CS 188: Artificial Intelligence
Fall 2011

Advanced Applications:
Robotics / Vision / Language

Dan Klein – UC Berkeley
Many slides from Pieter Abbeel, John DeNero

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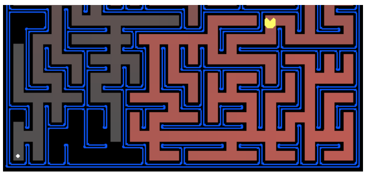
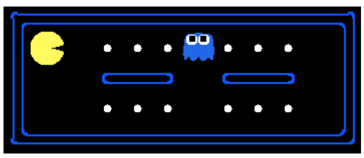
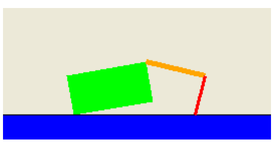
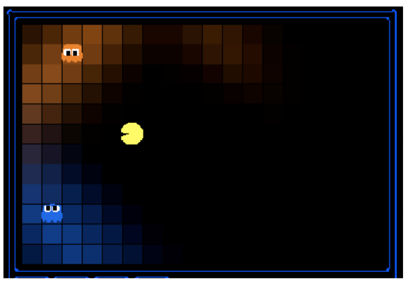
So Far: Foundational Methods









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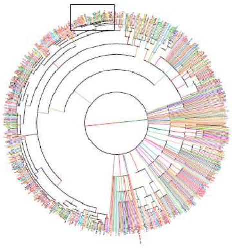
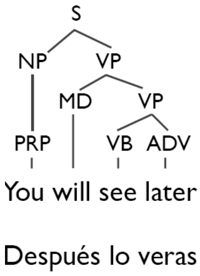
Now: Advanced Applications





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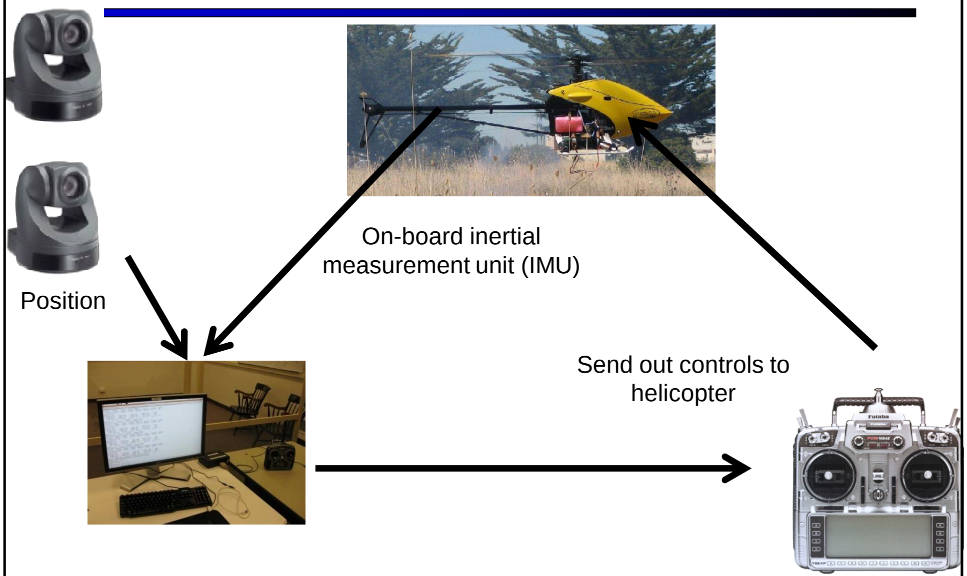
Inverse RL: Motivation

- How do we specify a task like this?

[demo: hover / autorotate]

Autonomous Helicopter Setup



Helicopter MDP

- State: $s = (x, y, z, \phi, \theta, \psi, \dot{x}, \dot{y}, \dot{z}, \dot{\psi}, \dot{\theta}, \dot{\psi})$
- Actions (control inputs):
  - a_{lon} : Main rotor longitudinal cyclic pitch control (affects pitch rate)
  - a_{lat} : Main rotor latitudinal cyclic pitch control (affects roll rate)
  - a_{coll} : Main rotor collective pitch (affects main rotor thrust)
  - a_{rud} : Tail rotor collective pitch (affects tail rotor thrust)
- Transitions (dynamics):
  - $s_{t+1} = f(s_t, a_t) + w_t$

  [f encodes helicopter dynamics]

  [w is a probabilistic noise model]

- Can we solve the MDP yet?

Problem: What's the Reward?

- Rewards for hovering:

[demo: hover / tic-toc]

$$\begin{aligned} R(s) &= -(\alpha_x(x-x^*)^2 + \alpha_y(y-y^*)^2 + \alpha_z(z-z^*)^2 \\ &\quad +\alpha_{\dot{x}}(\dot{x}-\dot{x}^*)^2 + \alpha_{\dot{y}}(\dot{y}-\dot{y}^*)^2 + \alpha_{\dot{z}}(\dot{z}-\dot{z}^*)^2) \end{aligned}$$

- Rewards for "Tic-Toc"?
  - Problem: what's the target trajectory?
  - Just write it down by hand?

[demo: bad]

Apprenticeship Learning

- Goal: learn reward function from expert demonstration
- Assume $R(s) = w \cdot f(s)$
- Get expert demonstrations $\mathbf{s} = (s_0, s_1, \ldots s_n)$
- Guess initial policy π_0
- Repeat:
  - Find w which make the expert better than $\{\pi_0, \pi_1, \ldots, \pi_{i-1}\}$

    $$w_i \leftarrow \text{distinguish}\left(\pi^*, \{\pi_0, \pi_1, \ldots, \pi_{i-1}\}\right)$$

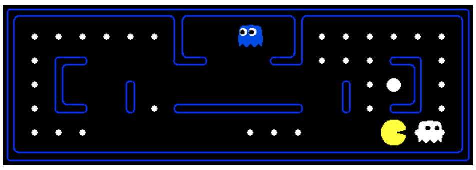
  - Solve MDP for new weights w:

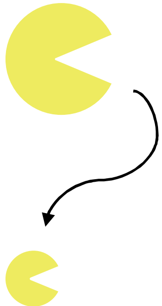
    $$\pi_i \leftarrow \text{solve}\left(MDP(w_i)\right)$$

[demo: pac apprentice]

Pacman Apprenticeship!

- Demonstrations are expert games





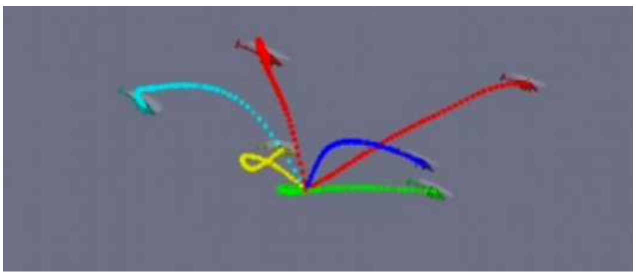
- Features defined over states s
- Score of a state given by:

$$w \cdot f(s)$$

- Learning goal: find weights which explain expert actions

[demo: unaligned / aligned]

Helicopter Apprenticeship?



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Probabilistic Alignment

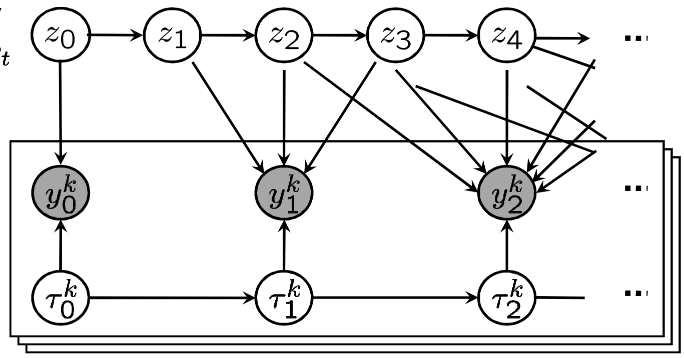
Intended trajectory

$$z_{t+1} = f(z_t) + \omega_t$$

Expert demonstrations

$$y_j = z_{\tau_j} + \nu_j$$

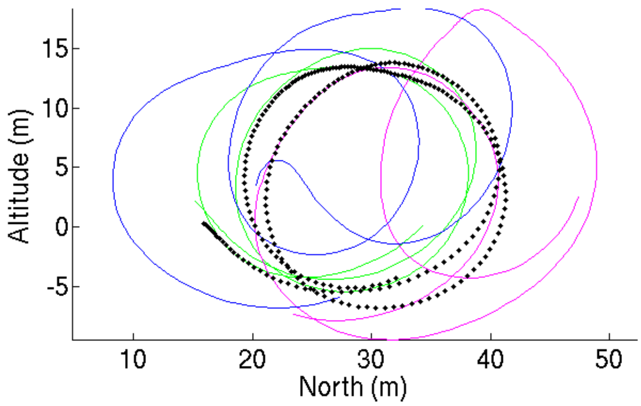
Time indices



- Intended trajectory satisfies dynamics.
- Expert trajectory is a noisy observation of one of the hidden states.
  - But we don't know exactly which one.

[demo: alignment]

Alignment of Samples



- Result: inferred sequence is much cleaner!

[demo: airshow]

Final Behavior

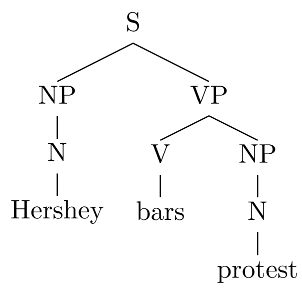
What is NLP?

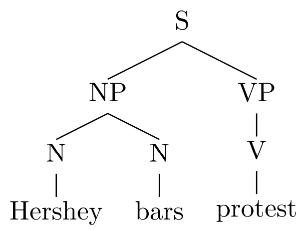
- Fundamental goal: analyze and process human language, broadly, robustly, accurately…
- End systems that we want to build:
  - Ambitious: speech recognition, machine translation, information extraction, dialog interfaces, question answering…
  - Modest: spelling correction, text categorization…

Problem: Ambiguities

- Headlines:
  - Enraged Cow Injures Farmer With Ax
  - Hospitals Are Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor's Desk
  - Iraqi Head Seeks Arms
  - Local HS Dropouts Cut in Half
  - Juvenile Court to Try Shooting Defendant
  - Stolen Painting Found by Tree
  - Kids Make Nutritious Snacks
- Why are these funny?

Parsing as Search





Hershey bars protest

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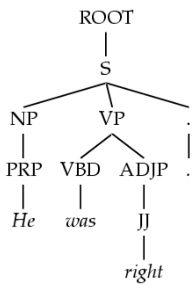
Grammar: PCFGs

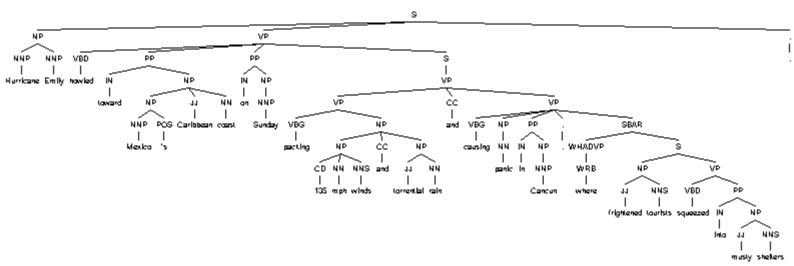
- Natural language grammars are very ambiguous!
- PCFGs are a formal probabilistic model of trees
  - Each “rule” has a conditional probability (like an HMM)
  - Tree’s probability is the product of all rules used
- Parsing: Given a sentence, find the best tree – search!



ROOT → S	375/420
S → NP VP .	320/392
NP → PRP	127/539
VP → VBD ADJP	32/401
…..	

Syntactic Analysis

[demo]



Hurricane Emily howled toward Mexico 's Caribbean coast on Sunday packing 135 mph winds and torrential rain and causing panic in Cancun, where frightened tourists squeezed into musty shelters .

Machine Translation


"Il est impossible aux journalistes de rentrer dans les régions tibétaines"

Bruno Philip, correspondant du "Monde" en Chine, estime que les journalistes de l'AFP qui ont été expulsés de la province tibétaine du Qinghai "n'étaient pas dans l'illégalité".

Les faits Le dalaï-lama dénonce l'"enfer" imposé au Tibet depuis sa fuite, en 1959
Vidéo Anniversaire de la rébellion


"It is impossible for journalists to enter Tibetan areas"

Philip Bruno, correspondent for "World" in China, said that journalists of the AFP who have been deported from the Tibetan province of Qinghai "were not illegal."

Facts The Dalai Lama denounces the "hell" imposed since he fled Tibet in 1959
Video Anniversary of the Tibetan rebellion: China on guard

- Translate text from one language to another
- Recombines fragments of example translations
- Challenges:
  - What fragments? [learning to translate]
  - How to make efficient? [fast translation search]

The Problem with Dictionary Look-ups

顶部	/**top**/roof/
顶端	/summit/peak/**top**/apex/
顶头	/coming directly towards one/**top**/end/
盖	/lid/**top**/cover/canopy/build/Gai/
盖帽	/surpass/**top**/
极	/extremely/pole/utmost/**top**/collect/receive/
尖峰	/peak/**top**/
面	/fade/side/surface/aspect/**top**/face/flour/
摘心	/**top**/topping/

Example from Douglas Hofstadter

A Brief and Biased History

When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."

Warren Weaver

"Machine Translation" presumably means going by algorithm from machine-readable source text to useful target text... In this context, there has been no machine translation...

John Pierce

- '47 — MT is the "first" non-numeral compute task
- '58 — Berkeley's first MT grant
- '66 — ALPAC report deems MT bad
- '90's — Statistical data-driven approach introduced
- '00's — Statistical MT thrives

Data-Driven Machine Translation

Target language corpus:

I will get to it soon	See you later	He will do it

Sentence-aligned parallel corpus:

Yo lo haré mañana I will do it tomorrow	Hasta pronto See you soon	Hasta pronto See you around

Machine translation system:

Yo lo haré pronto (NOVEL SENTENCE) → Model of translation → I will do it soon

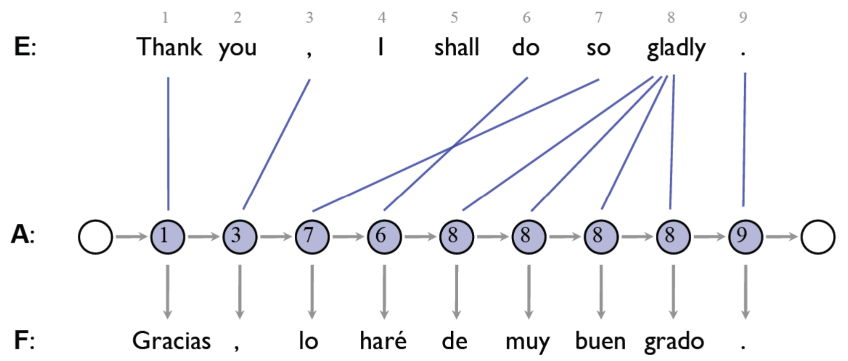
Learning to Translate

CLASSIC SOUPS

			Sm.	Lg.
清燉雞湯	57.	House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)	1.50	2.75
雞飯湯	58.	Chicken Rice Soup	1.85	3.25
雞麵湯	59.	Chicken Noodle Soup	1.85	3.25
廣東雲吞	60.	Cantonese Wonton Soup	1.50	2.75
蕃茄蛋湯	61.	Tomato Clear Egg Drop Soup	1.65	2.95
雲吞湯	62.	Regular Wonton Soup	1.10	2.10
酸辣湯	63.	Hot & Sour Soup	1.10	2.10
蛋花湯	64.	Egg Drop Soup	1.10	2.10
雲蛋湯	65.	Egg Drop Wonton Mix	1.10	2.10
豆腐菜湯	66.	Tofu Vegetable Soup	NA	3.50
雞玉米湯	67.	Chicken Corn Cream Soup	NA	3.50
蟹肉玉米湯	68.	Crab Meat Corn Cream Soup	NA	3.50
海鮮湯	69.	Seafood Soup	NA	3.50

Example from Adam Lopez

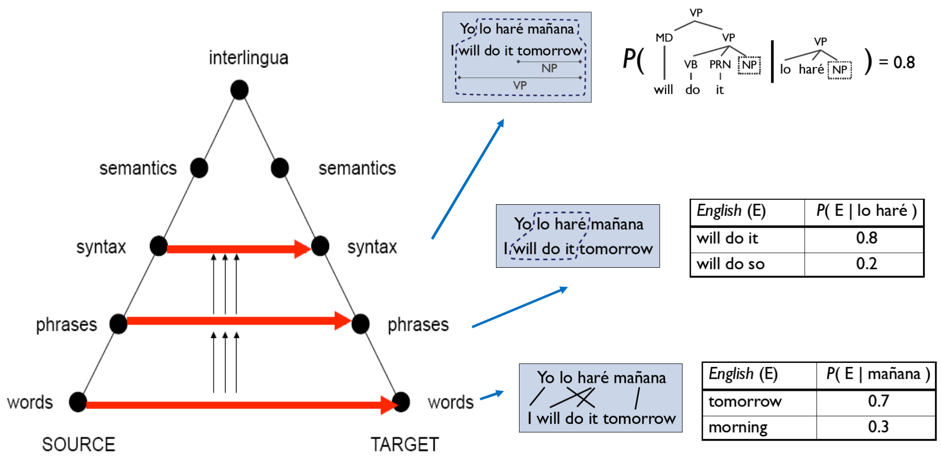
The HMM Model



Model Parameters

Emissions: P(F_1 = Gracias | E_{A_1} = Thank)   *Transitions:* P(A_2 = 3 | A_1 = 1)

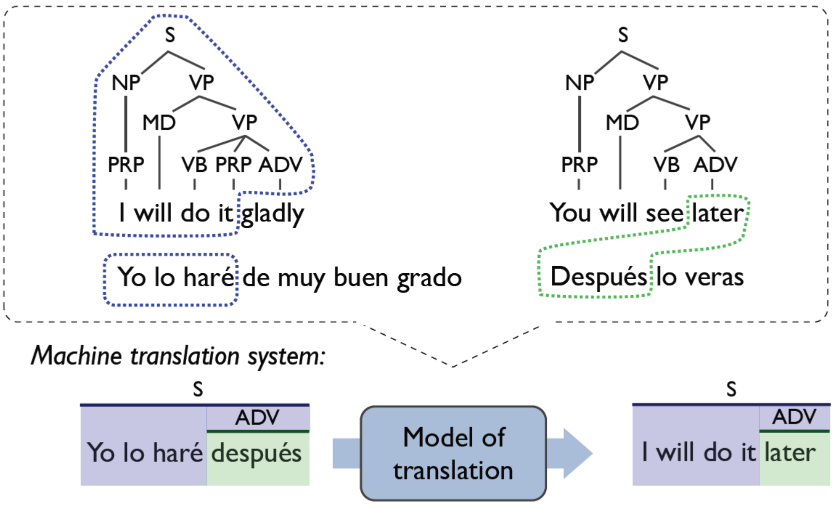
Levels of Transfer



English (E)	*P*(E | lo haré)
will do it	0.8
will do so	0.2

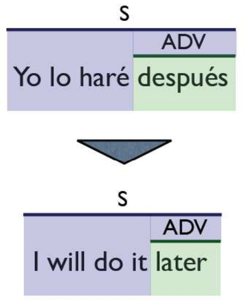
English (E)	*P*(E | mañana)
tomorrow	0.7
morning	0.3

Machine Translation



A Statistical Translation Model

Synchronous Derivation



Synchronous Grammar Rules

S → ⟨ Yo lo haré ADV ; I will do it ADV ⟩

ADV → ⟨ después ; later ⟩

A Statistical Model

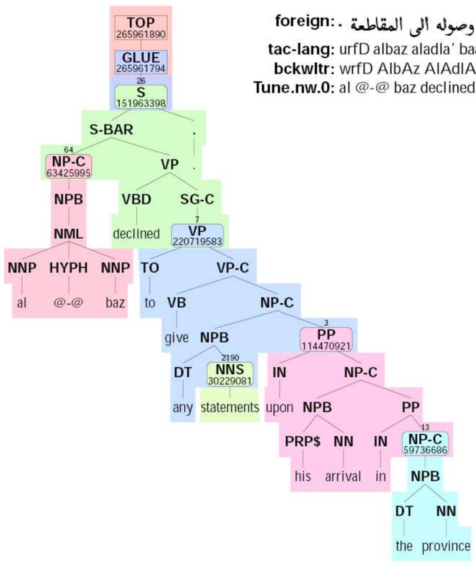
Translation model components factor over applied rules

How well are these rules supported by the data?

Language model factors over n-grams

How well is this output sentence supported by the data?

Example Syntax-Based Translation



foreign: . ورفض الباز الادلاء بأى تصريحات فور وصوله الى المقاطعة

tac-lang: urfD albaz aladla’ baá tSryHat fur uSulh alá almqaT`e .

bckwltr: wrfD AlbAz AlAdlA’ bAY tSryHAt fwr wSwlh AlY AlmqATEp .

Tune.nw.0: al @-@ baz declined to make any statements upon his arrival in the province .

[ISI MT system output]