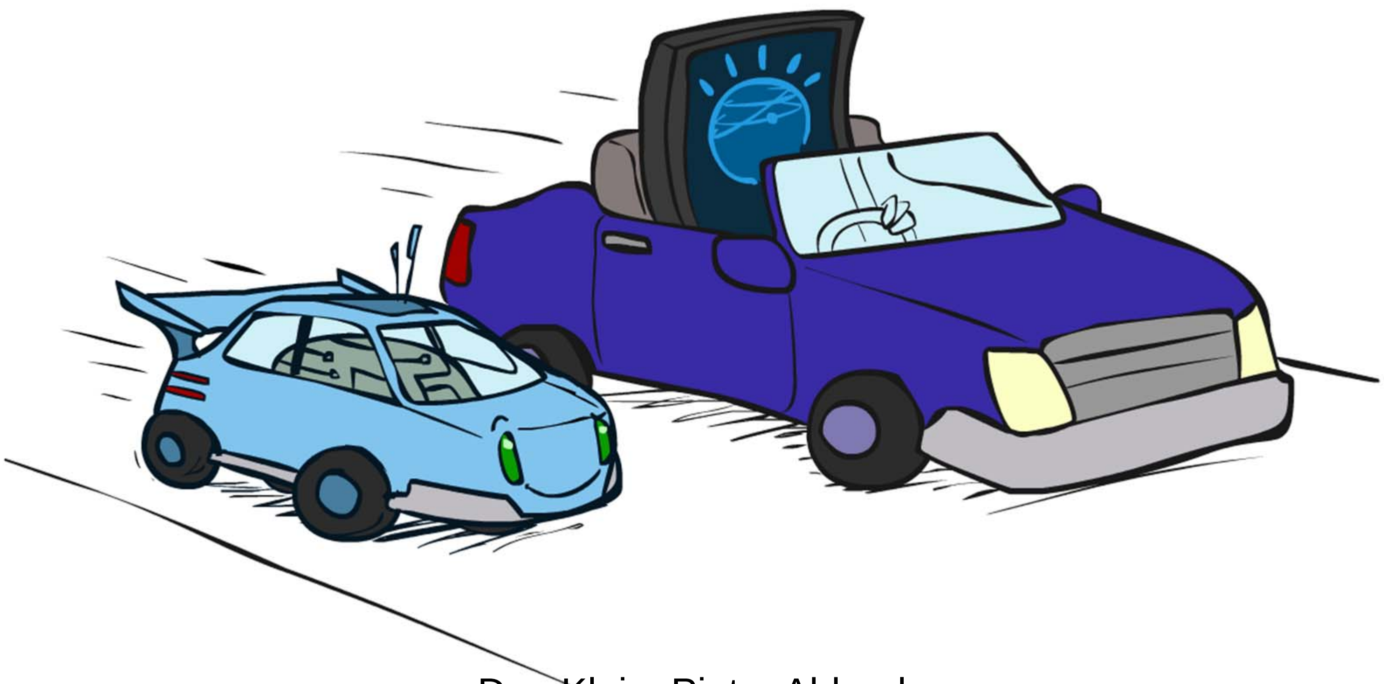
CS 188: Artificial Intelligence

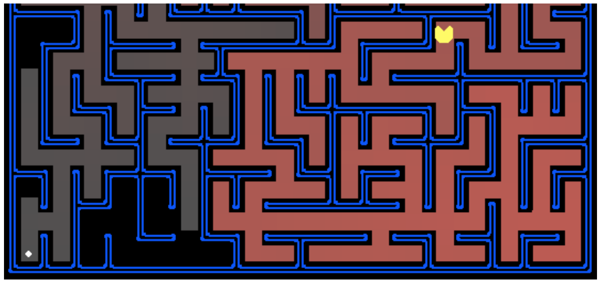
NLP and Robotics

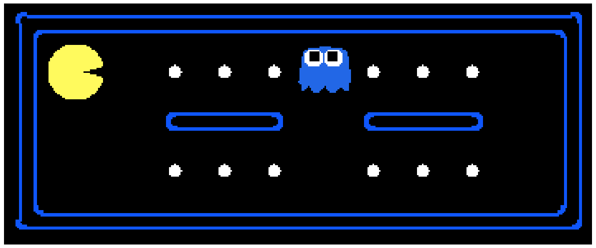


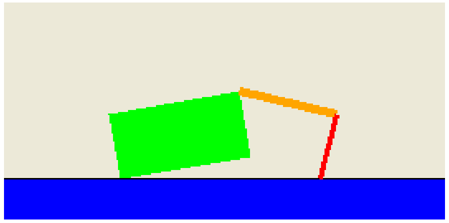
Dan Klein, Pieter Abbeel

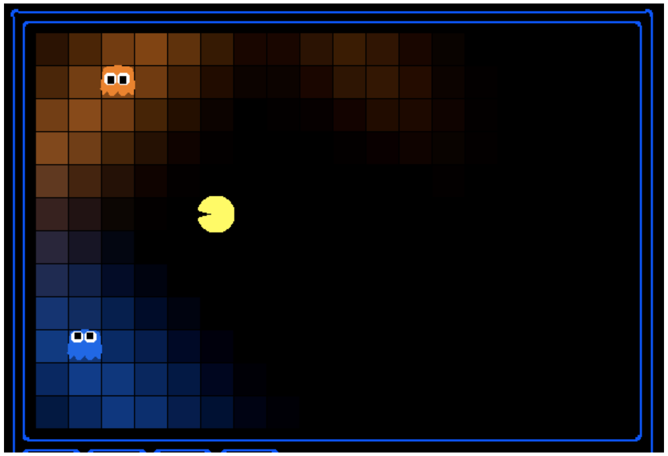
University of California, Berkeley

So Far: Foundational Methods

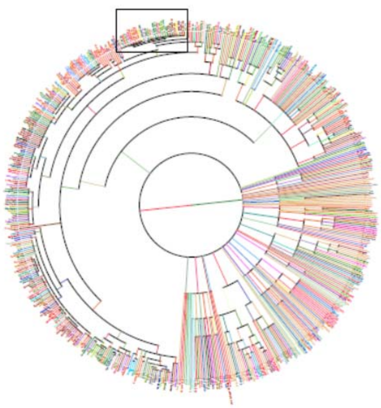


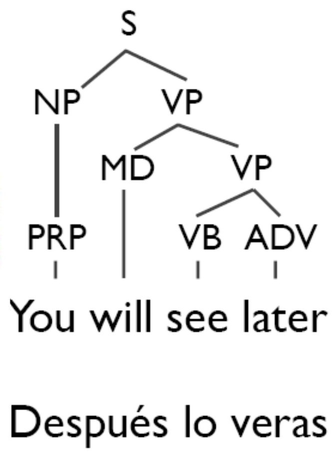






Now: Advanced Applications





Natural Language Processing

What is NLP?

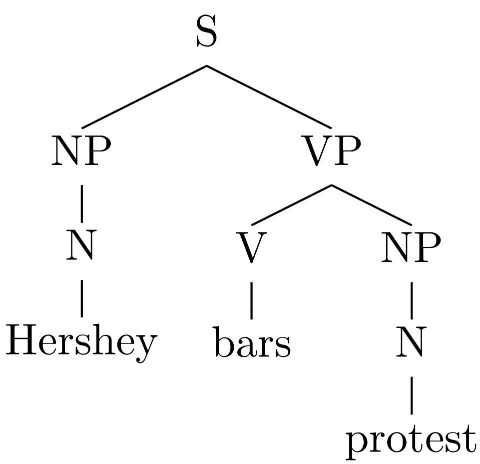
- Fundamental goal: analyze and process human language, broadly, robustly, accurately…
- End systems that we want to build:
  - Ambitious: speech recognition, machine translation, information extraction, dialog interfaces, question answering…
  - Modest: spelling correction, text categorization…

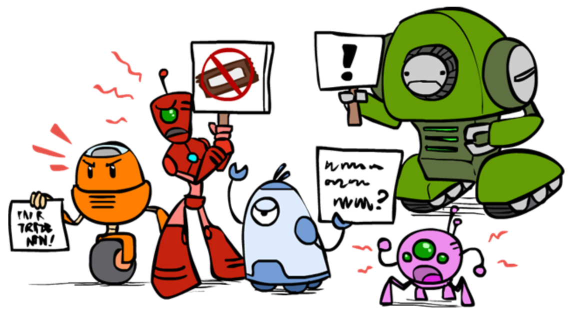
Problem: Ambiguities

- 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

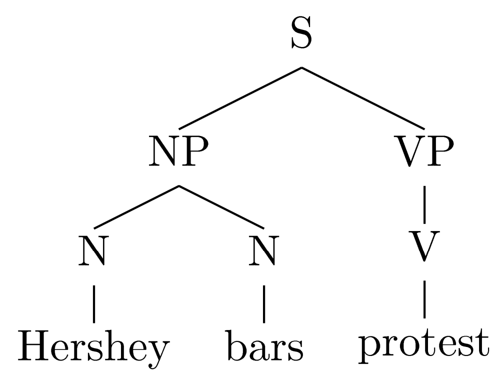
- Why are these funny?

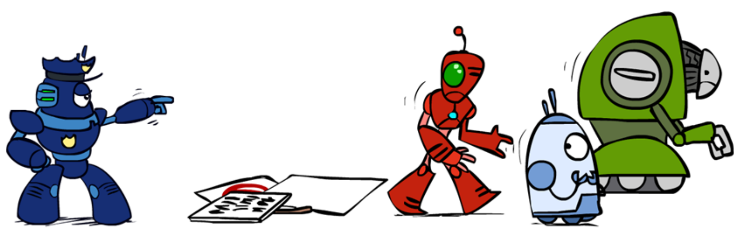
Parsing as Search





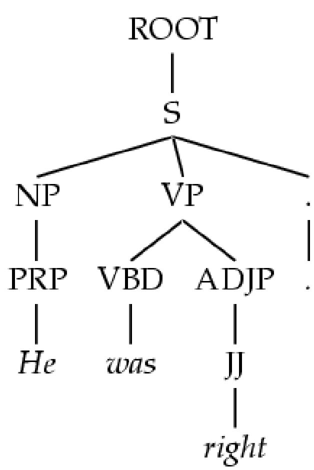
Hershey bars protest





Grammar: PCFGs

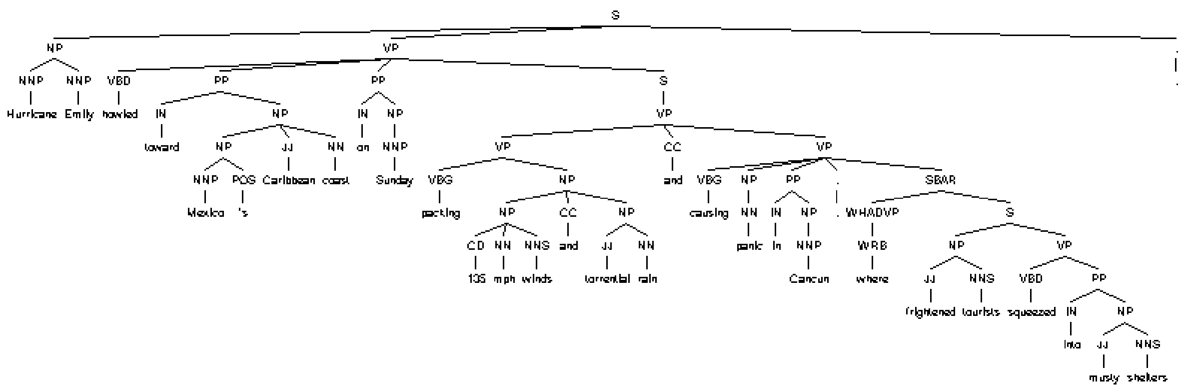
- Natural language grammars are very ambiguous!
- PCFGs are a formal probabilistic model of trees
  - Each “rule” has a conditional probability (like an HMM)
  - Tree’s probability is the product of all rules used
- Parsing: Given a sentence, find the best tree – search!



ROOT $\rightarrow$ S	375/420
S $\rightarrow$ NP VP .	320/392
NP $\rightarrow$ PRP	127/539
VP $\rightarrow$ 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 .

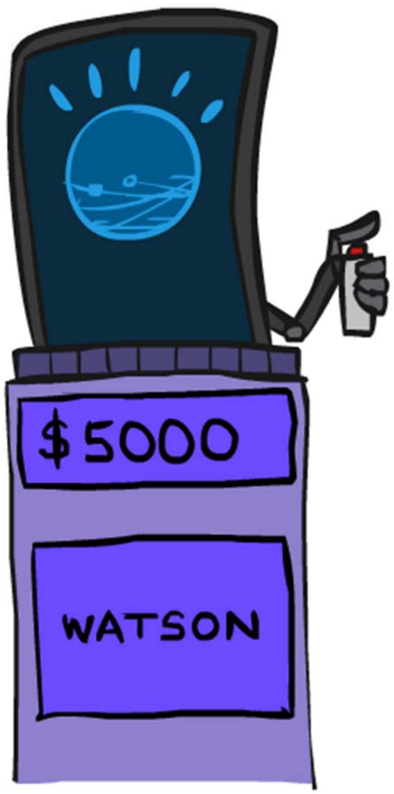
Dialog Systems

[demo]

ELIZA

- A “psychotherapist” agent (Weizenbaum, ~1964)
- Led to a long line of chatterbots
- How does it work:
  - Trivial NLP: string match and substitution
  - Trivial knowledge: tiny script / response database
  - Example: matching “I remember __” results in “Do you often think of __”?
- Can fool some people some of the time?

Watson


$5000
WATSON


"a camel is a horse designed by"
Wiktionary
['wɪkʃənrɪ] n.,
a wiki-based Open
Content dictionary
Main Page
Community portal
Preferences
Requested entries
Recent changes
Random entry
Help
Donations
Contact us
Toolbox
What links here
Related changes
Upload file
Special pages
Printable version
Permanent link
In other languages
Français
Русский
Log in / create account
Entry
Discussion
Read
Edit
History
Search
a camel is a horse designed by a committee
Contents [hide]
1 English
1.1 Alternative forms
The Phrase Finder
> Discussion Forum
Custom Search
Search
A camel is a horse designed by committee
Posted by Ruben P. Mendez on April 16, 2004
Does anyone know the origin of this maxim? I heard it way back at the United Nations, which is chockfull of committees. It may have originated there, but I'd like an authoritative explanation. Thanks
Re: A camel is a horse designed by committee SR 16/April/04
Re: A camel is a horse designed by committee Henry 18/April/04
www.smashingmagazine.com
If a camel is a horse de
If a camel is a horse designed by committee then what's this contemporary Routemaster?

What's in Watson?

- A question-answering system (IBM, 2011)
- Designed for the game of Jeopardy
- How does it work:
  - Sophisticated NLP: deep analysis of questions, noisy matching of questions to potential answers
  - Lots of data: onboard storage contains a huge collection of documents (e.g. Wikipedia, etc.), exploits redundancy
  - Lots of computation: 90+ servers
- Can beat all of the people all of the time?

Machine Translation

Machine Translation

- 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 Lookups

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

MT: 60 Years in 60 Seconds

Warren Weaver

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."

John Pierce

""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..."

'47 — MT is the "first" non-numeral compute task

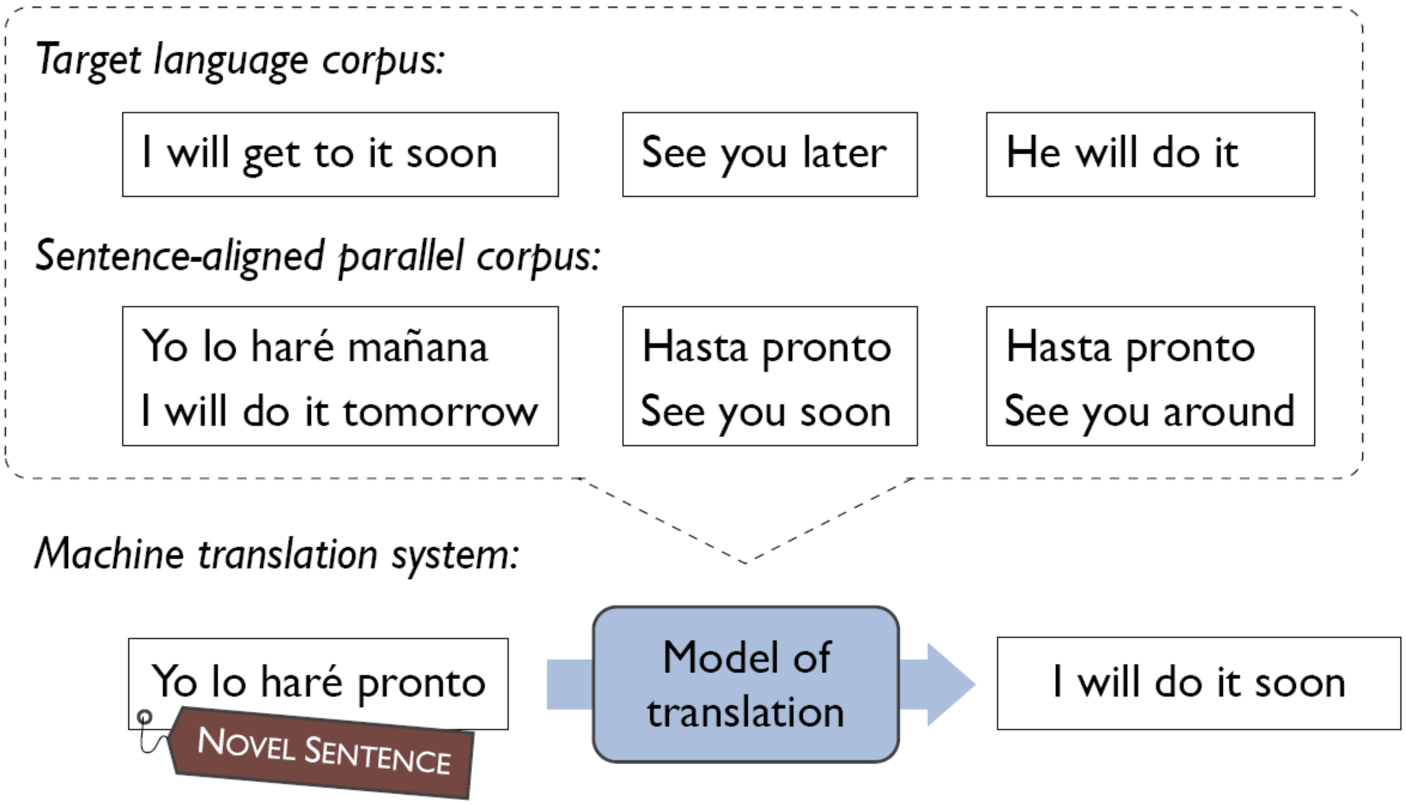
'58 — Berkeley's first MT grant

'66 — ALPAC report deems MT bad

'90's — Statistical data-driven approach introduced

'00's — Statistical MT thrives

Data-Driven Machine Translation



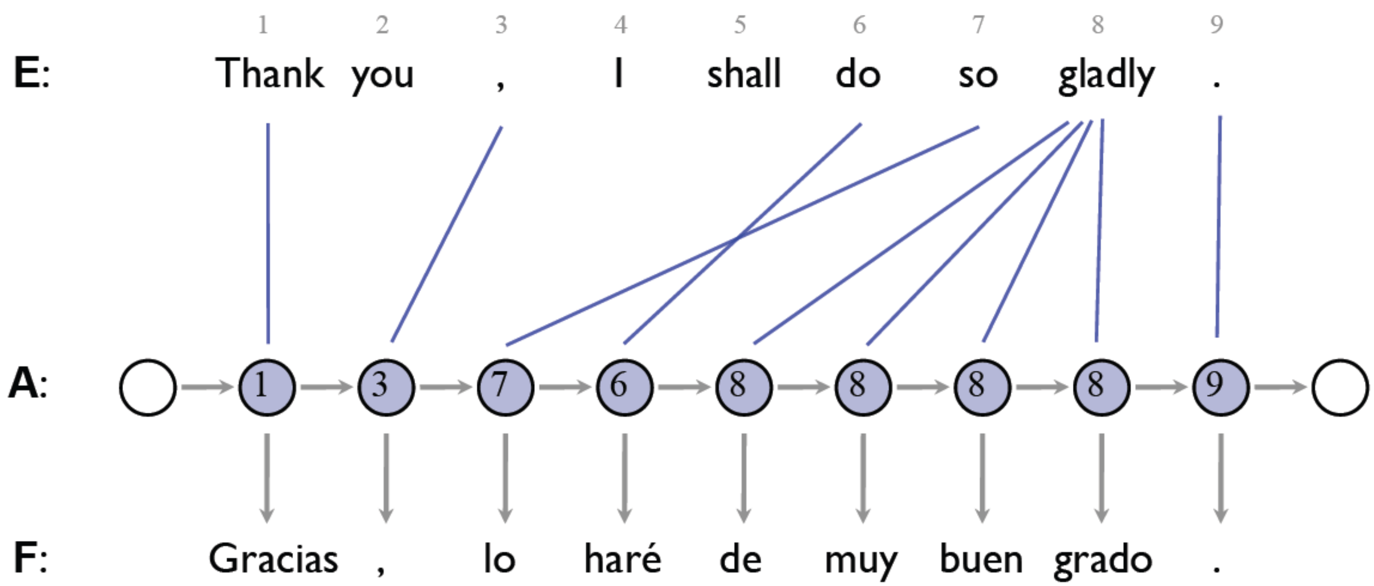
Learning to Translate

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
廣東雲呑	60.	Cantonese Wonton Soup	1.50	2.75
蕃茄蛋湯	61.	Tomato Clear Egg Drop Soup	1.65	2.95
雲呑湯	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

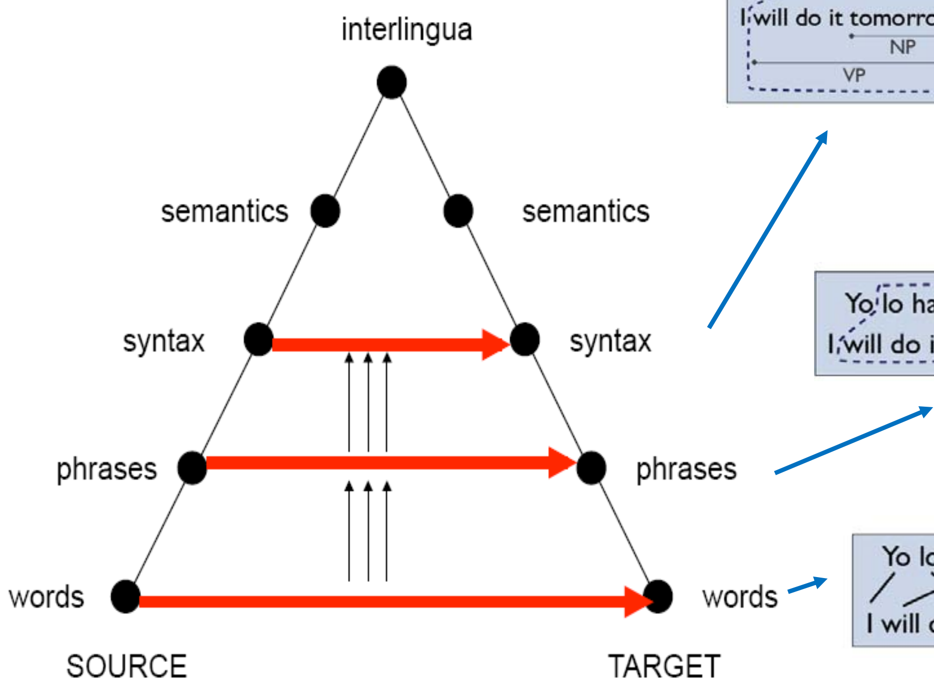
An HMM Translation Model

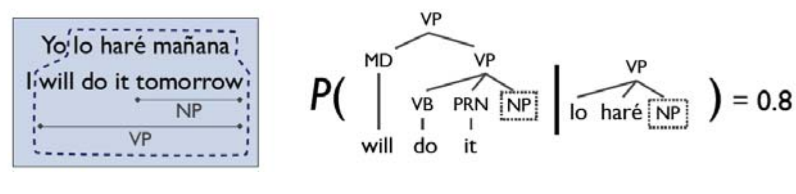


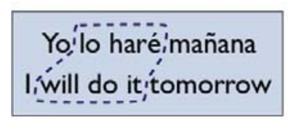
Model Parameters

Emissions: $P(F_1 = \text{Gracias} \mid E_{A_1} = \text{Thank})$ *Transitions:* $P(A_2 = 3 \mid A_1 = 1)$

Levels of Transfer



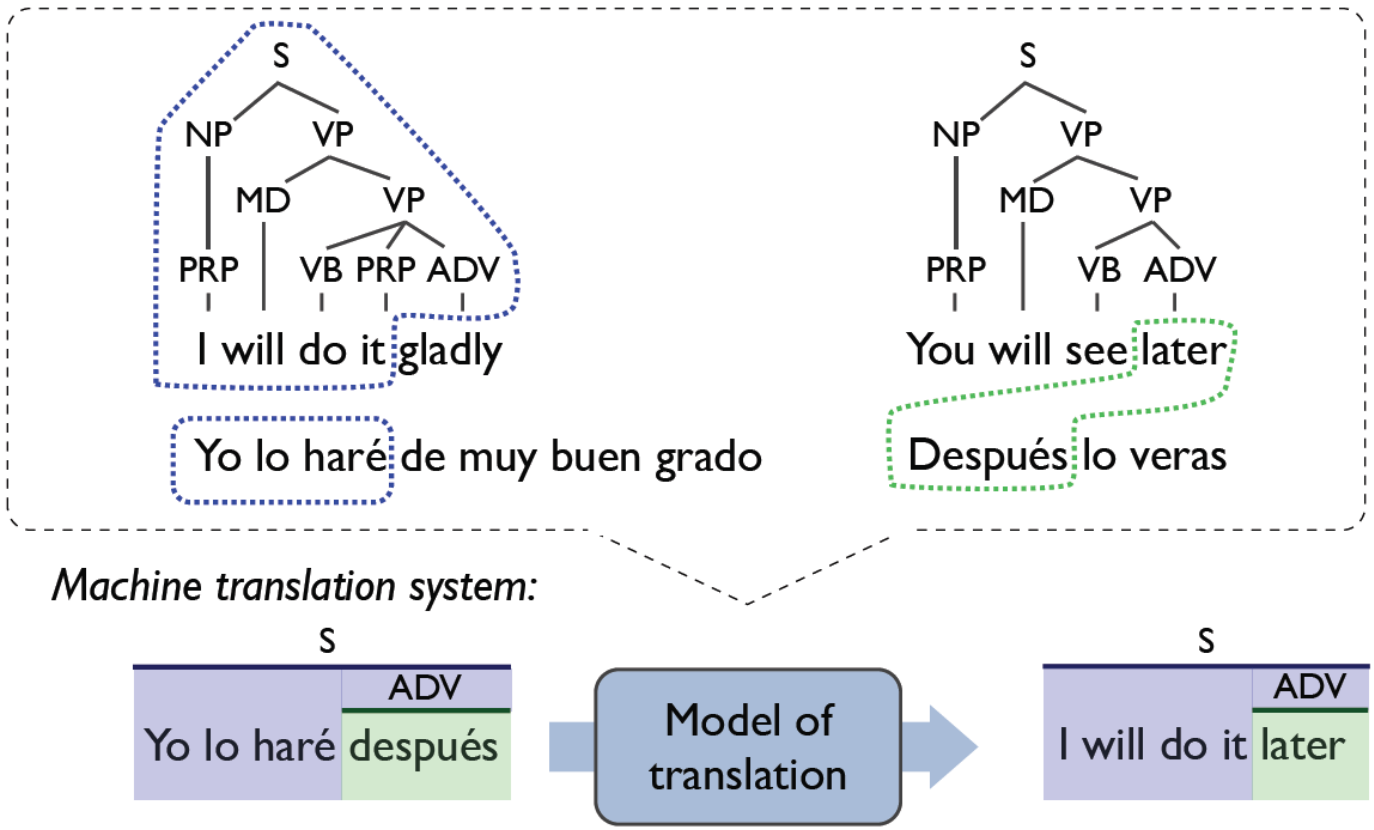




English (E)	*P*(E | lo haré)
will do it	0.8
will do so	0.2

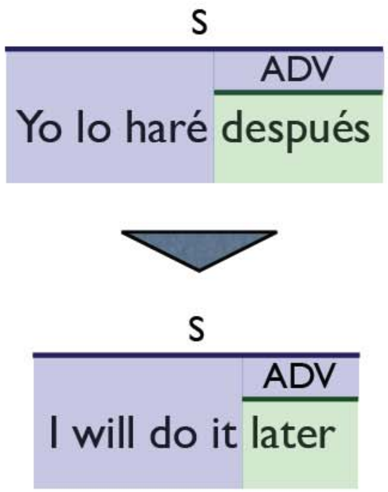
English (E)	*P*(E | mañana)
tomorrow	0.7
morning	0.3

Syntactic Translation



A Syntactic MT System

Synchronous Derivation



Synchronous Grammar Rules

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

ADV → ⟨ después ; later ⟩

A Statistical Model

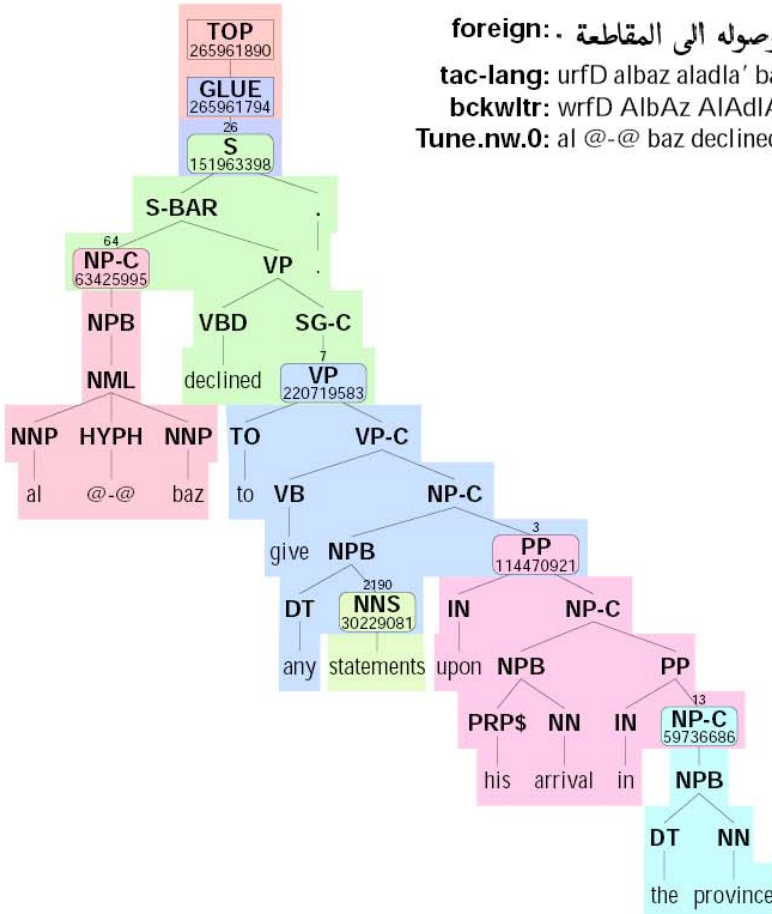
Translation model components factor over applied rules

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: Syntactic MT Output



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

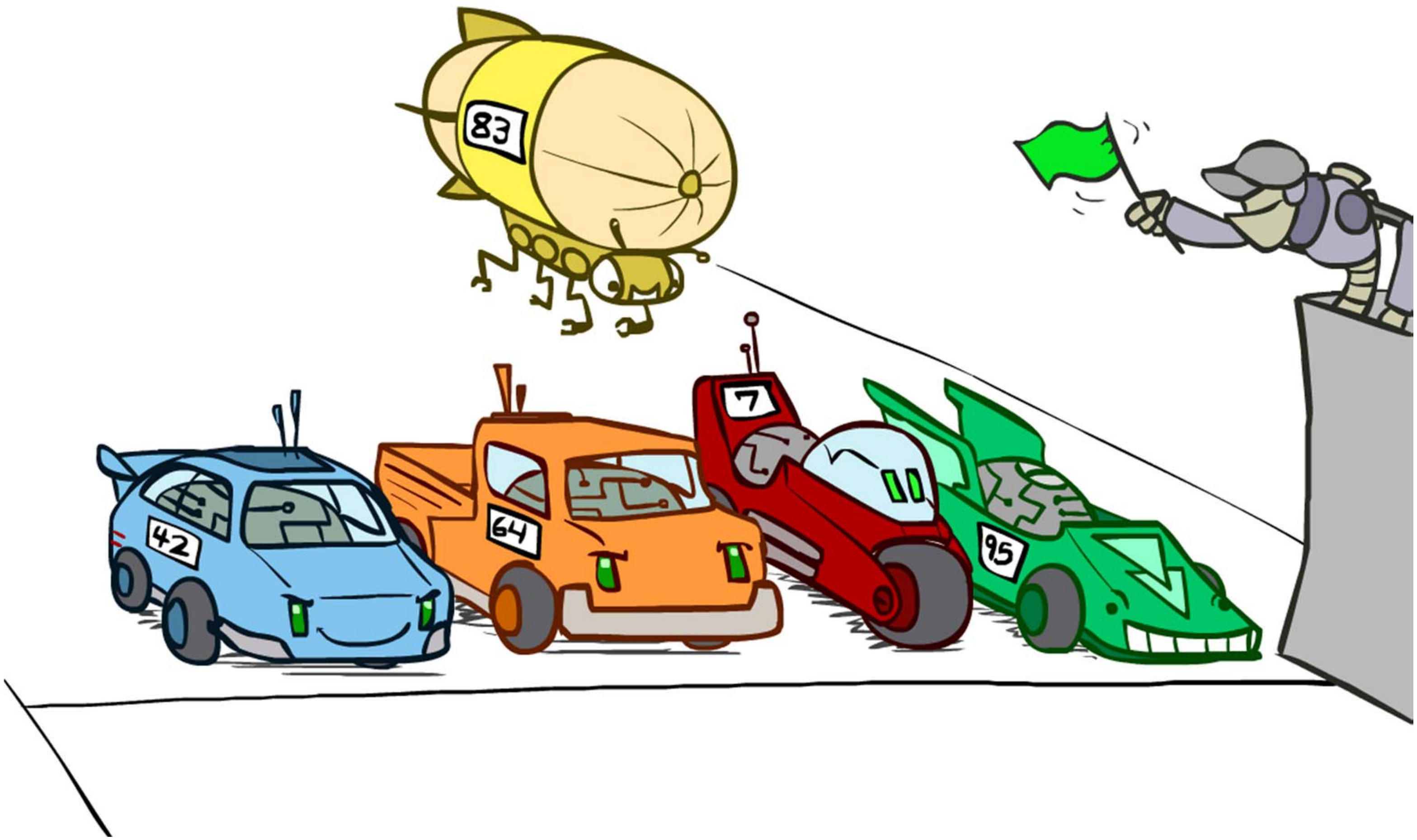
tac-lang: urfD albaz aladla' baá tSryHat fur uSulh alá almqaT`e .

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]

Autonomous Driving

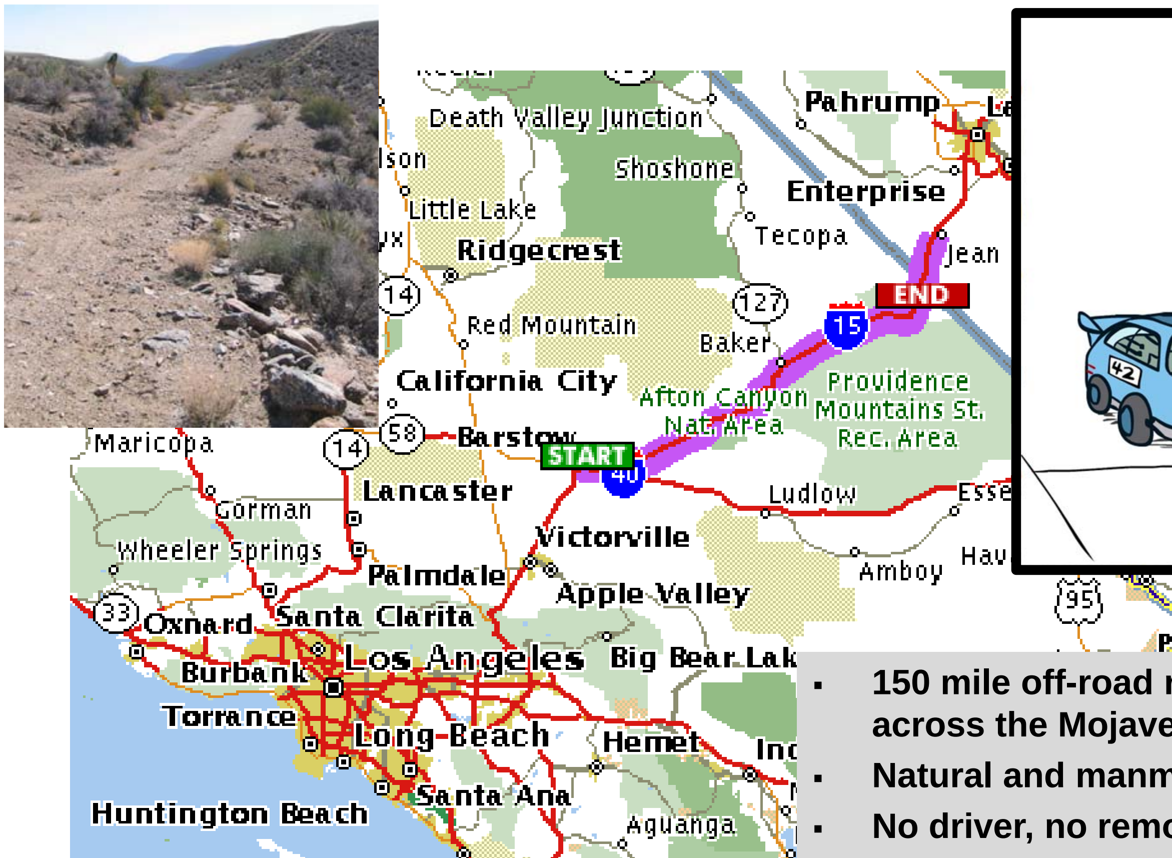


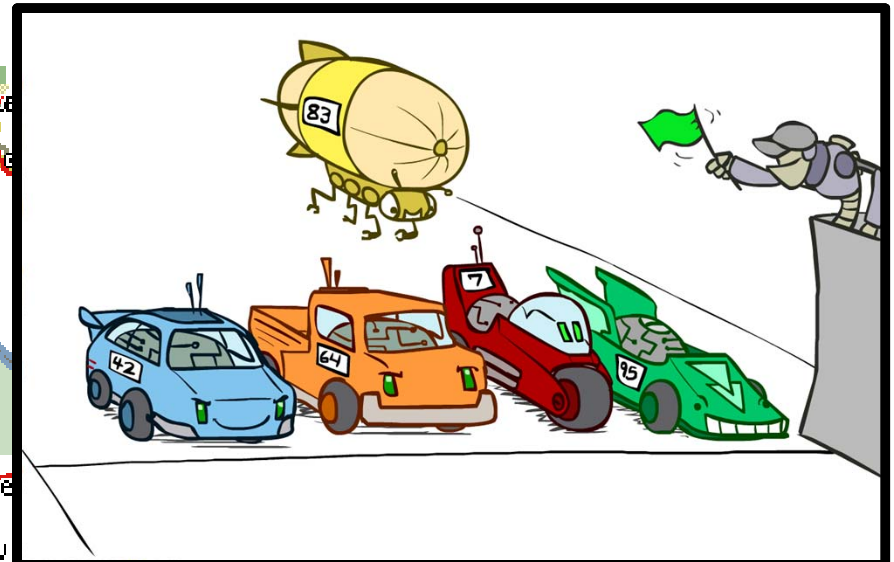
[DEMO: Race, Short]

Autonomous Vehicles

Autonomous vehicle slides adapted from Sebastian Thrun

Grand Challenge 2005: Barstow, CA, to Primm, NV

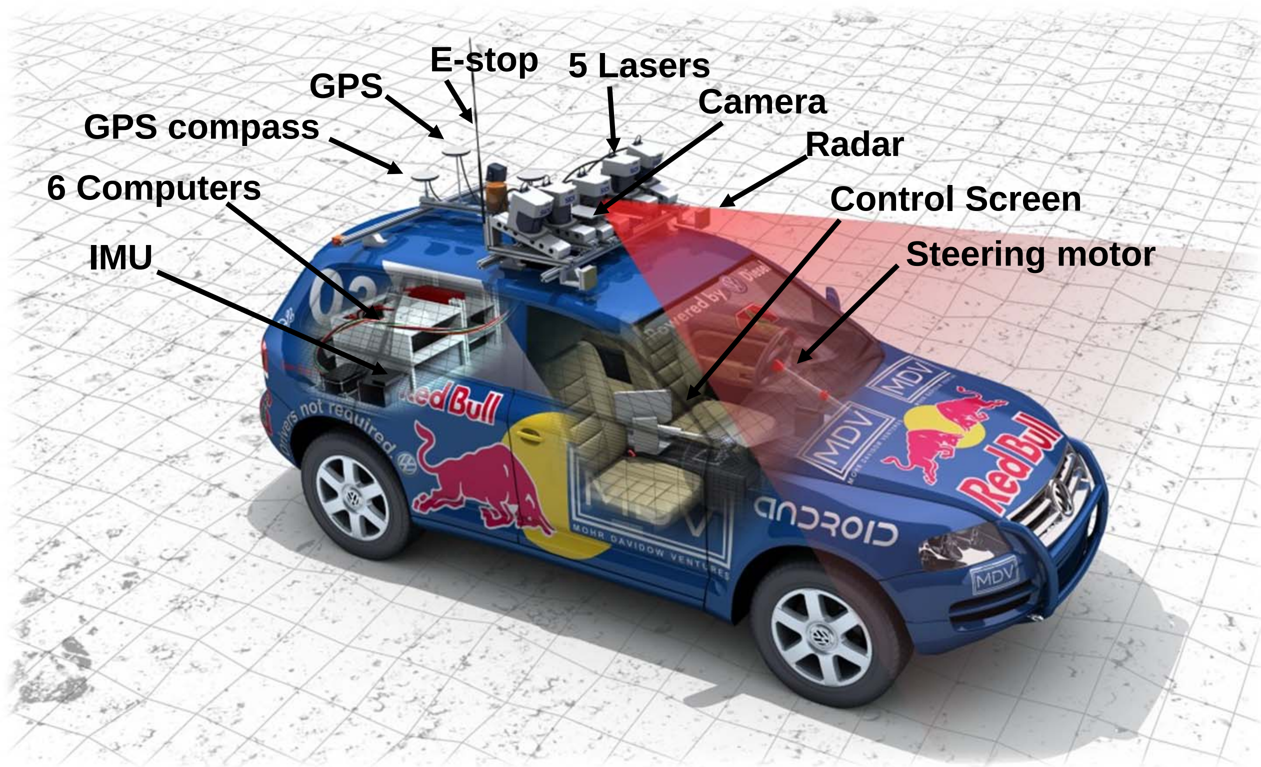




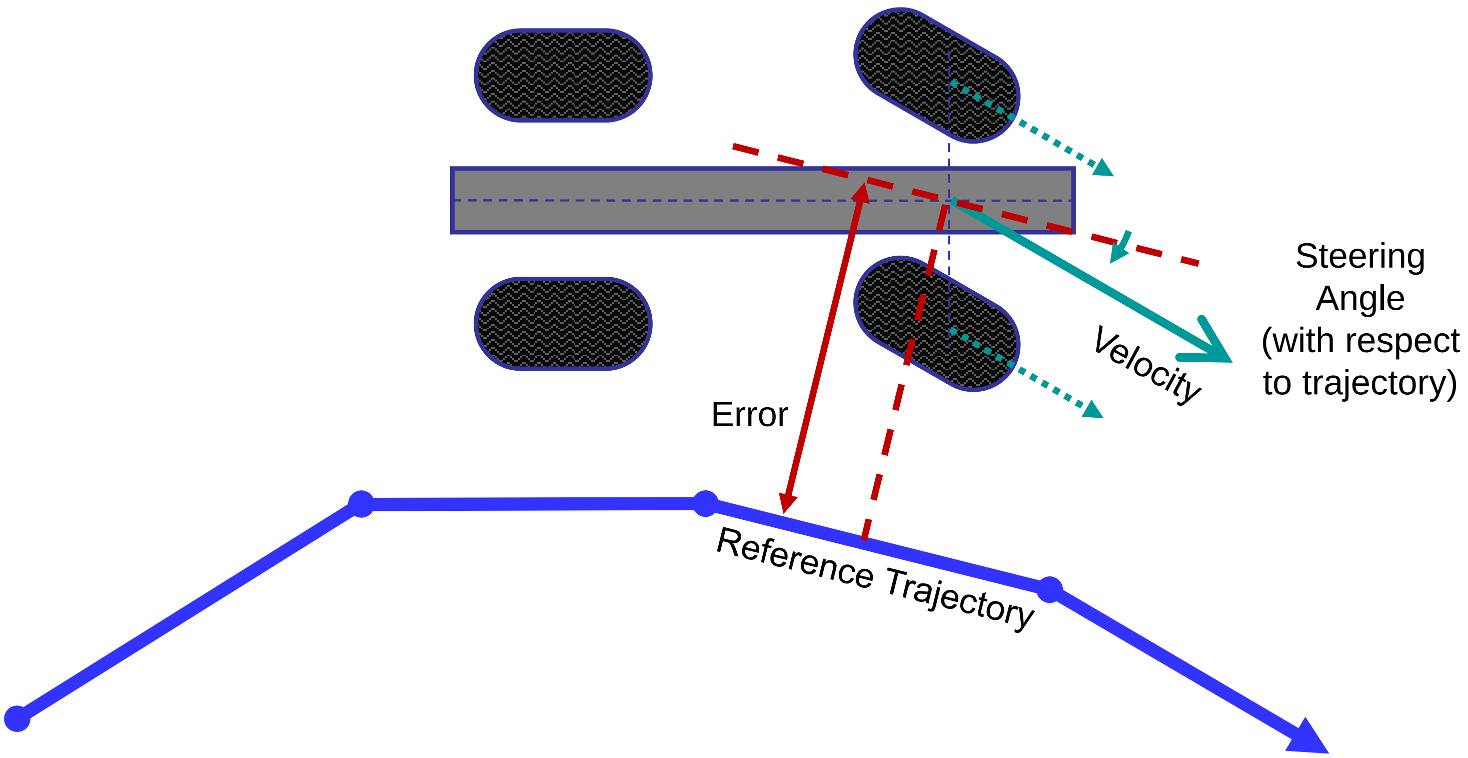
- 150 mile off-road robot race across the Mojave desert
- Natural and manmade hazards
- No driver, no remote control
- No dynamic passing

[DEMO: GC Bad, Good]

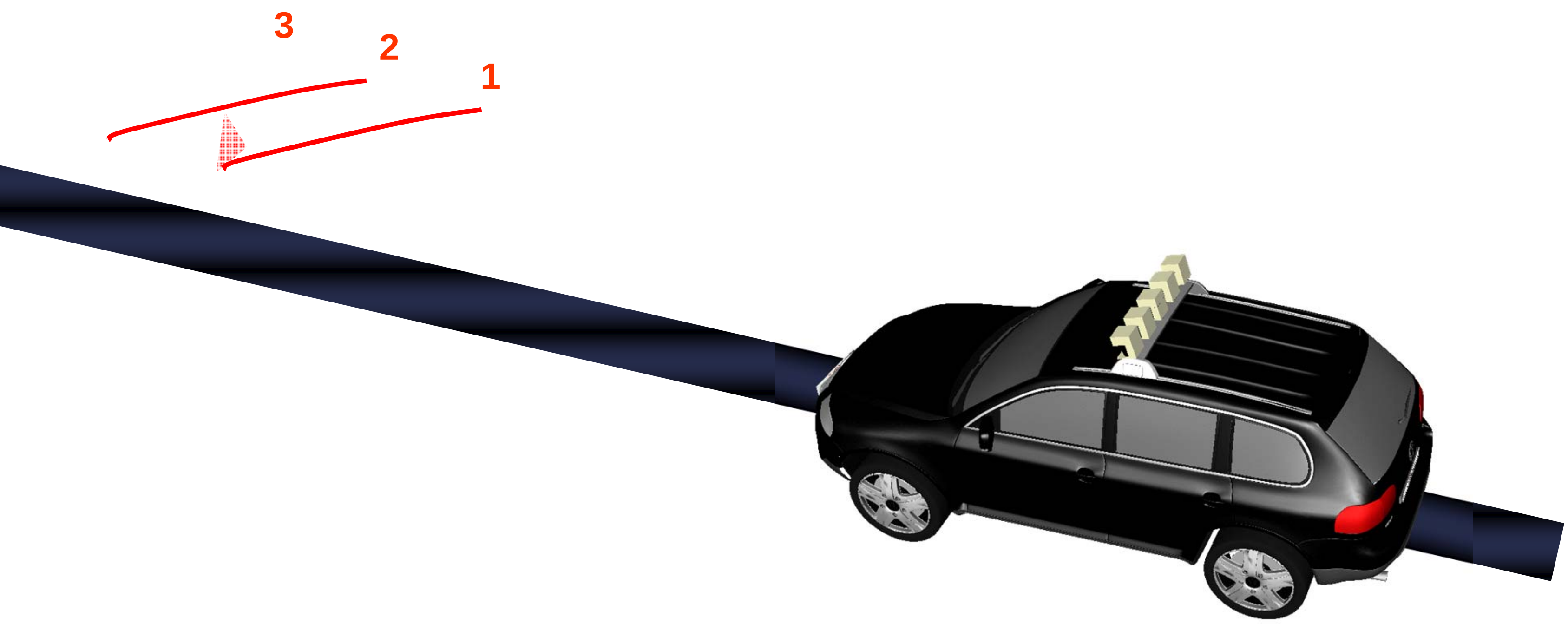
An Autonomous Car



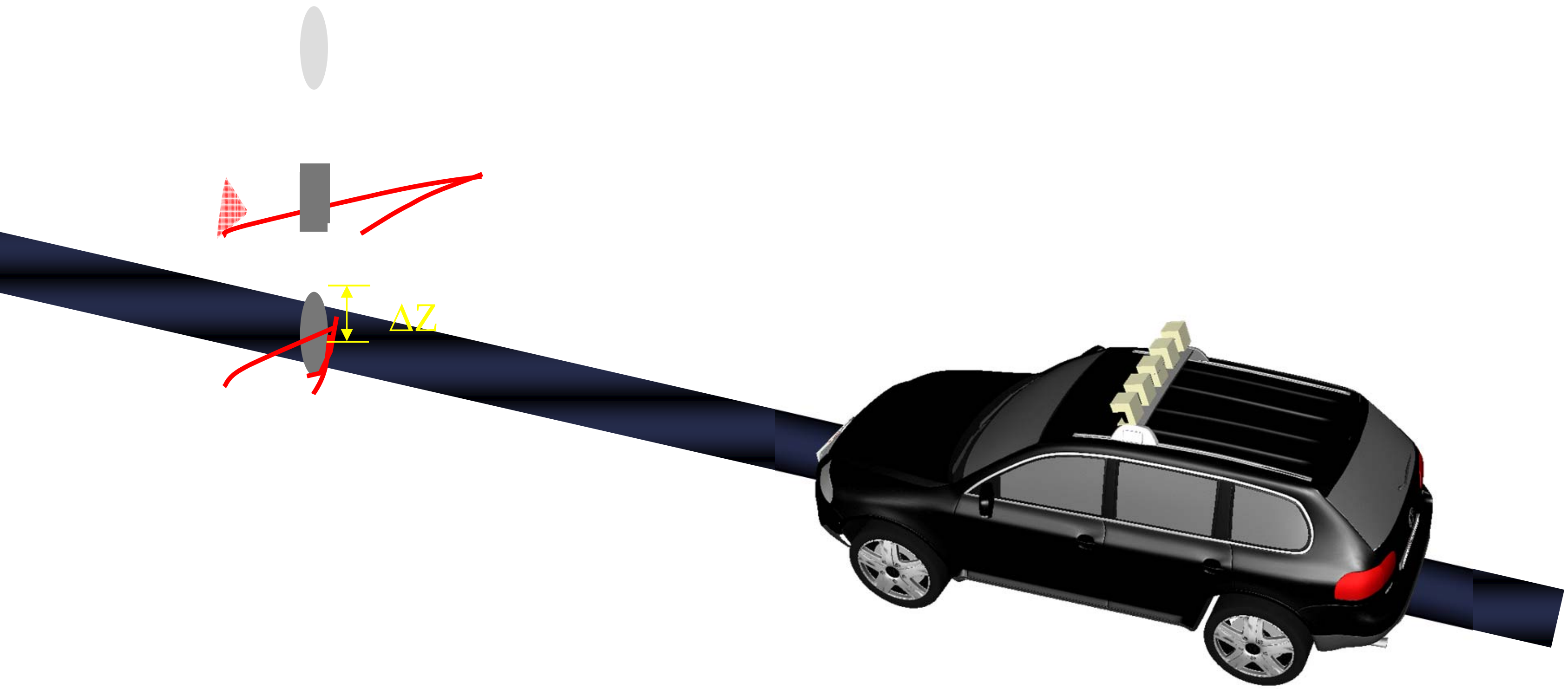
Actions: Steering Control



Readings: No Obstacles

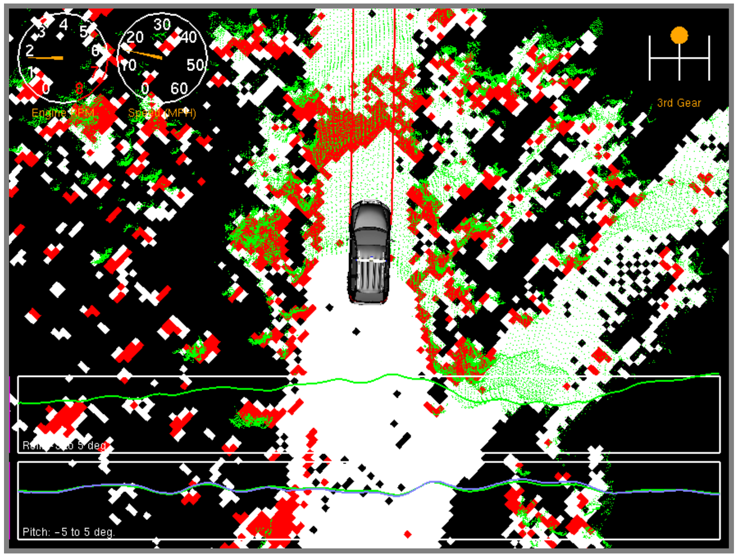


Readings: Obstacles



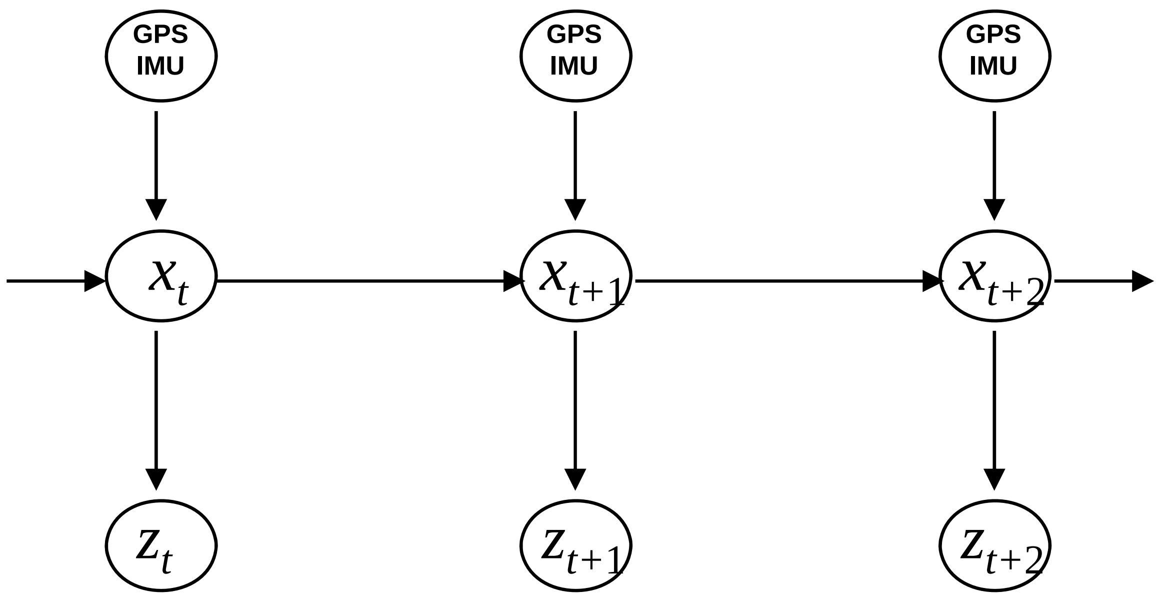
Obstacle Detection

Trigger if $|Z^i - Z^j| > 15\text{cm}$ for nearby z^i, z^j

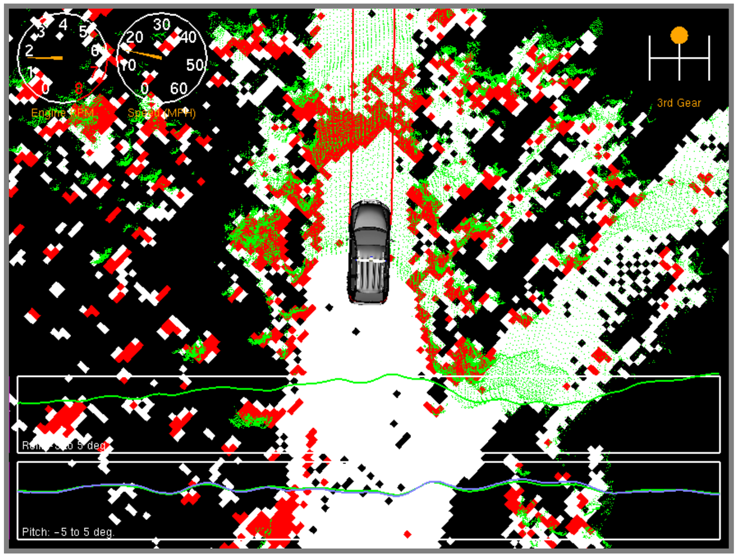


Raw Measurements: 12.6% false positives

Probabilistic Error Model



HMMs for Detection



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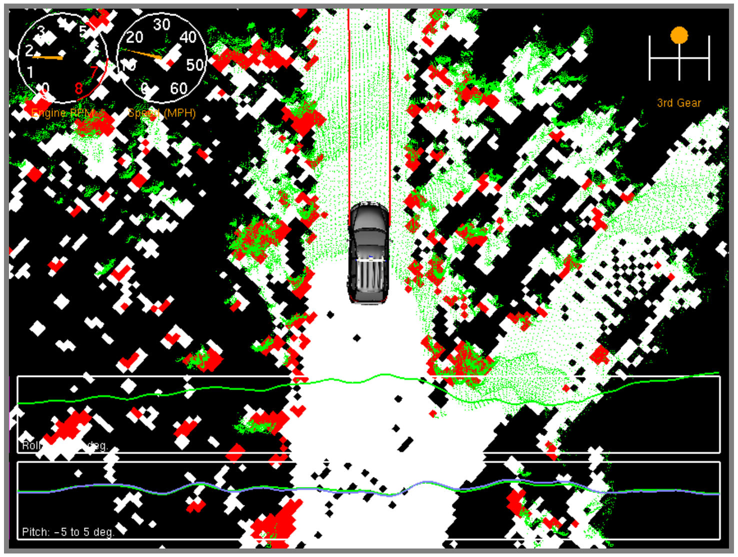
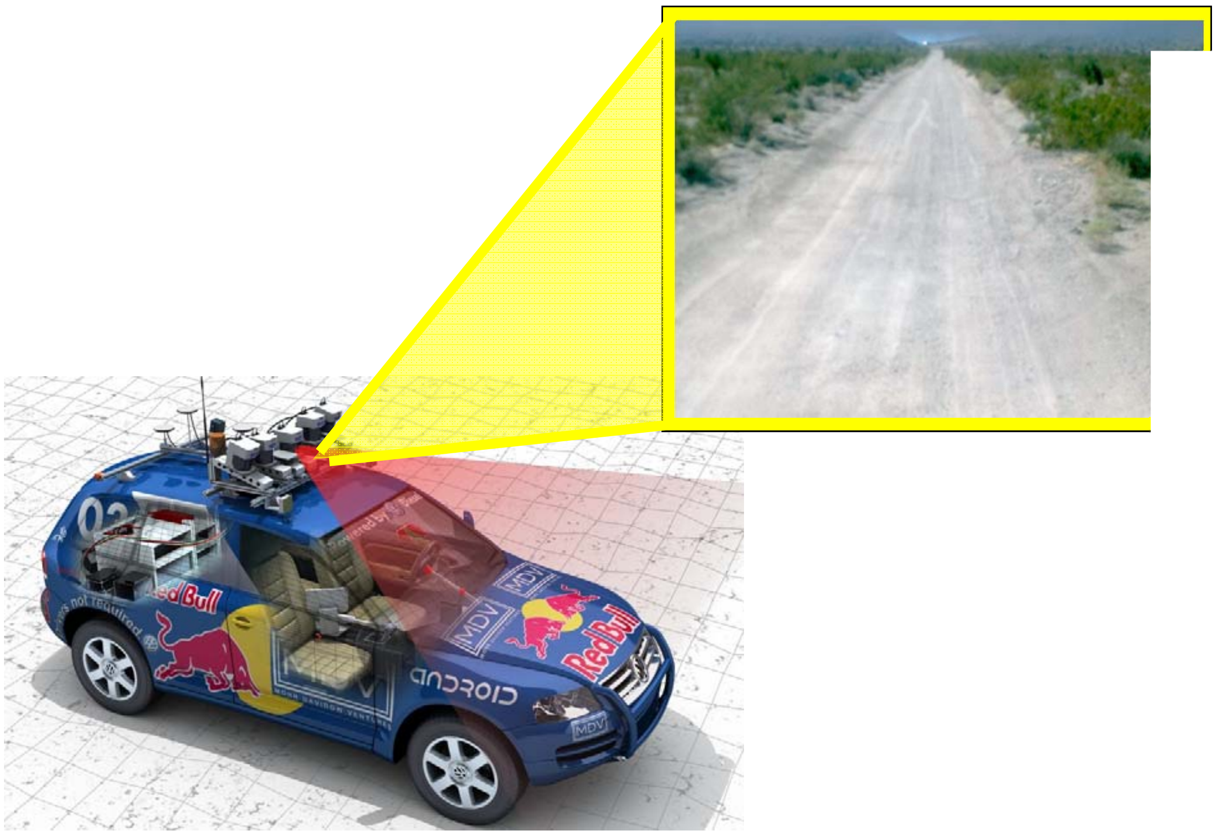


HMM Inference: 0.02% false positives

Sensors: Camera

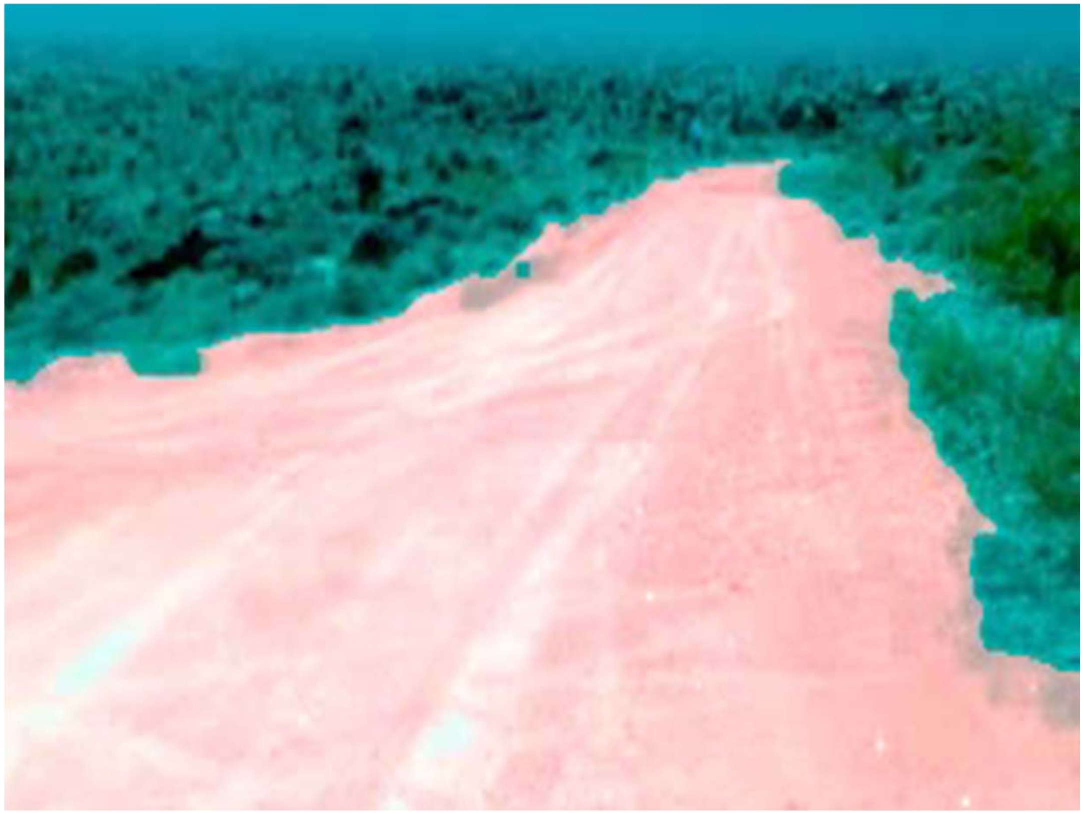


[DEMO: LIDAR 1]

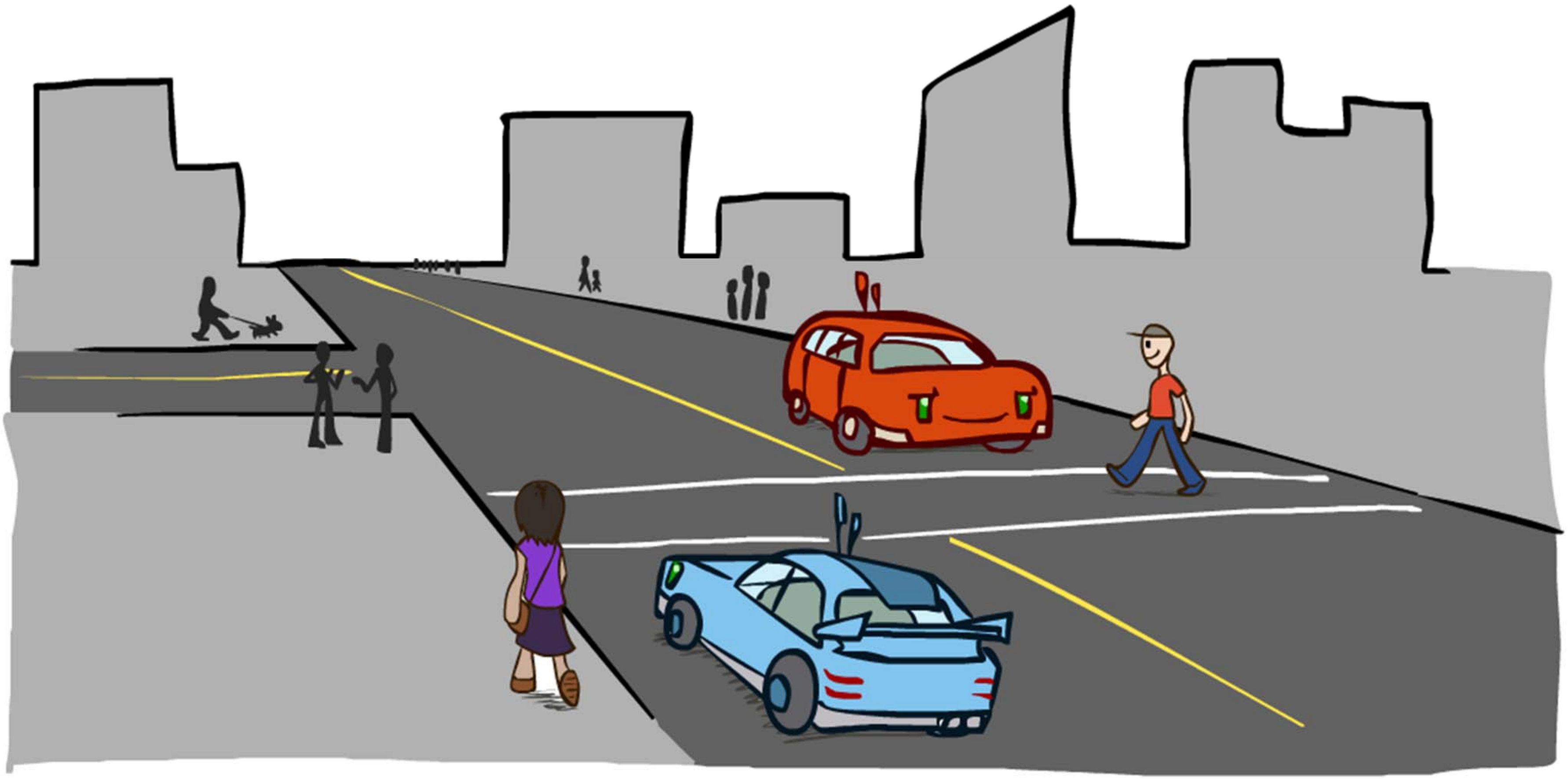
Vision for a Car

[DEMO: LIDAR 2]

Self-Supervised Vision

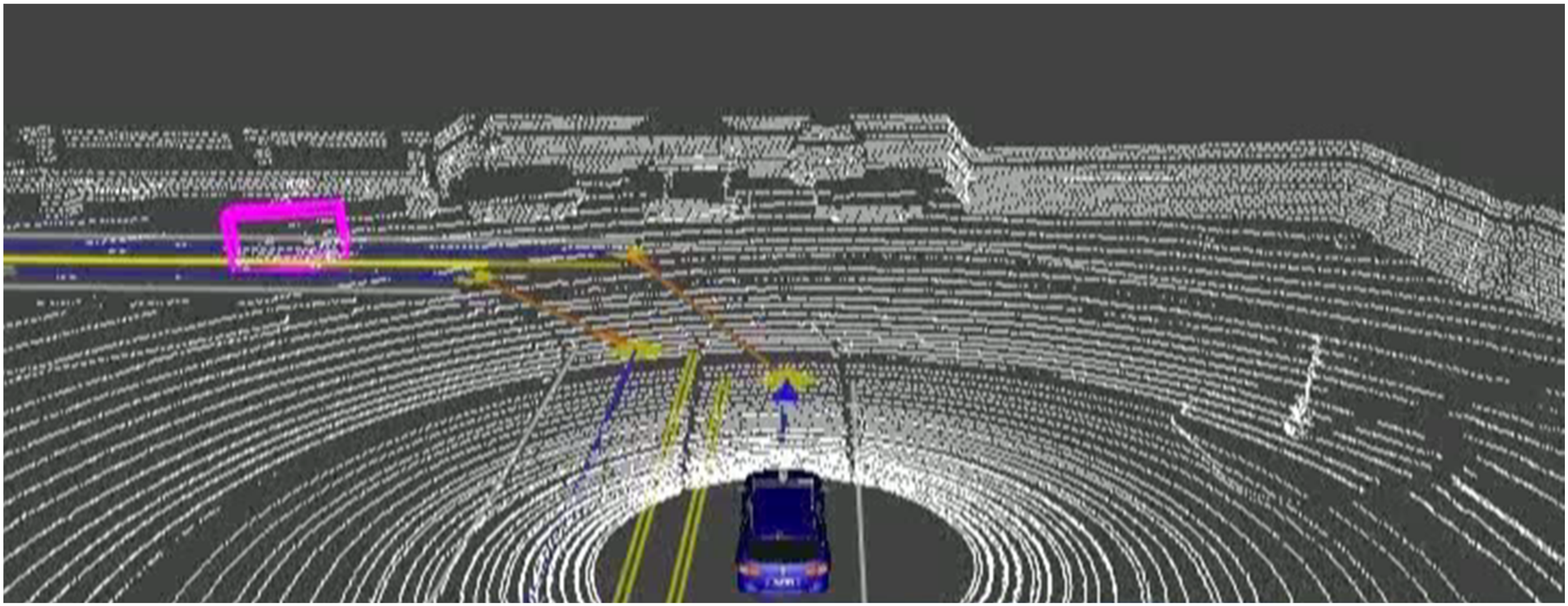


Urban Environments



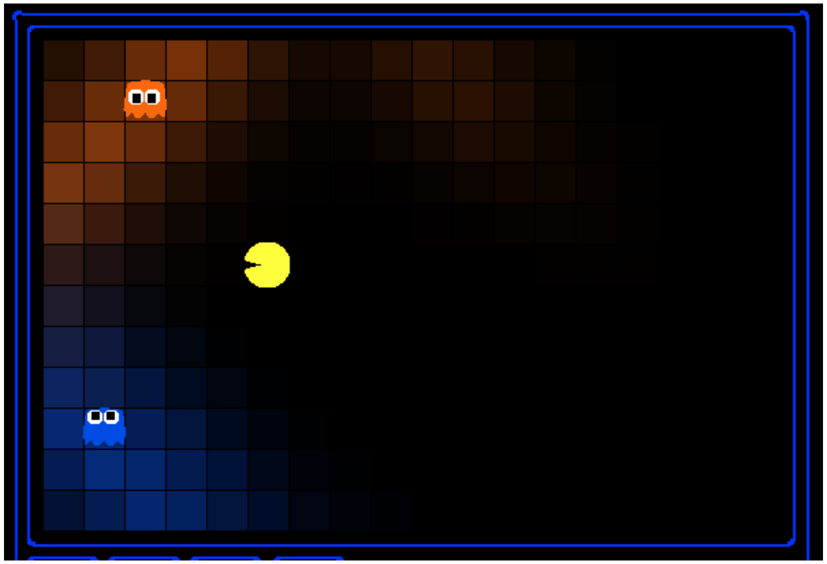
[DEMO: LIDAR]

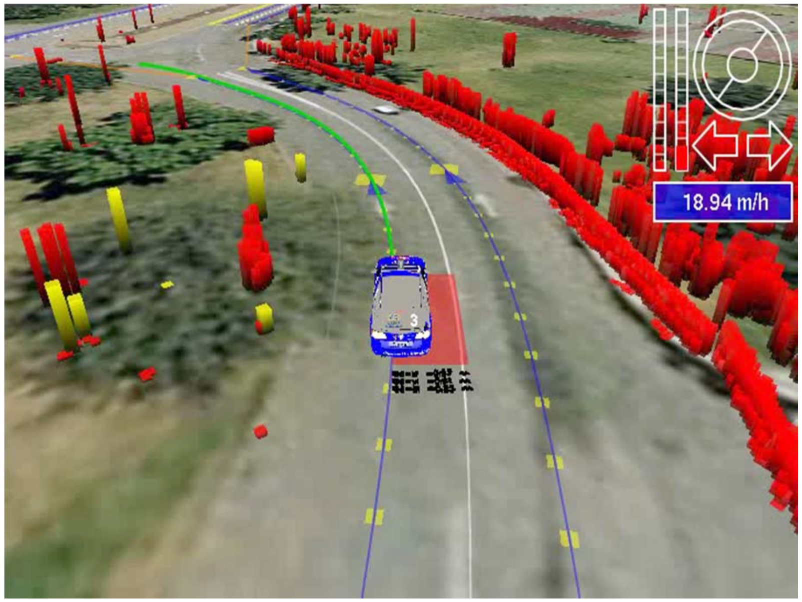
Sensors: Laser Readings



[DEMO: PEOPLE]

Environmental Tracking





Next Time: Games, Contest, Wrap-Up!