



Natural Language Processing

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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

Probability and Language

Quick guide to probability theory

Entropy and Information Theory

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:

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

- ▶ Computing $P(f)$ from axioms:

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

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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Entropy and Information Theory

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 $D(p\|q)$

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

- ▶ Note that

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

- ▶ 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:

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

- ▶ 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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