INTRODUCTION

CS 562/662: Natural Language Processing

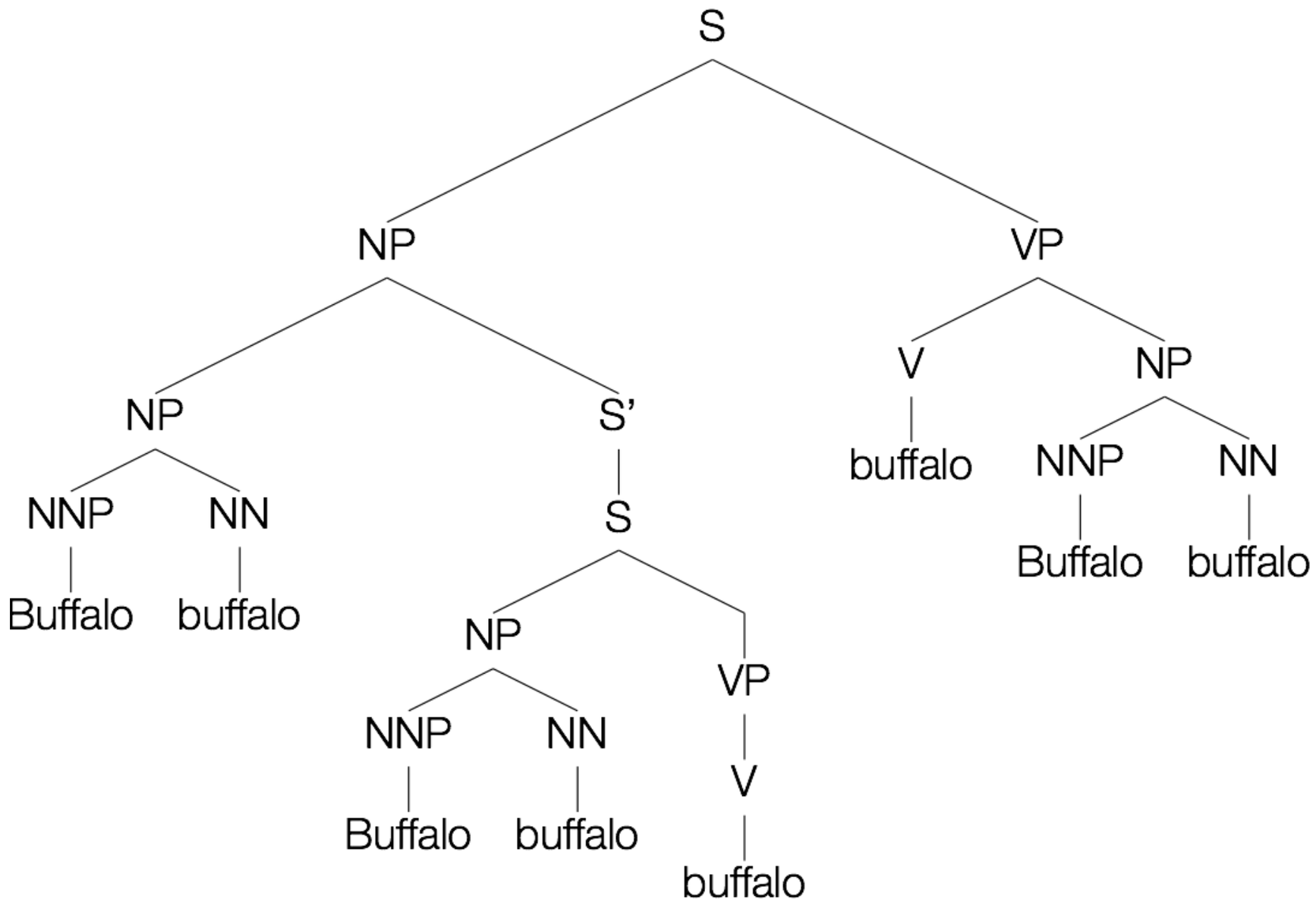
2015-01-06

COURSE WEBSITE:

http://cslu.ohsu.edu/~gormanky/courses/CS662

COURSE STRUCTURE

WHAT IS NATURAL LANGUAGE PROCESSING?



LANGUAGE IS AMBIGUOUS

Possible paraphrase: Upstate bison that other upstate bison bully, they also bully upstate NY bison.

Pope Francis on Saturday appointed a victim of sexual abuse and a senior cardinal known for his zero-tolerance approach to a new group charged with advising the Catholic Church on how to respond to the problem of sexual abuse of children.

(WSJ, 3/22/2014)

A WHIG HISTORY

THE DREAM OF THE ‘50S

Much of the early work in NLP focused on systems for *understanding* natural language. (Natural language must have seemed a particularly promising modality for user input in the teletype era.) Systems—when they worked—parsed and interpreted natural language input and generated natural language output.

SHRDLU (Winograd 1971):

```
Person: GRASP THE PYRAMID.
Computer: I DON'T UNDERSTAND WHICH PYRAMID
YOU MEAN.
Person: FIND A BLOCK WHICH IS TALLER THAN
THE ONE YOU ARE HOLDING AND PUT IT INTO THE
BOX.
Computer: BY "IT", I ASSUME YOU MEAN THE
BLOCK WHICH IS TALLER THAN THE ONE I AM
HOLDING.
Computer: OK. (does it)
Person: WHAT DOES THE BOX CONTAIN?
Computer: THE BLUE PYRAMID AND THE BLUE
BLOCK.
Person: WHAT IS THE PYRAMID SUPPORTED BY?
Computer: THE BOX.
Person: HOW MANY BLOCKS ARE NOT IN THE BOX?
Computer: FOUR OF THEM.
Person: IS AT LEAST ONE OF THEM NARROWER
THAN THE ONE WHICH I TOLD YOU TO PICK UP?
Computer: YES, THE RED CUBE.
```

[source: http://hci.stanford.edu/~winograd/shrdlu/]

LANGUAGE: NOT REALLY THAT SIMPLE

The *cognitive revolution* sparked by Chomsky (among others) revealed the enormous complexity of human languages.

The 1964 ALPAC report (more on that later) emphasized the need for *basic* (rather than applied) research in computational linguistics (but, unfortunately shifted funding elsewhere).

Meanwhile, *machine learning* was just getting started: the *perceptron* was published in 1958 and the term *machine learning* was coined in 1959.

SOME EARLY SUCCESSES

1965-1970: Efficient algorithms for parsing

1976-1980: Noisy channel models for statistical automatic speech recognition

1987-1993: Evaluation goes mainstream

1992: The Penn Treebank

NLP AS ANNOTATION

A new goal emerges in the ‘80s-‘90s: automated, linguistically-informed annotation of text

Not all useful tasks require full understanding, and when they do, it is still easier to design an pipeline of increasingly abstract annotations

SOME NLP TASKS AND APPLICATIONS

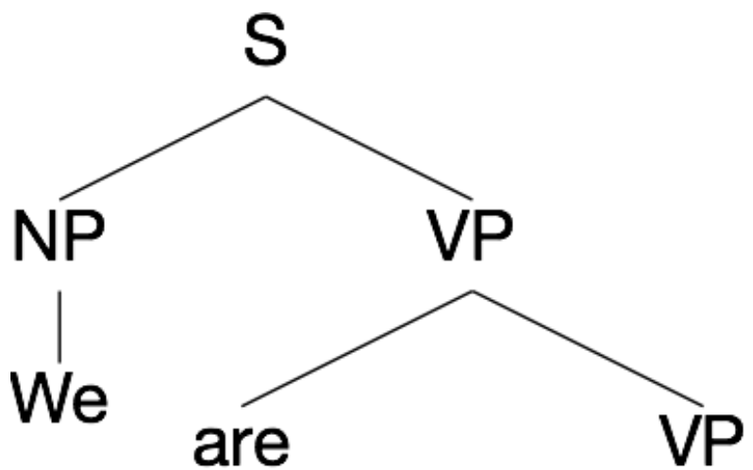
TAGGING

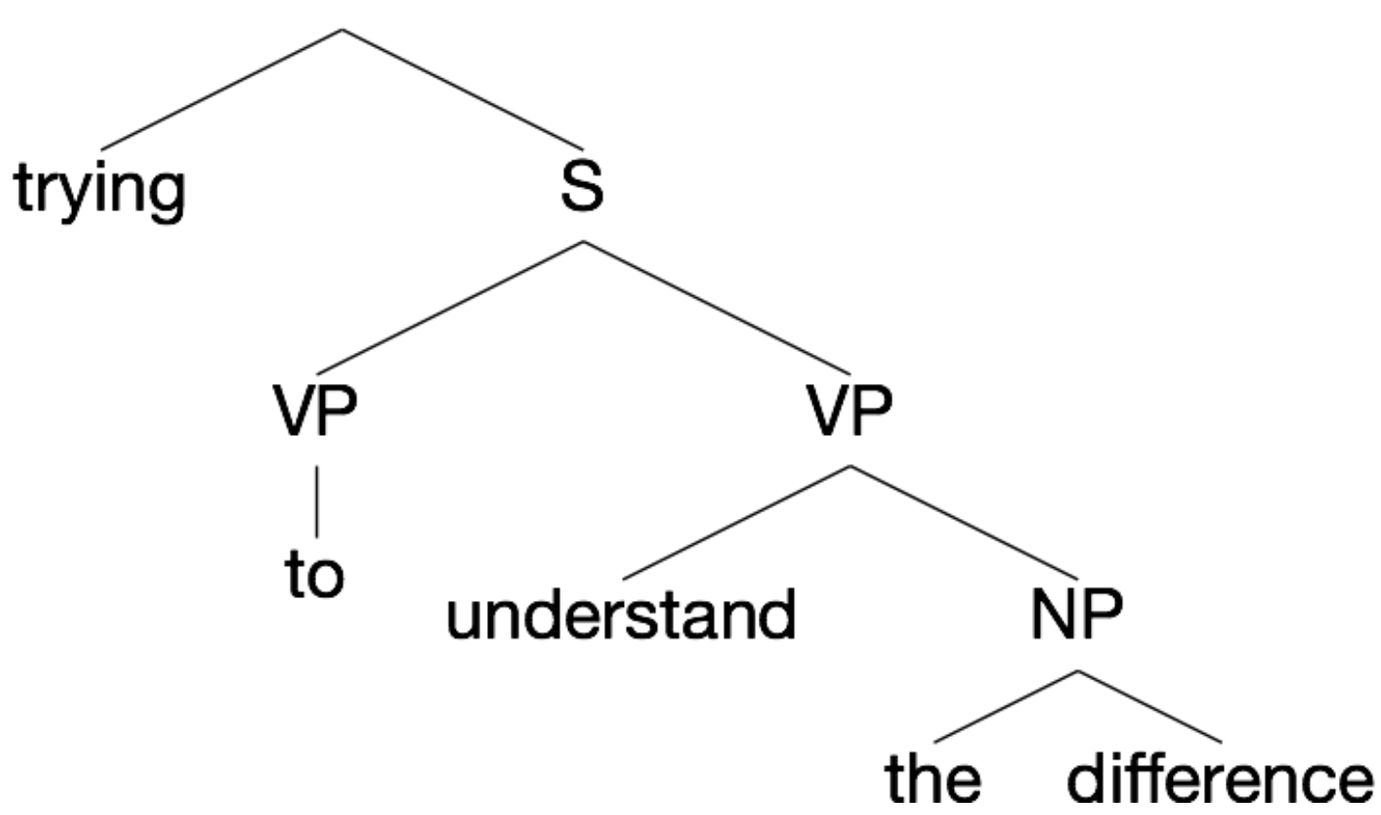
Do you really think it is weakness that yields to temptation? I tell you that there are terrible temptations which it requires strength, strength and courage to yield to. - Oscar Wilde

Do/VBP you/PRP really/RB think/VBP it/PRP is/VBZ weakness/NN that/IN yields/NNS to/TO temptation/NN ?/.

I/PRP tell/VBP you/PRP that/IN there/EX are/VBP terrible/JJ temptations/NNS which/WDT it/PRP requires/VBZ strength/NN ,/, strength/NN and/CC courage/NN to/TO yield/VB to/TO ./.

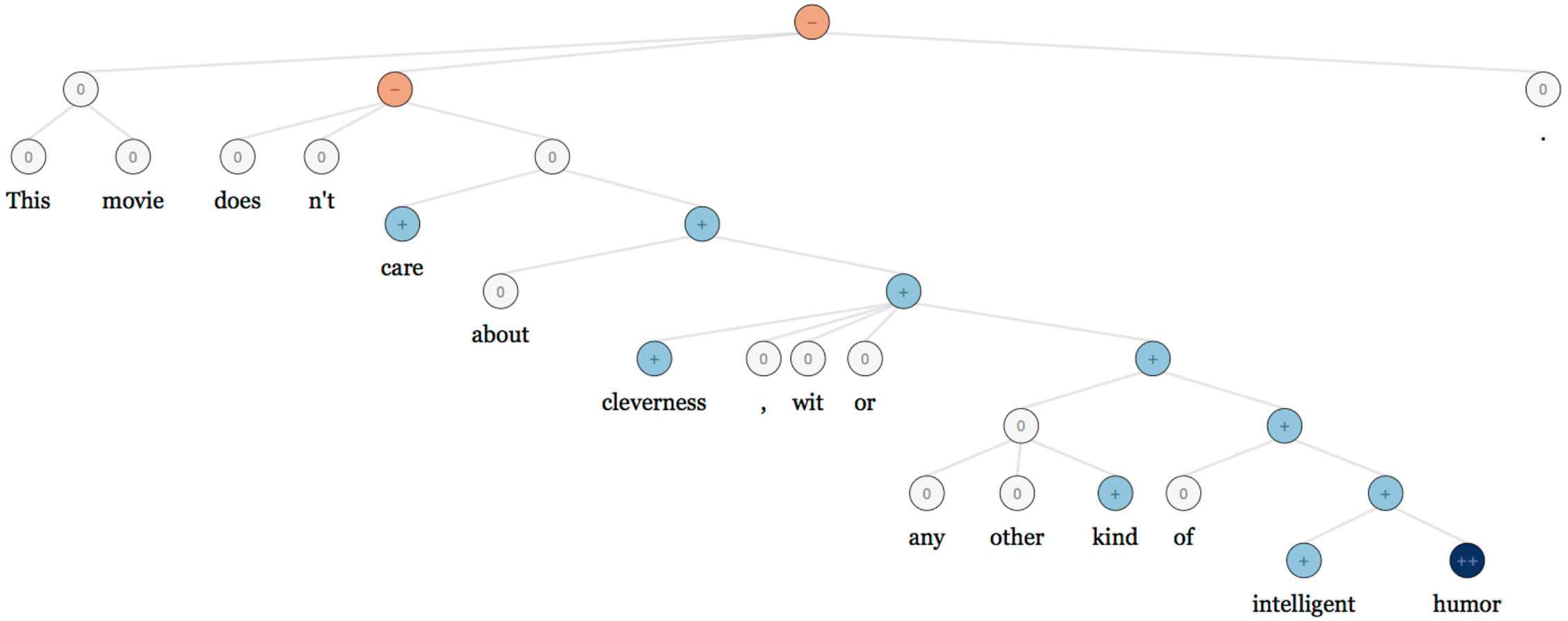
PARSING


S
NP
VP
We
are
VP

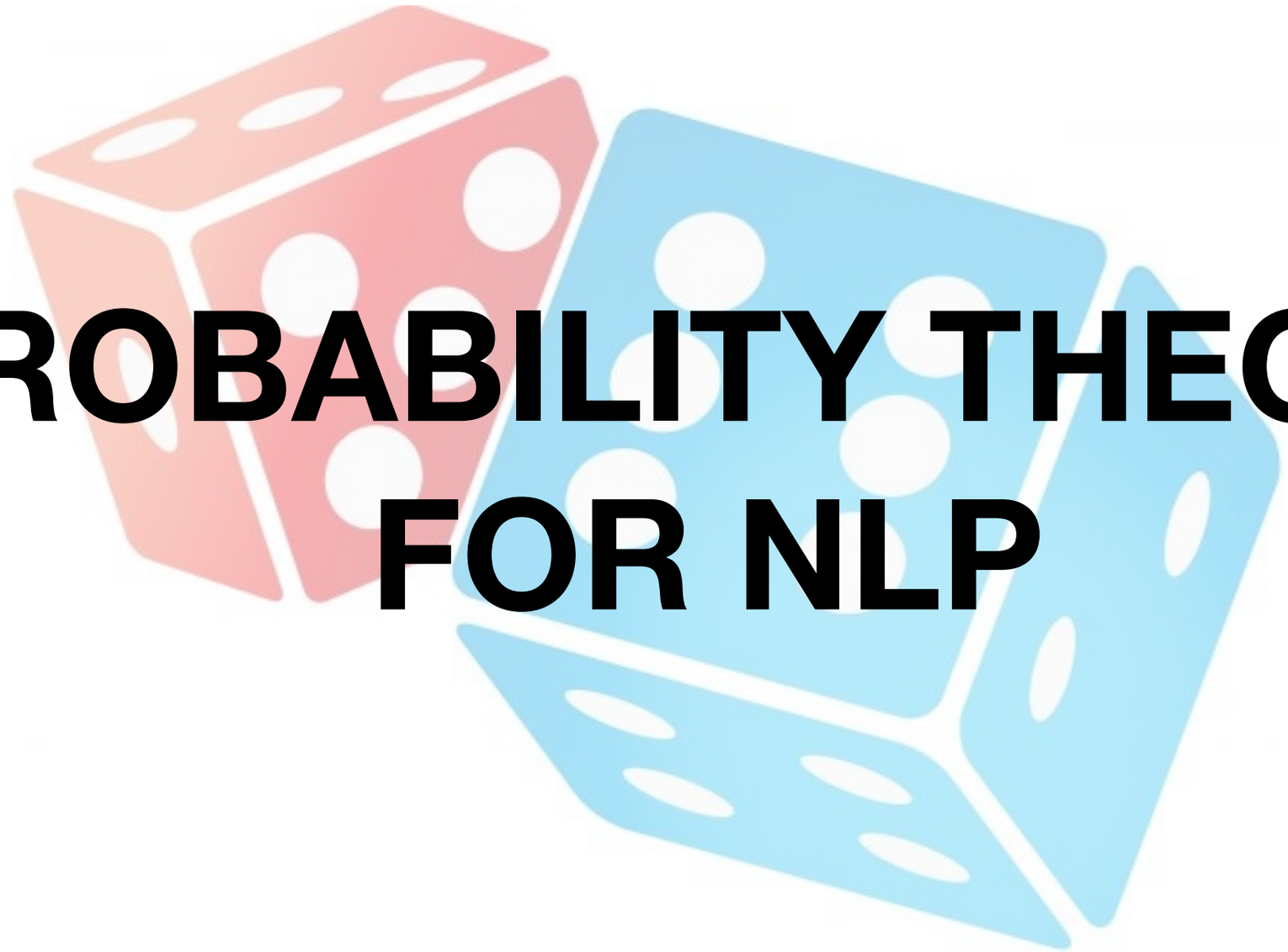

trying
S
VP
VP
to
understand
NP
the
difference

SENTIMENT ANALYSIS

“This movie doesn’t care about cleverness, wit or any other kind of intelligent humor.”



[source: http://nlp.stanford.edu:8080/sentiment/]



PROBABILITY THEORY FOR NLP

ARGMAX/ARGMIN

$$\underset{x}{\operatorname{argmax}}\, f(x)$$

The value(s) of x at which $f(x)$ is at its maximum; e.g.,

$$\underset{x}{\operatorname{argmax}}\, \sin x = \frac{\pi}{2}$$

JOINT PROBABILITY

The probability that two or more random variables each take on certain respective values

$$
\begin{aligned}
p(11) = &= p(\text{red} = 6) \cdot p(\text{blue} = 5) \quad + p(\text{red} = 5) \cdot p(\text{blue} = 6) \\
&= \frac{1}{6} \cdot \frac{1}{6} \quad + \frac{1}{6} \cdot \frac{1}{6} \\
&= \frac{1}{36} \quad + \frac{1}{36} \\
&= \frac{1}{18}
\end{aligned}
$$

CONDITIONAL PROBABILITY

The probability that one or more random variables have a respective value given that one or more *other* random variables have a respective value

$$p(A \mid B) := \frac{p(A \cap B)}{p(B)}$$

$$p(\text{red} = 2) = \frac{1}{6}$$

$$p(\text{red} + \text{blue} \leq 5) = \frac{5}{18}$$

$$p(\text{red} = 2 \mid \text{red} + \text{blue} \leq 5) = ?$$

$$p(\text{red} = 2, \text{red} + \text{blue} \leq 5) = \frac{1}{12}$$

$$p(\text{red} = 2 \mid \text{red} + \text{blue} \leq 5) = \frac{1/12}{5/18} = \frac{3}{10}$$

STATISTICAL INDEPENDENCE

Random variables A, B are independent iff

$$P(A \mid B) = P(A)$$

$$P(B \mid A) = P(B)$$

BAYES' THEOREM

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)}$$

[Source: Wikipedia. It is a crime to talk about Bayes' Theorem without showing this image.]

THE NOISY CHANNEL: WEAVER'S INTUITION

Warren Weaver, 1949 Rockefeller Foundation memorandum *Translation*:

"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."

THE NOISY CHANNEL: FORMAL DEFINITION

Given a ciphertext *ct*, select plaintext *pt* that maximizes the conditional probability of the plaintext

$$\underset{pt}{\operatorname{argmax}}\, p(pt \mid ct)$$

Bayes' theorem allows us to rewrite this as

$$\underset{pt}{\operatorname{argmax}}\, \frac{p(ct \mid pt)\, p(pt)}{p(ct)}$$

The denominator is constant in *ct*, so

$$\frac{p(ct \mid pt)\, p(pt)}{p(ct)} \propto p(ct \mid pt)\, p(pt)$$

Thus we can rewrite the objective as

$$\underset{pt}{\operatorname{argmax}}\, p(pt \mid ct) = \underset{pt}{\operatorname{argmax}}\, p(ct \mid pt)\, p(pt)$$

DATA STRUCTURES FOR CONDITIONAL FREQUENCIES AND PROBABILITIES

REPRESENTING CONDITIONAL PROBABILITIES IN MEMORY

- If the space of outcomes is finite, small, and dense, a square matrix is a possibility ("sparse matrix" packages don't apply here; we're not going to do any linear algebra)
- Represent them as a tuple key to a hashtable (assuming outcomes are immutable, hashable): problems with this?
    - Cannot efficiently convert from conditional frequencies to conditional probabilities
    - Cannot efficiently generate the conditional probabilities for all $a \in A$ once a particular $b \in B$ has been observed

HASHTABLE OF HASHTABLES: NAÏVE

```
>>> def make_cpdf(cdist):
...     cpdf = {}
...     for (a, b, p_a_given_b) in cdist:
...         try:
...             cpdf[b][a] = p_a_given_b
...         except KeyError:
...             cpdf[b] = {a: p_a_given_b}
...     return cpdf
...
>>> def cpdf_get(a, b, cpdf):
...     try:
...         return cpdf[b][a]
...     except KeyError:
...         return 0
```

INTRODUCTING DEFAULTDICT

```
>>> from collections import defaultdict
>>> def inner_fnc():
...     print 'Hello, world!'
...     return 0
...
>>> d = defaultdict(inner_fnc)
>>> x = d['a']
Hello, world!
>>> print x
0
```

HASHTABLE OF HASHTABLES: PYTHONIC

```
>>> from functools import partial
>>> def make_cpdf(cdist):
...     cpdf =
defaultdict(partial(defaultdict, int))
...     for (a, b, p_a_given_b) in cdist:
...         cpdf[b][a] = p_a_given_b
...     return cpdf
...
>>> def cpdf_get(a, b, cpdf):
...     return cpdf[b][a]
```

UNDERFLOW

- Can a computer compute a number smaller than it can represent (i.e., store in memory)?

```
>>> 2 ** -1000
9.332636185032189e-302
>>> 2 ** -2000
0.0
```

- Solution: represent small probabilities as negative log probabilities…enter `BitWeight`