



# Natural Language Processing

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[anoopsarkar.github.io/nlp-class](https://anoopsarkar.github.io/nlp-class)

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Part 1: Probability and Language

## Probability and Language

Quick guide to probability theory

Entropy and Information Theory

# Probability and Language

Assign a probability to an input sequence

Given a URL: choosespain.com. What is this website about?

| Input        | Scoring function |
|--------------|------------------|
| choose spain | -8.35            |
| chooses pain | -9.88            |
| ⋮            | ⋮                |

## The Goal

Find a good **scoring function** for input sequences.

# Scoring Hypotheses in Speech Recognition

## From acoustic signal to candidate transcriptions

| Hypothesis                                   | Score  |
|--|--------|
| the station signs are in deep in english     | -14732 |
| the stations signs are in deep in english    | -14735 |
| the station signs are in deep into english   | -14739 |
| the station 's signs are in deep in english  | -14740 |
| the station signs are in deep in the english | -14741 |
| the station signs are indeed in english      | -14757 |
| the station 's signs are indeed in english   | -14760 |
| the station signs are indians in english     | -14790 |
| the station signs are indian in english      | -14799 |
| the stations signs are indians in english    | -14807 |
| the stations signs are indians and english   | -14815 |

# Scoring Hypotheses in Machine Translation

From source language to target language candidates

| Hypothesis                          | Score  |
|-------------------------------------|--------|
| we must also discuss a vision .     | -29.63 |
| we must also discuss on a vision .  | -31.58 |
| it is also discuss a vision .       | -31.96 |
| we must discuss on greater vision . | -36.09 |
| ⋮                                   | ⋮      |

# Scoring Hypotheses in Decryption

## Character substitutions on ciphertext to plaintext candidates

| Hypothesis                            | Score |
|---------------------------------------|-------|
| Heopaj, zk ukq swjp pk gjks w oaynap? | -93   |
| Urbcnw, mx hxd fjwc cx twxf j bnanc?  | -92   |
| Wtdepy, oz jzf hlye ez vyzh l dpncpe? | -91   |
| Mjtufo, ep zpv xbou up lopx b tfdsfu? | -89   |
| Nkuvgp, fq aqw ycpv vq mpqy c ugetgv? | -87   |
| Gdnozi, yj tjp rvio oj fijr v nzxmzo? | -86   |
| Czjkve, uf pfl nrek kf befn r jvtivk? | -85   |
| Yvfgra, qb lbh jnag gb xabj n frperg? | -84   |
| Zwghsb, rc mci kobh hc ybck o gsqfsh? | -83   |
| Byijud, te oek mqdj je adem q iushuj? | -77   |
| Jgqrcl, bm wms uylr rm ilmu y qcapcr? | -76   |
| Listen, do you want to know a secret? | -25   |

# The Goal

- ▶ Write down a **model** over sequences of words or letters.
- ▶ **Learn** the parameters of the model from data.
- ▶ Use the model to **predict** the probability of new sequences.



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Part 2: Quick guide to probability theory

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# Probability: The Basics

- ▶ Sample space
- ▶ Event space
- ▶ Random variable

# Probability distributions

- ▶  $P(X)$ : probability of random variable  $X$  having a certain value.
  - ▶  $P(X = \text{killer}) = 1.05\text{e-}05$
  - ▶  $P(X = \text{app}) = 1.19\text{e-}05$

## Joint probability

- ▶  $P(X,Y)$ : probability that  $X$  and  $Y$  each have a certain value.
  - ▶ Let  $Y$  stand for choice of a word
  - ▶ Let  $X$  stand for the choice of a word that occurs before  $Y$
  - ▶  $P(X = \text{killer}, Y = \text{app}) = 1.24\text{e-}10$

### Joint Probability: $P(X=\text{value AND } Y=\text{value})$

- ▶ Since  $X=\text{value AND } Y=\text{value}$ , the order does not matter
- ▶  $P(X = \text{killer}, Y = \text{app}) \Leftrightarrow P(Y = \text{app}, X = \text{killer})$
- ▶ In both cases it is  $P(X,Y) = P(Y,X) = P(\text{'killer app'})$
- ▶ In NLP, we often use numerical indices to express this:  
 $P(W_{i-1} = \text{killer}, W_i = \text{app})$

# Joint probability

## Joint probability table

| $W_{i-1}$           | $W_i = \text{app}$ | $P(W_{i-1}, W_i)$ |
|---------------------|--------------------|-------------------|
| $\langle S \rangle$ | app                | 1.16e-19          |
| an                  | app                | 1.76e-08          |
| killer              | app                | 1.24e-10          |
| the                 | app                | 2.68e-07          |
| this                | app                | 3.74e-08          |
| your                | app                | 2.39e-08          |

There will be a similar table for each choice of  $W_i$ .

Get  $P(W_i)$  from  $P(W_{i-1}, W_i)$

$$P(W_i = \text{app}) = \sum_x P(W_{i-1} = x, W_i = \text{app}) = 1.19e - 05$$

## Conditional probability

- ▶  $P(W_i \mid W_{i-1})$ : probability that  $W_i$  has a certain value after fixing value of  $W_{i-1}$ .
- ▶  $P(W_i = \text{app} \mid W_{i-1} = \text{killer})$
- ▶  $P(W_i = \text{app} \mid W_{i-1} = \text{the})$

### Conditional probability from Joint probability

$$P(W_i \mid W_{i-1}) = \frac{P(W_{i-1}, W_i)}{P(W_{i-1})}$$

- ▶  $P(\text{killer}) = 1.05\text{e-}05$
- ▶  $P(\text{killer}, \text{app}) = 1.24\text{e-}10$
- ▶  $P(\text{app} \mid \text{killer}) = 0.0096$
- ▶  $P(\text{the} \mid \text{killer}) = 1.82\text{e-}05$

# Basic Terms

- ▶  $P(e)$  – *a priori* probability or just *prior*
- ▶  $P(f \mid e)$  – *conditional* probability. The chance of  $f$  given  $e$
- ▶  $P(e, f)$  – *joint* probability. The chance of  $e$  and  $f$  both happening.
- ▶ If  $e$  and  $f$  are *independent* then we can write
$$P(e, f) = P(e) \times P(f)$$
- ▶ If  $e$  and  $f$  are not *independent* then we can write
$$P(e, f) = P(e) \times P(f \mid e)$$
$$P(e, f) = P(f) \times ?$$



# Basic Terms

- ▶ Addition of integers:

$$\sum_{i=1}^n i = 1 + 2 + 3 + \dots + n$$

- ▶ Product of integers:

$$\prod_{i=1}^n i = 1 \times 2 \times 3 \times \dots \times n$$

- ▶ Factoring:

$$\sum_{i=1}^n i \times k = k + 2k + 3k + \dots + nk = k \sum_{i=1}^n i$$

- ▶ Product with constant:

$$\prod_{i=1}^n i \times k = 1k \times 2k \dots \times nk = k^n \times \prod_{i=1}^n i$$

# Probability: Axioms

- ▶  $P$  measures total probability of a set of events
- ▶  $P(\emptyset) = 0$
- ▶  $P(\text{all events}) = 1$
- ▶  $P(X) \leq P(Y)$  for any  $X \subseteq Y$
- ▶  $P(X) + P(Y) = P(X \cup Y)$  provided that  $X \cap Y = \emptyset$

# Probability Axioms

- ▶ All events sum to 1:

$$\sum_e P(e) = 1$$

- ▶ Marginal probability  $P(f)$ :

$$P(f) = \sum_e P(e, f)$$

- ▶ Conditional probability:

$$\sum_e P(e \mid f) = \sum_e \frac{P(e, f)}{P(f)} = \frac{1}{P(f)} \sum_e P(e, f) = 1$$

- ▶ Computing  $P(f)$  from axioms:

$$P(f) = \sum_e P(e) \times P(f \mid e)$$

# Probability: The Chain Rule

- ▶  $P(a, b, c, d \mid e)$
- ▶ We cannot simply remove items from the left of  $|$  (verify that it violates the definitions we have given based on sets)
- ▶ In this case we can use the chain rule of probability to rescue us
- ▶  $P(a, b, c, d \mid e) = P(d \mid e) \cdot P(c \mid d, e) \cdot P(b \mid c, d, e) \cdot P(a \mid b, c, d, e)$
- ▶ To see why this is possible, recall that  $P(X \mid Y) = \frac{p(X, Y)}{p(Y)}$ 
  - ▶  $\frac{p(a, b, c, d, e)}{p(e)} = \frac{p(d, e)}{p(e)} \cdot \frac{p(c, d, e)}{p(d, e)} \cdot \frac{p(b, c, d, e)}{p(c, d, e)} \cdot \frac{p(a, b, c, d, e)}{p(b, c, d, e)}$
- ▶ Use chain rule and simplify:

$$P(a, b, c, d \mid e) = P(d \mid e) \cdot P(c \mid d, e) \cdot P(b \mid c, e) \cdot P(a \mid b, e)$$

## Probability: The Chain Rule

►  $P(e_1, e_2, \dots, e_n) = P(e_1) \times P(e_2 \mid e_1) \times P(e_3 \mid e_1, e_2) \dots$

$$P(e_1, e_2, \dots, e_n) = \prod_{i=1}^n P(e_i \mid e_{i-1}, e_{i-2}, \dots, e_1)$$

# Probability: Random Variables and Events

- ▶ What is  $y$  in  $P(y)$  ?
- ▶ Shorthand for value assigned to a random variable  $Y$ , e.g.  
 $Y = y$
- ▶  $y$  is an element of some implicit **event space**:  $\mathcal{E}$

# Probability: Random Variables and Events

- ▶ The *marginal probability*  $P(y)$  can be computed from  $P(x, y)$  as follows:

$$P(y) = \sum_{x \in \mathcal{E}} P(x, y)$$

- ▶ Finding the value that maximizes the probability value:

$$\hat{x} = \arg \max_{x \in \mathcal{E}} P(x)$$

# Log Probability Arithmetic

- ▶ Practical problem with tiny  $P(e)$  numbers: underflow
- ▶ One solution is to use log probabilities:

$$\begin{aligned}\log(P(e)) &= \log(p_1 \times p_2 \times \dots \times p_n) \\ &= \log(p_1) + \log(p_2) + \dots + \log(p_n)\end{aligned}$$

- ▶ Note that:

$$x = \exp(\log(x))$$

- ▶ Also more efficient: addition instead of multiplication



# Log Probability Arithmetic

| $p$ | $\log(p)$ |
|-----|-----------|
| 0.0 | $-\infty$ |
| 0.1 | -3.32     |
| 0.2 | -2.32     |
| 0.3 | -1.74     |
| 0.4 | -1.32     |
| 0.5 | -1.00     |
| 0.6 | -0.74     |
| 0.7 | -0.51     |
| 0.8 | -0.32     |
| 0.9 | -0.15     |
| 1.0 | 0.00      |

# Log Probability Arithmetic

- ▶ So:  $(0.5 \times 0.5 \times \dots 0.5) = (0.5)^n$  might get too small but  $(-1 - 1 - 1 - 1) = -n$  is manageable
- ▶ Another useful fact when writing code ( $\log_2$  is *log to the base 2*):

$$\log_2(x) = \frac{\log_{10}(x)}{\log_{10}(2)}$$

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Part 3: Entropy and Information Theory

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# Information Theory

- ▶ Information theory is the use of probability theory to quantify and measure “information”.
- ▶ Consider the task of efficiently sending a message. Sender Alice wants to send several messages to Receiver Bob. Alice wants to do this as efficiently as possible.
- ▶ Let's say that Alice is sending a message where the entire message is just one character  $a$ , e.g.  $aaaa\dots$ . In this case we can save space by simply sending the length of the message and the single character.

# Information Theory

- ▶ Now let's say that Alice is sending a completely random signal to Bob. If it is random then we cannot exploit anything in the message to compress it any further.
- ▶ The *expected* number of bits it takes to transmit some infinite set of messages is what is called entropy.
- ▶ This formulation of entropy by Claude Shannon was adapted from thermodynamics, converting information into a quantity that can be measured.
- ▶ Information theory is built around this notion of message compression as a way to evaluate the amount of information.

# Expectation

- ▶ For a probability distribution  $p$
- ▶ **Expectation** with respect to  $p$  is a weighted average:

$$\begin{aligned} E_p[x] &= \frac{x_1 \cdot p_1 + x_2 \cdot p_2 + \dots + x_n p_n}{p_1 + p_2 + \dots + p_n} \\ &= x_1 \cdot p_1 + x_2 \cdot p_2 + \dots + x_n p_n \\ &= \sum_{x \in \mathcal{E}} x \cdot p(x) \end{aligned}$$

- ▶ Example: for a six-sided die the expectation is:

$$E_p[x] = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 6 \cdot \frac{1}{6} = 3.5$$

# Entropy

- ▶ For a probability distribution  $p$
- ▶ **Entropy** of  $p$  is:

$$H(p) = - \sum_{x \in \mathcal{E}} p(x) \cdot \log_2 p(x)$$

- ▶ Any base can be used for the log, but base 2 means that entropy is measured in bits.
- ▶ What is the *expected* number of bits with respect to  $p$ :

$$-E_p[\log_2 p(x)] = H(p)$$

- ▶ Entropy answers the question: *What is the expected number of bits needed to transmit messages from event space  $\mathcal{E}$ , where  $p(x)$  defines the probability of observing  $x$ ?*



# Entropy

- ▶ Alice wants to bet on a horse race. She has to send a message to her bookie Bob to tell him which horse to bet on.
- ▶ There are 8 horses. One encoding scheme for the messages is to use a number for each horse. So in bits this would be 001, 010, ...  
(lower bound on message length = 3 bits in this encoding scheme)
- ▶ Can we do better?

# Entropy

|         |                |         |                |
|---------|----------------|---------|----------------|
| Horse 1 | $\frac{1}{2}$  | Horse 5 | $\frac{1}{64}$ |
| Horse 2 | $\frac{1}{4}$  | Horse 6 | $\frac{1}{64}$ |
| Horse 3 | $\frac{1}{8}$  | Horse 7 | $\frac{1}{64}$ |
| Horse 4 | $\frac{1}{16}$ | Horse 8 | $\frac{1}{64}$ |

- ▶ If we know how likely we are to bet on each horse, say based on the horse's probability of winning, then we can do better.
- ▶ Let  $p$  be the probability distribution given in the table above. The entropy of  $p$  is  $H(p)$

# Entropy

$$\begin{aligned}H(p) &= \\&= - \sum_{i=1}^8 p(i) \log_2 p(i) \\&= - \left( \frac{1}{2} \log_2 \frac{1}{2} + \frac{1}{4} \log_2 \frac{1}{4} + \frac{1}{8} \log_2 \frac{1}{8} + \frac{1}{16} \log_2 \frac{1}{16} + 4 \left( \frac{1}{64} \log_2 \frac{1}{64} \right) \right) \\&= - \left( \frac{1}{2} \times -1 + \frac{1}{4} \times -2 + \frac{1}{8} \times -3 + \frac{1}{16} \times -4 + 4 \left( \frac{1}{64} \times -6 \right) \right) \\&= - \left( -\frac{1}{2} - \frac{1}{2} - \frac{3}{8} - \frac{1}{4} - \frac{3}{8} \right) \\&= 2 \text{ bits}\end{aligned}$$

- What is the entropy when the horses are equally likely to win?

$$H(\text{uniform distribution}) = -8 \left( \frac{1}{8} \times -3 \right) = 3 \text{ bits}$$

# Entropy

- ▶ e.g., most likely horse gets code 0, next most likely gets 10, and then 110, 1110, ...  
many possible coding schemes, this is a simple code to illustrate number of bits needed for a large number of messages ...
- ▶ Assume there are 320 messages (one for each race):  
code 0 occurs 160 times, code 10 occurs 80 times, code 110 occurs 40 times, code 1110 occurs 20 times, code 11110 occurs 5 times.
- ▶ Total number of bits for all messages:  $160 \cdot \text{len}(0) + 80 \cdot \text{len}(10) + 40 \cdot \text{len}(110) + 20 \cdot \text{len}(1110) + 5 \cdot \text{len}(11110)$
- ▶ Number of bits:  $160 \cdot 1 + 80 \cdot 2 + 40 \cdot 3 + 20 \cdot 4 + 5 \cdot 5 = 545$
- ▶ Total number of bits per message (per race):  $\frac{545}{320} \approx 1.7$  bits  
(always less than 2 bits)

# Perplexity

- ▶ The value  $2^{H(p)}$  is called the **perplexity** of a distribution  $p$
- ▶ Perplexity is the weighted average number of choices a random variable has to make.
- ▶ Choosing between 8 equally likely horses ( $H=3$ ) is  $2^3 = 8$ .
- ▶ Choosing between the biased horses from before ( $H=2$ ) is  $2^2 = 4$ .

# Relative Entropy

- ▶ In real life, we cannot know for sure the exact winning probability for each horse.
- ▶ Let's say  $q$  is the estimate and  $p$  is the true probability (say we got  $q$  by observing previous races with these horses)
- ▶ We define the *distance* between  $p$  and  $q$  as the **relative entropy**: written as  $D(p\|q)$

$$D(p\|q) = - \sum_{x \in \mathcal{E}} p(x) \log_2 \frac{p(x)}{q(x)}$$

- ▶ Note that

$$D(p\|q) = -E_{p(x)} \left[ \log_2 \frac{p(x)}{q(x)} \right]$$

- ▶ The relative entropy is also called the *Kullback-Leibler divergence*.

# Cross Entropy and Relative Entropy

- ▶ The **relative entropy** can be written as the sum of two terms:

$$\begin{aligned} D(p\|q) &= - \sum_{x \in \mathcal{E}} p(x) \log_2 \frac{p(x)}{q(x)} \\ &= - \sum_x p(x) \log_2 q(x) + \sum_x p(x) \log_2 p(x) \end{aligned}$$

- ▶ We know that  $H(p) = - \sum_x p(x) \log_2 p(x)$
- ▶ Similarly define  $H(p, q) = - \sum_x p(x) \log_2 q(x)$

$$\begin{aligned} D(p\|q) &= H(p, q) - H(p) \\ \text{relative entropy}(p, q) &= \text{cross entropy}(p, q) - \text{entropy}(p) \end{aligned}$$

- ▶ The term  $H(p, q)$  is called the **cross entropy**.

# Cross Entropy and Relative Entropy

- ▶  $H(p, q) \geq H(p)$  always.
- ▶  $D(p\|q) \geq 0$  always, and  $D(p\|q) = 0$  iff  $p = q$
- ▶  $D(p\|q)$  is not a true distance:
  - ▶ It is asymmetric:  $D(p\|q) \neq D(q\|p)$ ,
  - ▶ It does not obey the triangle inequality:  
 $D(p\|q) \not\leq D(p\|r) + D(r\|q)$



# Conditional Entropy and Mutual Information

- ▶ *Entropy* of a random variable  $X$ :

$$H(X) = - \sum_{x \in \mathcal{E}} p(x) \log_2 p(x)$$

- ▶ *Conditional Entropy* between two random variables  $X$  and  $Y$ :

$$H(X | Y) = - \sum_{x, y \in \mathcal{E}} p(x, y) \log_2 p(x | y)$$

- ▶ *Mutual Information* between two random variables  $X$  and  $Y$ :

$$I(X; Y) = D(p(x, y) \| p(x)p(y)) = \sum_x \sum_y p(x, y) \log_2 \frac{p(x, y)}{p(x)p(y)}$$

## Log Probability Arithmetic

```
// In Python: use numpy.logaddexp2(x1,x2) for base 2
// computes log(a + b) given log(a) and log(b)
double logadd(double lna, double lnb)
{
    if (lna == 1.0) return lnb;
    if (lnb == 1.0) return lna;
    double diff = lna - lnb;
    // 500 is log of large constant
    if (diff < 500.0)
        return log1p(exp(diff)) + lnb;
        // log1p(x) computes log(1+x)
    else
        return lna;
}
```

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