So Far: Foundational Methods
Now: Advanced Applications

S
 NP    VP
  MD    VP
   PRP  VB  ADV

You will see later

Después lo veras
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

S
  NP  VP
    |    |
    N   V   NP
    Hershey bars N
    protest

Hershey bars protest

S
  NP  VP
    |    |
    N   N   V
    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 → S          375/420
S → NP VP .       320/392
NP → PRP          127/539
VP → VBD ADJP     32/401
```

```
ROOT
   ↓
S
   ↓
NP
   ↓
PRP  VBD  ADJP
   |    |    |
  He  was  right
```
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 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?

[Demo: http://nlp-addiction.com/eliza]
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?

- Watson and the Jeopardy! Challenge 2013 – YouTube
- https://www.youtube.com/watch?v=P18EdAKuC1U
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.”

“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...

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

Novel sentence
Learning to Translate

<table>
<thead>
<tr>
<th>CLASSIC SOUPS</th>
<th>Sm.</th>
<th>Lg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>香脆雞湯 57.</td>
<td>House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)</td>
<td>1.50</td>
</tr>
<tr>
<td>雞飯湯 58.</td>
<td>Chicken Rice Soup</td>
<td>1.85</td>
</tr>
<tr>
<td>雞麪湯 59.</td>
<td>Chicken Noodle Soup</td>
<td>1.85</td>
</tr>
<tr>
<td>廣東雲吞 60.</td>
<td>Cantonese Wonton Soup</td>
<td>1.50</td>
</tr>
<tr>
<td>番茄蛋汤 61.</td>
<td>Tomato Clear Egg Drop Soup</td>
<td>1.65</td>
</tr>
<tr>
<td>雲吞湯 62.</td>
<td>Regular Wonton Soup</td>
<td>1.10</td>
</tr>
<tr>
<td>酸辣湯 63.</td>
<td>Hot &amp; Sour Soup</td>
<td>1.10</td>
</tr>
<tr>
<td>蛋花湯 64.</td>
<td>Egg Drop Soup</td>
<td>1.10</td>
</tr>
<tr>
<td>雲蛋湯 65.</td>
<td>Egg Drop Wonton Mix</td>
<td>1.10</td>
</tr>
<tr>
<td>豆腐菜湯 66.</td>
<td>Tofu Vegetable Soup</td>
<td>NA</td>
</tr>
<tr>
<td>雞玉米湯 67.</td>
<td>Chicken Corn Cream Soup</td>
<td>NA</td>
</tr>
<tr>
<td>鮑魚玉米湯 68.</td>
<td>Crab Meat Corn Cream Soup</td>
<td>NA</td>
</tr>
<tr>
<td>海鮮湯 69.</td>
<td>Seafood Soup</td>
<td>NA</td>
</tr>
</tbody>
</table>

Example from Adam Lopez
An HMM Translation Model

E: Thank you, I shall do so gladly.

A: 1 2 3 4 5 6 7 8 9

F: Gracias, lo haré de muy buen grado.

Model Parameters

Emissions: \( P( F_1 = \text{Gracias} \mid E_1 = \text{Thank} ) \)  
Transitions: \( P( A_2 = 3 \mid A_1 = 1 ) \)
Levels of Transfer

Yo lo haré mañana

I will do it tomorrow

P(E | lo haré) = 0.8

| English (E)     | P(E | mañana) |
|----------------|-------------|
| tomorrow        | 0.7         |
| morning         | 0.3         |
Example: Syntactic MT Output

ورفض الباز نادلإ بآي تصريحات فور وصوله الى المقاطعة.

tac-lang: urfD alba’aladla’ baat tseyHaf fur usulh ala almqaT’e.
Tune.nw.0: al @-@ baz declined to make any statements upon his arrival in the province.

[ISI MT system output]
Starcraft
Starcraft
What is Starcraft?
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...

```cpp
onFrame() {
    units = Broodwar->getAllUnits();
    unit->attackUnit(enemyUnit);
}
```
The Berkeley Overmind

Search: path planning
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
Mutarlisk Hit and Run
Machine Learning for Micro Control
Berkeley Overmind

Valhalla (High Templars)
Inference / VPI / Scouting
AIIDE 2010 Competition
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

[VIDEO: nova-race-supershort.mp4]
Grand Challenge 2005 – Bad

[VIDEO: grand challenge – bad.wmv]
An Autonomous Car

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

- Error
- Velocity
- Steering Angle (with respect to trajectory)
- Reference Trajectory
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

\[ x_t \rightarrow x_{t+1} \rightarrow x_{t+2} \]

\[ Z_t \rightarrow Z_{t+1} \rightarrow Z_{t+2} \]
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

[VIDEO: lidar vision for a car]
Self-Supervised Vision
Self-Supervised Vision
Urban Environments
Sensors: Laser Readings

[VIDEO: Urban Challenge (Lidar)]
Environmental Tracking
Google Self-Driving Car

[VIDEO: ROBOTICS – gcar.m4v]
Next Time: Computer Vision, Robotic Helicopters, and Walking Robots!