CS 343: Artificial Intelligence

NLP, Games, and Autonomous Vehicles

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[These slides based on those of Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at http://ai.berkeley.edu.]
So Far: Foundational Methods
Now: Advanced Applications

S
NP
PRP
MD
VB
ADV

You will see later

Después lo verás
Natural Language Processing

Hello, I am Eliza.

Hi, my name is Watson.
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
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
......
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

Hello, I am Eliza.

Hi, my name is Watson.
ELIZA

- A “psychotherapist” agent (Weizenbaum, ~1964)
- Led to a long line of chatbots
- 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?
"a camel is a horse designed by"

Watson

The Phrase Finder

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
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

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

- Berkeley’s first MT grant
- MT is the “first” non-numeral compute task
- ALPAC report deems MT bad
- Statistical MT thrives
- Statistical data-driven approach introduced

- ’47
- ’58
- ’66
- ’90’s
- ’00’s
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
- Model of translation
- I will do it soon
# Learning to Translate

## Classic Soups

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Sm.</th>
<th>Lg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>57</td>
<td>House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)</td>
<td>1.50</td>
<td>2.75</td>
</tr>
<tr>
<td>58</td>
<td>Chicken Rice Soup</td>
<td>1.85</td>
<td>3.25</td>
</tr>
<tr>
<td>59</td>
<td>Chicken Noodle Soup</td>
<td>1.85</td>
<td>3.25</td>
</tr>
<tr>
<td>60</td>
<td>Cantonese Wonton Soup</td>
<td>1.50</td>
<td>2.75</td>
</tr>
<tr>
<td>61</td>
<td>Tomato Clear Egg Drop Soup</td>
<td>1.65</td>
<td>2.95</td>
</tr>
<tr>
<td>62</td>
<td>Regular Wonton Soup</td>
<td>1.10</td>
<td>2.10</td>
</tr>
<tr>
<td>63</td>
<td>Hot &amp; Sour Soup</td>
<td>1.10</td>
<td>2.10</td>
</tr>
<tr>
<td>64</td>
<td>Egg Drop Soup</td>
<td>1.10</td>
<td>2.10</td>
</tr>
<tr>
<td>65</td>
<td>Egg Drop Wonton Mix</td>
<td>1.10</td>
<td>2.10</td>
</tr>
<tr>
<td>66</td>
<td>Tofu Vegetable Soup</td>
<td>NA</td>
<td>3.50</td>
</tr>
<tr>
<td>67</td>
<td>Chicken Corn Cream Soup</td>
<td>NA</td>
<td>3.50</td>
</tr>
<tr>
<td>68</td>
<td>Crab Meat Corn Cream Soup</td>
<td>NA</td>
<td>3.50</td>
</tr>
<tr>
<td>69</td>
<td>Seafood Soup</td>
<td>NA</td>
<td>3.50</td>
</tr>
</tbody>
</table>

*Example from Adam Lopez*
An HMM Translation Model

E: Thank you, I shall do so gladly.

A:

F: Gracias, lo haré de muy buen grado.

Model Parameters

Emissions: \( P(F_1 = \text{Gracias} | E_{A1} = \text{Thank}) \)

Transitions: \( P(A_2 = 3 | A_1 = 1) \)
Levels of Transfer
Example: Syntactic MT Output

[ISI MT system output]
Machine Translation
Starcraft
Starcraft
What is Starcraft?

Image from Ben Weber
Why is Starcraft Hard?

- The game of Starcraft is:
  - Adversarial
  - Long Horizon
  - Partially Observable
  - Realtime
  - Huge branching factor
  - Concurrent
  - Resource-rich
  - ...

- No single algorithm (e.g. minimax) will solve it off-the-shelf!
Starcraft AIs: AIIDE 2010

- 28 Teams: international entrants, universities, research labs...
The Berkeley Overmind

Search: path planning
CSPs: base layout
Minimax: targeting
Learning: micro control
Inference: tracking units
Scheduling: resources
Hierarchical control

http://overmind.eecs.berkeley.edu
Search for Pathing
Berkeley Overmind

presents

Sparky the Wonder Drone
Minimax for Targeting
Berkeley Overmind

Mutalisk Hit and Run
Machine Learning for Micro Control

[RL, Potential Fields]
Berkeley Overmind

Valhalla (High Templars)
Inference / VPI / Scouting
Autonomous Driving
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
Autonomous Vehicles

Autonomous vehicle slides adapted from Sebastian Thrun
Grand Challenge 2005 Nova Video
Grand Challenge 2005 – Bad
An Autonomous Car

- Lasers
- Camera
- Radar
- E-stop
- GPS
- GPS compass
- 6 Computers
- IMU
- Control Screen
- Steering motor
Actions: Steering Control

Reference Trajectory

Error

Steering Angle (with respect to trajectory)

Velocity
Laser Readings for Flat / Empty Road
Laser Readings for Road with Obstacle
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

\[ x_{t+1} = x_t + \mu + \epsilon \]

\[ z_{t+1} = z_t + \nu + \delta \]

GPS IMU

\[ x_t \]

\[ z_t \]

\[ x_{t+1} \]

\[ z_{t+1} \]

\[ x_{t+2} \]

\[ z_{t+2} \]
HMMs for Detection

Raw Measurements: 12.6% false positives

HMM Inference: 0.02% false positives
Sensors: Camera
Vision for a Car
Vision for a Car
Self-Supervised Vision
Self-Supervised Vision
Urban Environments
Sensors: Laser Readings
Environmental Tracking
Google Self-Driving Car
Next Time: Computer Vision, Robotic Helicopters, and Walking Robots!