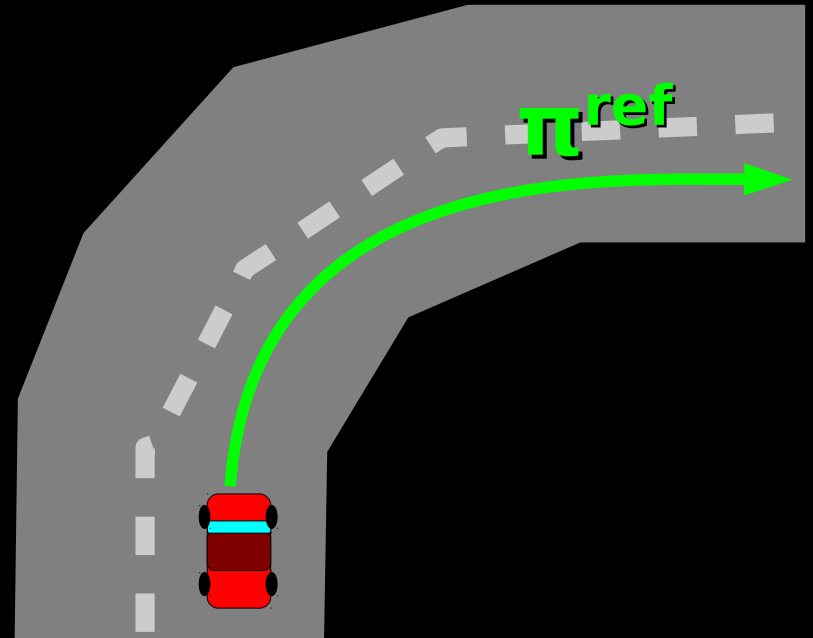
Test-time execution (sup. learning)



What's the (biggest) failure mode?

The expert never gets stuck next to pipes

⇒ Classifier doesn't learn to recover!



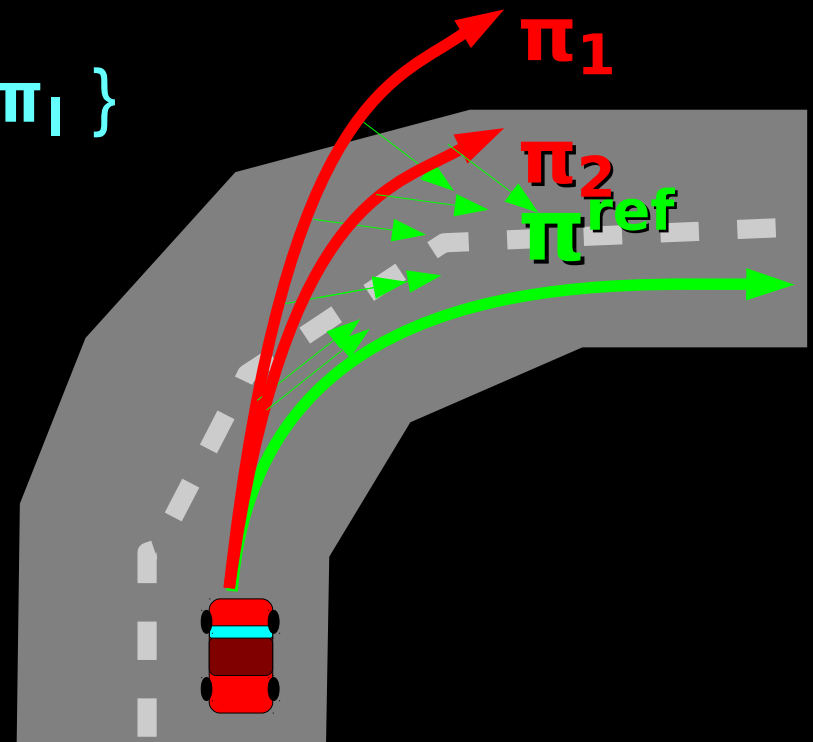
Warm-up II: Imitation learning

1. Collect trajectories from expert π^{ref}
2. Dataset $\mathbf{D}_0 = \{ (o, \pi^{\text{ref}}(o, y)) \mid o \sim \pi^{\text{ref}} \}$
3. Train π_1 on \mathbf{D}_0
4. Collect new trajectories from π_1
 - But let the *expert* steer!
5. Dataset $\mathbf{D}_1 = \{ (o, \pi^{\text{ref}}(o, y)) \mid o \sim \pi_1 \}$
6. Train π_2 on $\mathbf{D}_0 \cup \mathbf{D}_1$

- In general:
 - $\mathbf{D}_n = \{ (o, \pi^{\text{ref}}(o, y)) \mid o \sim \pi_n \}$
 - Train π_{n+1} on $\bigcup_{i \leq n} \mathbf{D}_i$

If $N = T \log T$,
$$L(\pi_n) < T \epsilon_N + O(1)$$

for some n



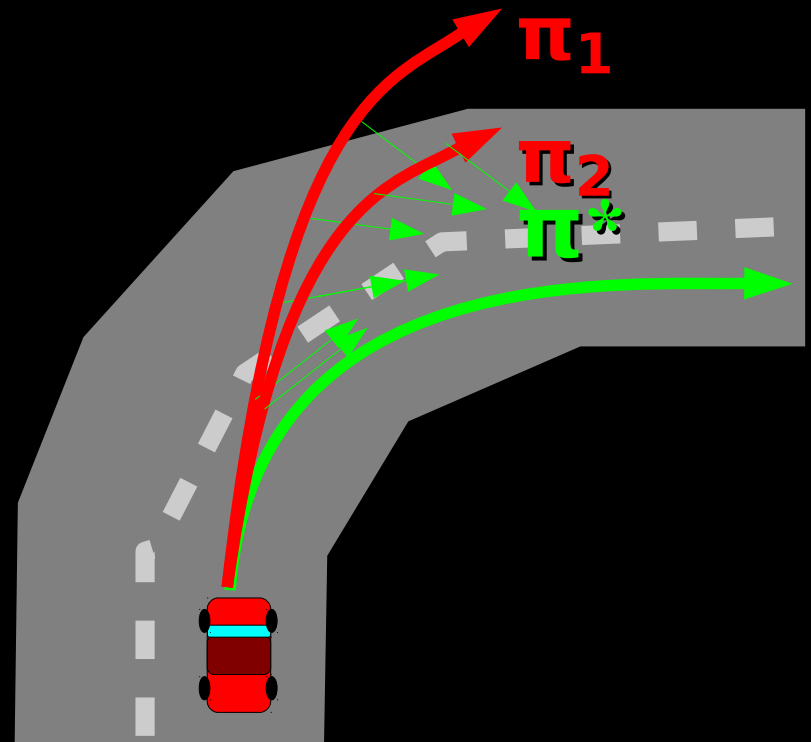
Test-time execution (Dagger)



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



Aside: cost-sensitive classification

Classifier: $h : \mathbf{x} \rightarrow [K]$

Multiclass classification

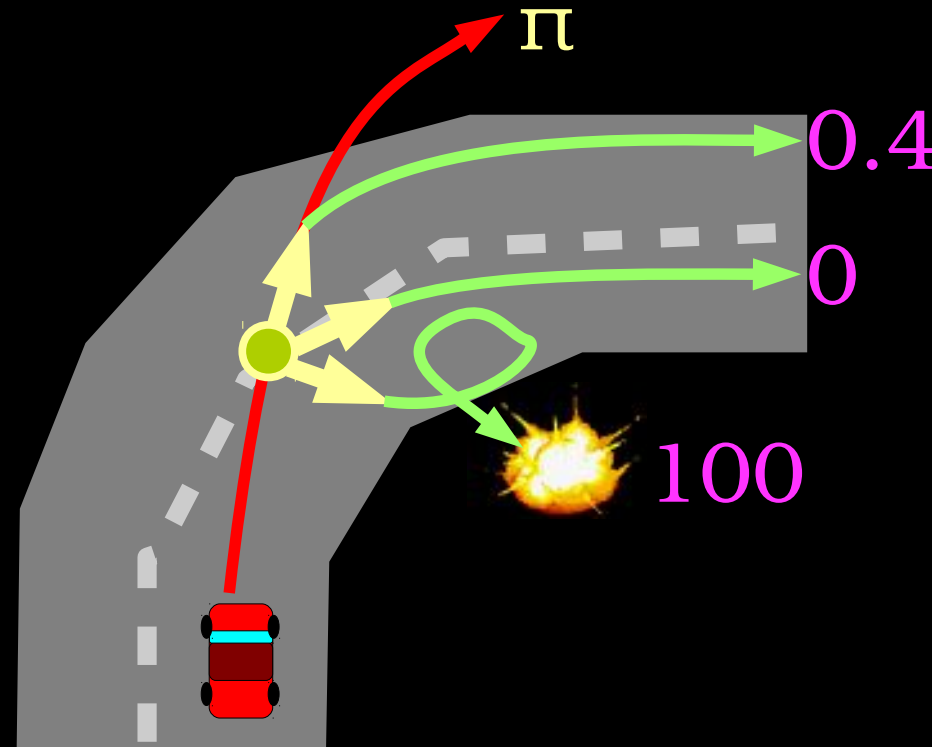
- Data: $(\mathbf{x}, y) \in X \times [K]$
- Goal: $\min_h \Pr(h(\mathbf{x}) \neq y)$

Cost-sensitive classification

- Data: $(\mathbf{x}, \mathbf{c}) \in X \times [0, \infty)^K$
- Goal: $\min_h E_{(\mathbf{x}, \vec{c})} [c_{h(\mathbf{x})}]$

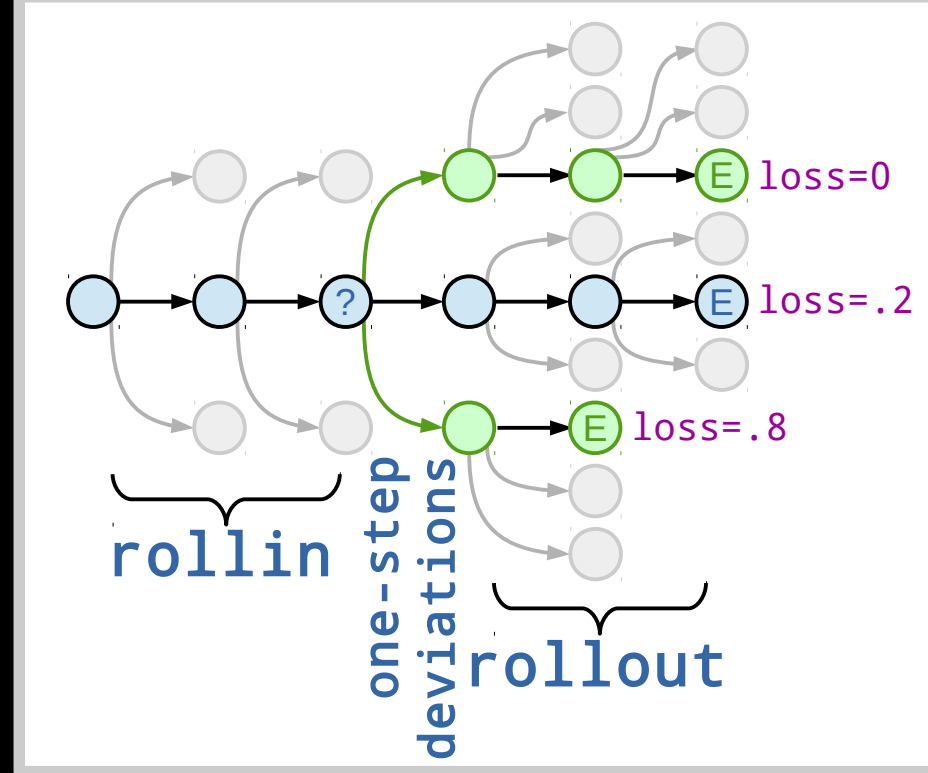
Learning to search: AggraVaTe

1. Let learned policy π drive for t timesteps to obs. o
2. For each possible action a :
 - Take action a , and let expert π^{ref} drive the rest
 - Record the overall loss, c_a
3. Update π based on example:
 $(o, \langle c_1, c_2, \dots, c_K \rangle)$
4. Goto (1)



Learning to search: AggraVaTe

1. Generate **an initial trajectory** using the *current policy*



2. Foreach decision on that trajectory with obs. **o**:

a) Foreach possible action **a** (one-step deviations)

i. Take that action

ii. Complete **this trajectory** using reference policy

iii. Obtain a **final loss**, C_a

b) Generate a cost-sensitive classification example:

(o, \vec{c})

Learning to search: AggraVaTe

1. Generate **an initial trajectory** using the *current policy*

2. Foreach decision on that trajectory with obs. **o**:

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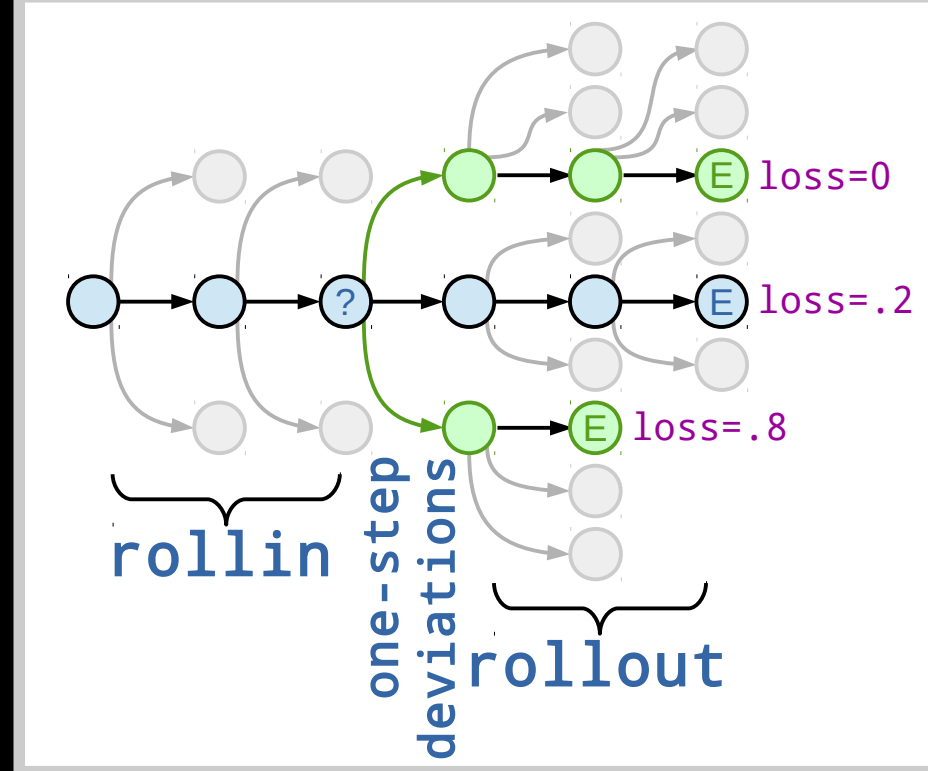
ii. Complete **this trajectory** using *reference policy*

iii. Obtain a **final loss**, C_a

Often it's possible to analytically compute this loss *without* having to execute a roll-out!

b) Generate a cost-sensitive classification example:

(o, \vec{c})



Example I: Sequence labeling

- Receive input:

x = the monster ate the sandwich
 y = Dt Nn Vb Dt Nn

- Make a sequence of predictions:

x = the monster ate the sandwich
 \hat{y} = Dt Dt Dt Dt Dt

- Pick a timestep and try all perturbations there:

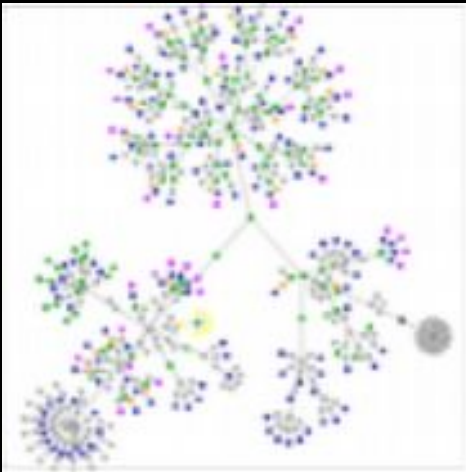
x = the monster ate the sandwich
 $\hat{y}_{Dt} = Dt \quad Dt$
 $\hat{y}_{Nn} = Dt \quad Nn$
 $\hat{y}_{Vb} = Dt \quad Vb$

- Compute losses and construct example:

({ $w=monster$, $p=Dt$, ... } ,
 $[1, 0, 1]$)

Example II: Graph labeling

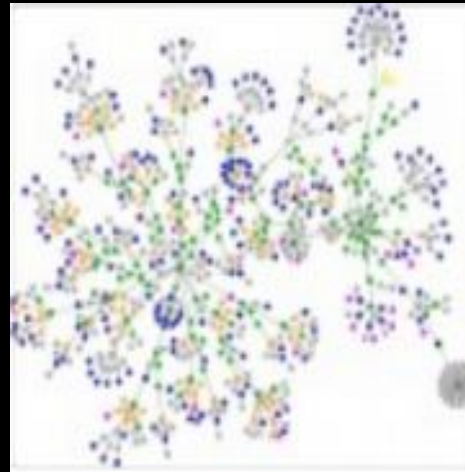
- Task: label nodes of a graph given node features (and possibly edge features)
- Example: WebKB webpage labeling



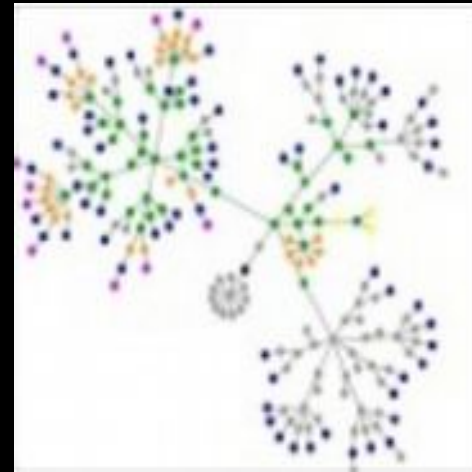
U Wisconsin



U Washington



U Texas

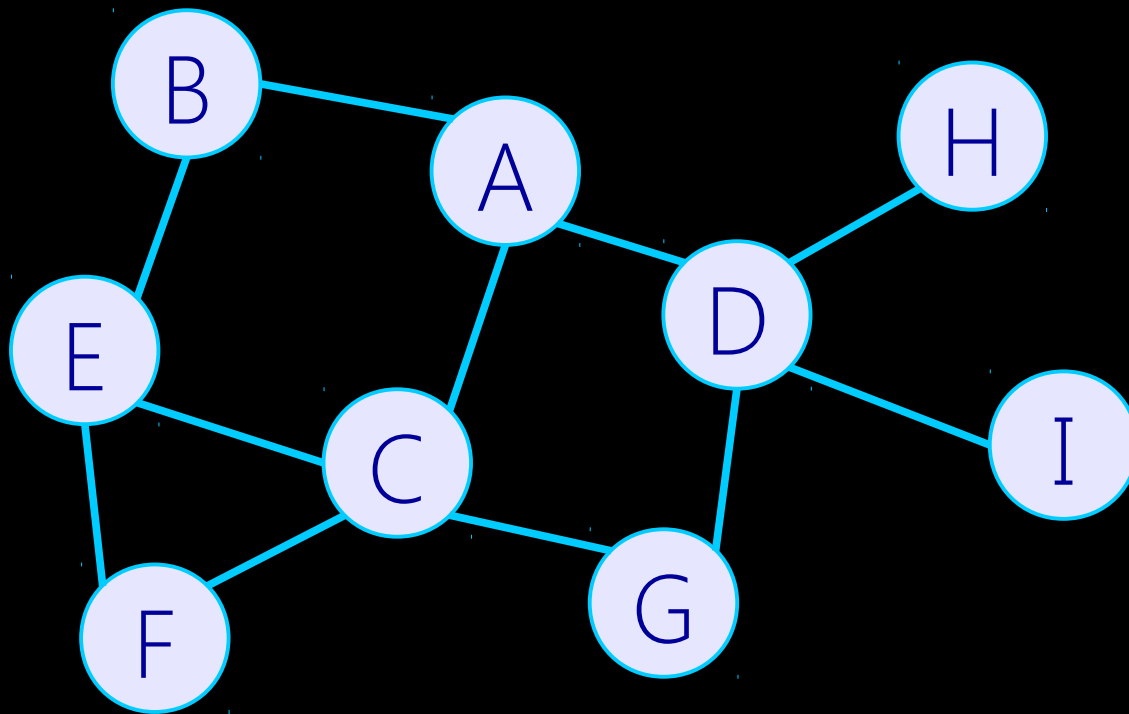


Cornell

- Node features: text on web page
- Edge features: text in hyperlinks

Example II: Graph labeling

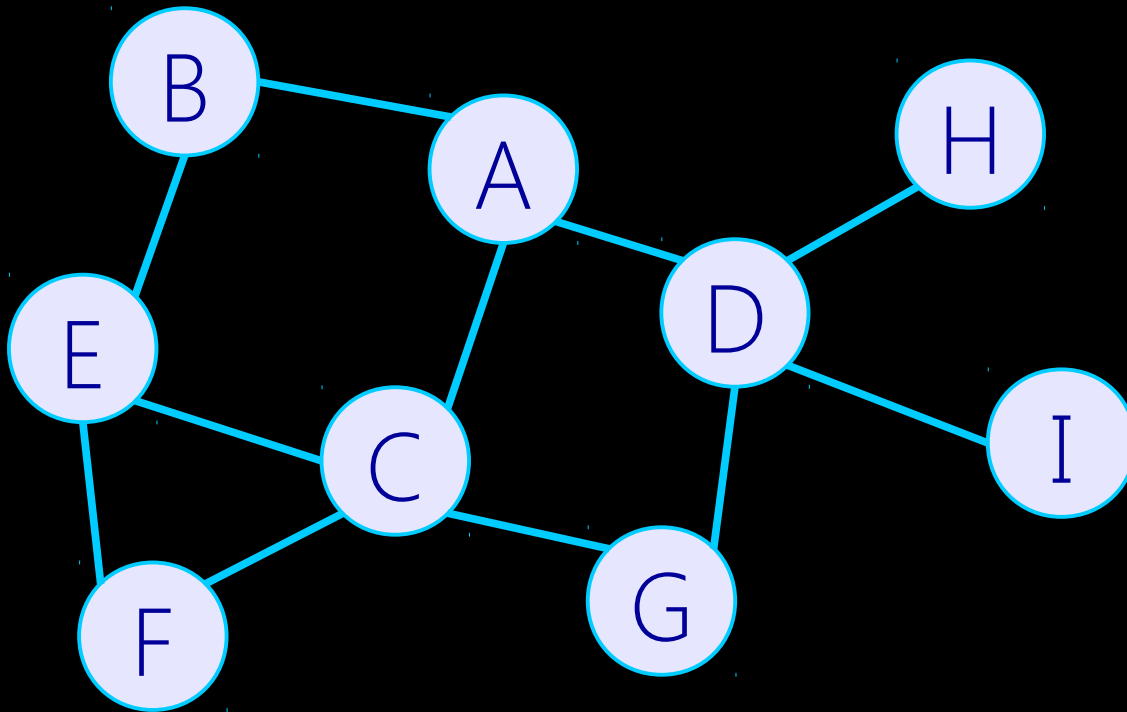
- How to linearize? Like belief propagation might!
- Pick a starting node (A), run BFS out
- Alternate outward and inward passes



Linearization:
ABCDEFGHI
HGFEDCBA
BCDEFGHI
HGFEDCBA
...

Example II: Graph labeling

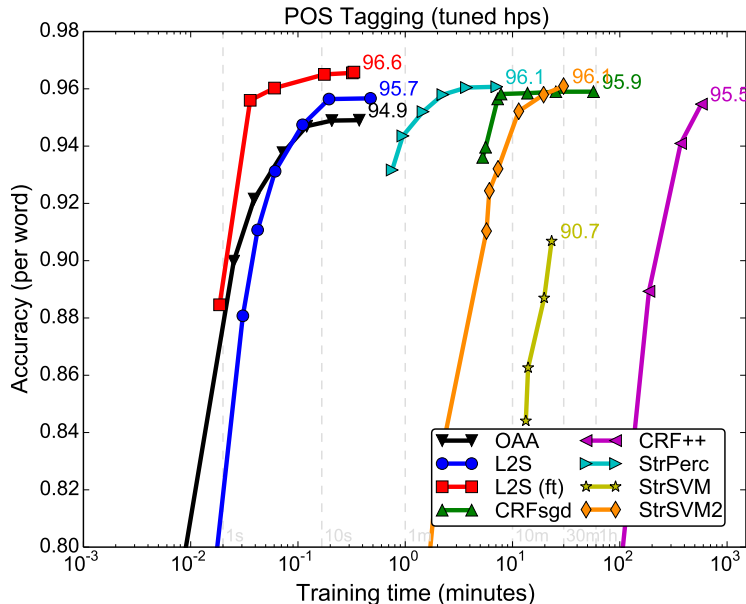
1. Pick a node (= timestep)
2. Construct example based on neighbors' labels
3. Perturb current node's label to get losses



Outline

- 1 Empirics
- 2 Analysis
- 3 Programming
- 4 Others and Issues

What part of speech are the words?



A demonstration

1 | w Despite
2 | w continuing
3 | w problems
1 | w in
4 | w its
5 | w newsprint
5 | w business
...

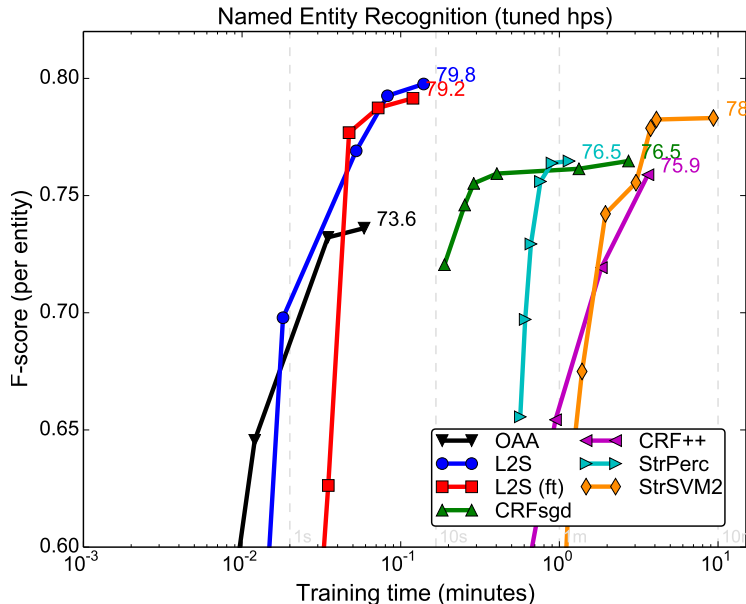
A demonstration

```
1 | w Despite
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```

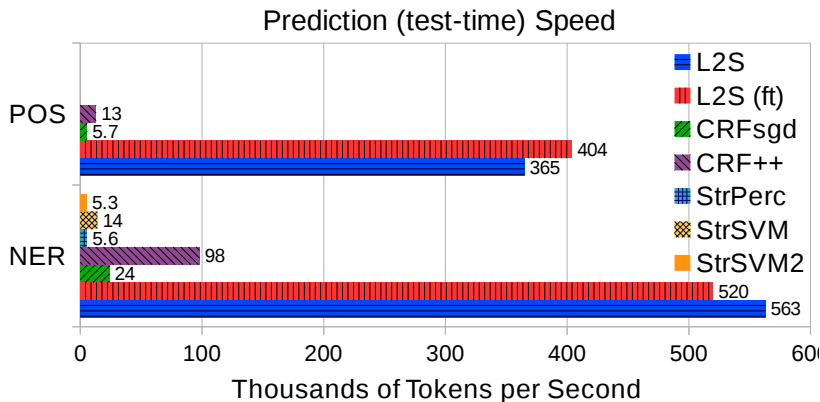
...

```
vw -b 24 -d wsj.train.vw -c --search_task sequence --search 45
--search_alpha 1e-8 --search_neighbor_features -1:w,1:w
--affix -1w,+1w -f foo.reg
vw -t -i foo.reg wsj.test.vw
```

Is this word a name or not?



How fast in evaluation?



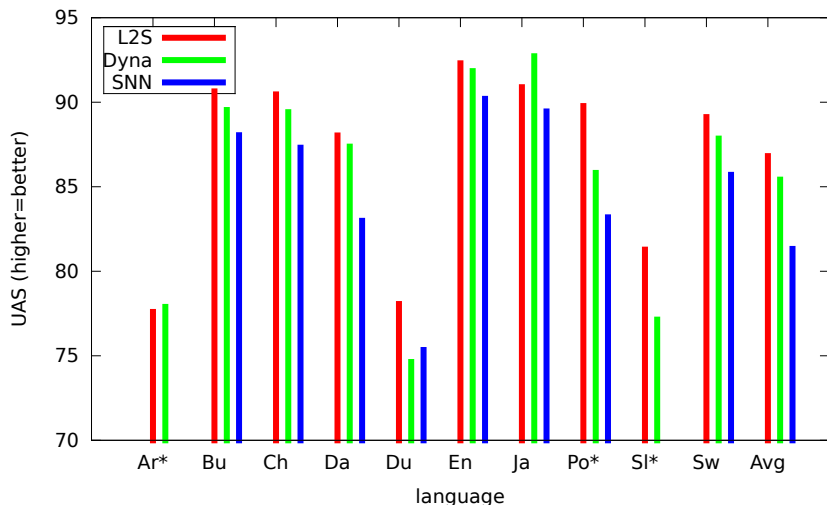
Entity Relation

Goal: find the Entities and then find their Relations

Method	Entity F1	Relation F1	Train Time
Structured SVM	88.00	50.04	300 seconds
L2S	92.51	52.03	13 seconds

L2S uses ~100 LOC.

Find dependency structure of sentences.



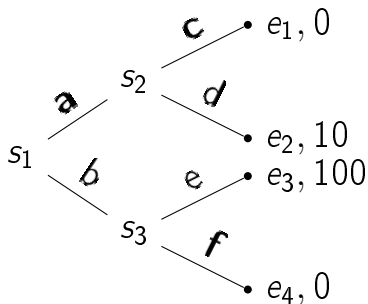
L2S uses ~300 LOC.

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- 1 Empirics
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Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	.		



Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned			

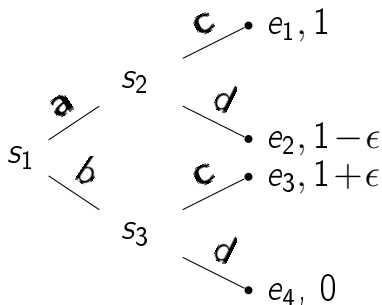
Theorem

Roll-in with ref:

0 cost-sensitive regret \Rightarrow unbounded joint regret

Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt		



Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt		

Theorem

Roll-out with Ref:

*0 cost-sensitive regret \Rightarrow 0 joint regret
(but not local optimality)*

Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt		Reinf. L.

Theorem

Ignore Ref:

\Rightarrow *Equivalent to reinforcement learning.*

Effect of Roll-in and Roll-out Policies

roll-out \rightarrow \downarrow roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt	Consistent Local Opt	Reinf. L.

Theorem

*Roll-out with $p = 0.5$ Ref and $p = 0.5$ Learned:
0 cost-sensitive regret \Rightarrow 0 joint regret + locally optimal*

See LOLS paper, Wednesday 11:20 Van Gogh

AggreVaTe Regret Decomposition

π^{ref} = reference policy

$\bar{\pi}$ = stochastic average learned policy

$J(\pi)$ = expected loss of π .

Theorem

$$J(\bar{\pi}) - J(\pi^{\text{ref}}) \leq$$

AggreVaTe Regret Decomposition

π^{ref} = reference policy

$\bar{\pi}$ = stochastic average learned policy

$J(\pi)$ = expected loss of π .

Theorem

$$J(\bar{\pi}) - J(\pi^{\text{ref}}) \leq T \mathbb{E}_{n,t} \mathbb{E}_{x \sim D_{\hat{\pi}_n}^t} \left[Q^{\pi^{\text{ref}}}(x, \hat{\pi}_n) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right]$$

T = number of steps

$\hat{\pi}_n$ = n th learned policy

$D_{\hat{\pi}_n}^t$ = distribution over x at time t induced by $\hat{\pi}_n$

$Q^{\pi}(x, \pi')$ = loss of π' at x then π to finish

Proof

For all π let π^t play π for rounds $1 \dots t$ then play π^{ref} for rounds $t + 1 \dots T$. So $\pi^T = \pi$ and $\pi^0 = \pi^{\text{ref}}$

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$$\begin{aligned} J(\pi) - J(\pi^{\text{ref}}) \\ = \sum_{t=1}^T J(\pi^t) - J(\pi^{t-1}) \quad (\text{Telescoping sum}) \end{aligned}$$

Proof

For all π let π^t play π for rounds $1 \dots t$ then play π^{ref} for rounds $t + 1 \dots T$. So $\pi^T = \pi$ and $\pi^0 = \pi^{\text{ref}}$

$$\begin{aligned} J(\pi) - J(\pi^{\text{ref}}) &= \sum_{t=1}^T J(\pi^t) - J(\pi^{t-1}) \text{ (Telescoping sum)} \\ &= \sum_{t=1}^T \mathbb{E}_{x \sim D_{\pi}^t} \left[Q^{\pi^{\text{ref}}}(x, \pi) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right] \end{aligned}$$

since for all π, t , $J(\pi) = \mathbb{E}_{x \sim D_{\pi}^t} Q^{\pi}(x, \pi)$

Proof

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since for all π, t , $J(\pi) = \mathbb{E}_{x \sim D_{\pi}^t} Q^{\pi}(x, \pi)$

$$= T \mathbb{E}_t \mathbb{E}_{x \sim D_{\pi}^t} \left[Q^{\pi^{\text{ref}}}(x, \pi) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right]$$

Proof

For all π let π^t play π for rounds $1 \dots t$ then play π^{ref} for rounds $t + 1 \dots T$. So $\pi^T = \pi$ and $\pi^0 = \pi^{\text{ref}}$

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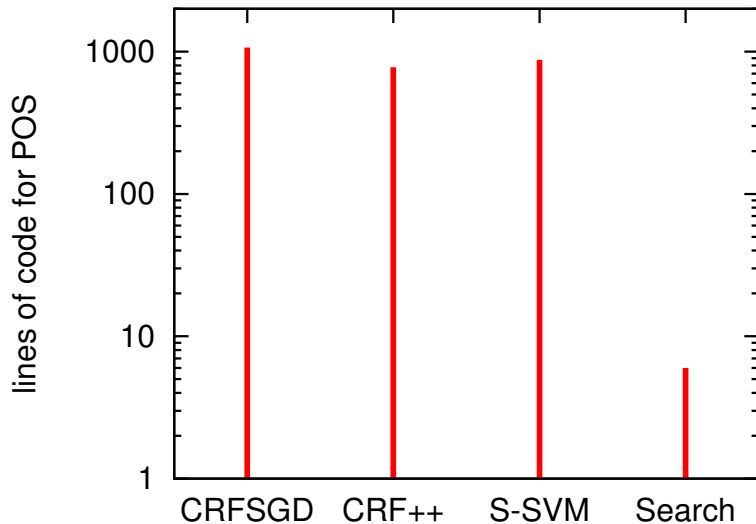
So $J(\bar{\pi}) - J(\pi^{\text{ref}})$

$$= T \mathbb{E}_{t,n} \mathbb{E}_{x \sim D_{\hat{\pi}_n}^t} \left[Q^{\pi^{\text{ref}}}(x, \hat{\pi}_n) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right]$$

Outline

- 1 Empirics
- 2 Analysis
- 3 Programming
- 4 Others and Issues

Lines of Code



How?

Sequential_RUN(*examples*)

```
1: for  $i = 1$  to  $\text{len}(\text{examples})$  do  
2:    $\text{prediction} \leftarrow \text{predict}(\text{examples}[i], \text{examples}[i].\text{label})$   
3:    $\text{loss}(\text{prediction} \neq \text{examples}[i].\text{label})$   
4: end for
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Decoder + loss + reference advice

RunParser(*sentence*)

```
1: stack S  $\leftarrow \{\mathbf{Root}\}$ 
2: buffer B  $\leftarrow$  [words in sentence]
3: arcs A  $\leftarrow \emptyset$ 
4: while  $B \neq \emptyset$  or  $|S| > 1$  do
5:   ValidActs  $\leftarrow$  GetValidActions(S, B)
6:   features  $\leftarrow$  GetFeat(S, B, A)
7:   ref  $\leftarrow$  GetGoldAction(S, B)
8:   action  $\leftarrow$  predict(features, ref, ValidActs)
9:   S, B, A  $\leftarrow$  Transition(S, B, A, action)
10: end while
11: loss( $A[w] \neq A^*[w]$ ,  $\forall w \in \text{sentence}$ )
12: return output
```

Program/Search equivalence

Theorem: Every algorithm which:

- 1 Always terminates.
- 2 Takes as input relevant feature information X .
- 3 Make $0+$ calls to **predict**.
- 4 Reports **loss** on termination.

defines a search space, and such an algorithm exists for every search space.

It even works in Python

```
def _run(self, sentence):  
    output = []  
    for n in range(len(sentence)):  
        pos, word = sentence[n]  
        with self.vw.example('w': [word],  
                             'p': [prev_word]) as ex:  
            pred = self.sch.predict(examples=ex,  
                                    my_tag=n+1, oracle=pos,  
                                    condition=[(n, 'p'), (n-1, 'q')])  
            output.append(pred)  
    return output
```

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- 1 Never train/test mismatch.
- 2 Never unexplained slow.
- 3 Never fail to compensate for cascading failure.

Outline

- ① Empirics
- ② Analysis
- ③ Programming
- ④ Others and Issues
 - ① Families of algorithms.
 - ② What's missing from learning to search?

Imitation Learning

Use perceptron-like update when learned deviates from gold standard.

Inc. P. Collins & Roark, ACL 2004.

LaSo Daume III & Marcu, ICML 2005.

Local Liang et al, ACL 2006.

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Inexact Huang et al, NAACL 2012.

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Inexact Huang et al, NAACL 2012.

Train a classifier to mimic an expert's behavior

DAgger Ross et al., AISTATS 2011.

Dyna O Goldberg et al., TACL 2014.

Learning to Search

When the reference policy is optimal

Seam Daume III et al., MLJ 2009.

Aggra Ross & Bagnell,
<http://arxiv.org/pdf/1406.5979>

Learning to Search

When the reference policy is optimal

Searn Daume III et al., MLJ 2009.

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When it's not

LOLS Chang et al., ICML 2015.

Learning to Search

When the reference policy is optimal

Search Daume III et al., MLJ 2009.

Aggra Ross & Bagnell,
<http://arxiv.org/pdf/1406.5979>

When it's not

LOLS Chang et al., ICML 2015.

Code in Vowpal Wabbit <http://hunch.net/~vw>

Inverse Reinforcement Learning

Given observed expert behavior, infer the underlying reward function the expert seems to be optimizing

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Ng & Russell, ICML 2000

for apprenticeship learning

Apprent. Abbeel & Ng, ICML 2004

Maxmar. Ratliff et al., NIPS 2005

MaxEnt Ziebart et al., AAAI 2008

What's missing? Automatic Search order

Learning to search \simeq dependency + search order.
Graphical models “work” given dependencies only.

What's missing? The reference policy

A good reference policy is often nonobvious... yet critical to performance.

What's missing?

Efficient Cost-Sensitive Learning

When choosing 1-of- k things, $O(k)$ time is not exciting for machine translation.

What's missing? GPU fun

Vision often requires a GPU. Can that be done?

How to optimize discrete joint loss?

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- 4 **Test speed**. Application efficiency