Cross Entropy

PA154 Jazykové modelování (2.1)

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March 9, 2021

Source: Introduction to Natural Language Processing (600.465)
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“Coding” Interpretation of Entropy

- The least (average) number of bits needed to encode a message (string, sequence, series, ...) (each element having being a result of a random process with some distribution p): $= H(p)$
- Remember various compressing algorithms?
  - they do well on data with repeating (= easily predictable = = low entropy) patterns
  - their results though have high entropy $\Rightarrow$ compressing compressed data does nothing

Coding: Example

- How many bits do we need for ISO Latin 1?
  - $\Rightarrow$ the trivial answer: 8
- Experience: some chars are more common, some (very) rare:
  - ...so what if we use more bits for the rare, and less bits for the frequent? (be careful: want to decode (easily)!)
  - suppose: p('a') = 0.3, p('b') = 0.3, p('c') = 0.3, the rest: p(x)$\cong$.0004
  - code: 'a' $\sim$ 00, 'b' $\sim$ 01, 'c' $\sim$ 10, rest: $11 b_1 b_2 b_3 b_4 b_5 b_6 b_7 b_8$
  - code 'acbbécbaac':

00	10	01	01	<u>1100001111</u>	10	01	00	00	10
a	c	b	b	é	c	b	a	a	c

  - number of bits used: 28 (vs. 80 using "naive" coding)
- code length $\sim -log(probability)$

Entropy of Language

- Imagine that we produce the next letter using

$$p(l_{n+1}|l_1, \dots l_n),$$

  where $l_1, \dots l_n$ is the sequence of **all** the letters which had been uttered so far (i.e. n is really big!); let's call $l_1, \dots l_n$ the **history** $h(h_{n+1})$, and all histories H:
- Then compute its entropy:
  - $-\sum_{h \in H} \sum_{l \in A} p(l, h) \log_2 p(l|h)$
- Not very practical, isn't it?

Cross-Entropy

- Typical case: we've got series of observations $T = \{t_1, t_2, t_3, t_4, \ldots, t_n\}$ (numbers, words, ...; $t_1 \in \Omega$); estimate (sample): $\forall y \in \Omega : \tilde{p}(y) = \dfrac{c(y)}{|T|}$,
  def. $c(y) = |\{t \in T; t = y\}|$
- ... but the true p is unknown; every sample is too small!
- Natural question: how well do we do using $\tilde{p}$ (instead of p)?
- Idea: simulate actual p by using a different T (or rather: by using different observation we simulate the insufficiency of T vs. some other data ("random" difference))

Cross Entropy: The Formula

- $H_{p'}(\tilde{p}) = H(p') + D(p'||\tilde{p})$

$$\boxed{H_{p'}(\tilde{p}) = -\sum_{x\in\Omega} p'(x)\log_2 \tilde{p}(x)}$$

- p' is certainly not the true p, but we can consider it the "real world" distribution against which we test $\tilde{p}$
- note on notation (confusing . . .): $\frac{p}{p'} \leftrightarrow \tilde{p}$, also $H_{T'}(p)$
- (Cross)Perplexity: $G_{p'}(p) = G_{T'}(p) = 2^{H_{p'}(\tilde{p})}$

Conditional Cross Entropy

- So far: "unconditional" distribution(s) $p(x), p'(x)\ldots$
- In practice: virtually always conditioning on context
- Interested in: sample space Ψ, r.v. Y, $y \in \Psi$;
  context: sample space Ω, r.v.X, $x \in \Omega$:
  "our" distribution $p(y|x)$, test against $p'(y,x)$, which is taken from some independent data:

$$H_{p'}(p) = -\sum_{y \in \Psi, x \in \Omega} p'(y,x) \log_2 p(y|x)$$

Sample Space vs. Data

- In practice, it is often inconvenient to sum over the space(s) Ψ, Ω (especially for cross entropy!)
- Use the following formula: $H_{p'}(p) = -\sum_{y \in \Psi, x \in \Omega} p'(y,x) \log_2 p(y|x) = -1/|T'| \sum_{i=1 \ldots |T'|} \log_2 p(y_i|x_i)$
- This is in fact the normalized log probability of the "test" data:

$$H_{p'}(p) = -1/|T'| log_2 \prod_{i=1 \ldots |T'|} p(y_i|x_i)$$

Computation Example

- $\Omega = \{a, b, .., z\}$, prob. distribution (assumed/estimated from data): p(a) = .25, p(b) = .5, p(α) = $\frac{1}{64}$ for $\alpha \in \{c..r\}$, p(α)= 0 for the rest: s,t,u,v,w,x,y,z
- Data (test): <u>barb</u> p'(a) = p'(r) = .25, p'(b) = .5
- Sum over Ω:

α	**a b c d e f g ... p q r s t ... z**
$-p'(\alpha)\log_2 p(\alpha)$	**.5+.5+0+0+0+0+0+0+0+0+0+1.5+0+0+0+0+0 = 2 .**

- Sum over data:

i / s_i	**1/b**		**2/a**		**3/r**		**4/b**		$1/\lvert T'\rvert$	
$-\log_2 p(s_i)$	**1**	**+**	**2**	**+**	**6**	**+**	**1**	**= 10**	**(1/4) × 10**	**= 2 .**

Cross Entropy: Some Observations

- $H(p)$??$<, =, >$?? $H_{p'}(p)$: ALL!
- Previous example:

  p(a) = .25, p(b) = .5, p(α)= $\frac{1}{64}$ for $\alpha \in \{c..r\}$, = 0 for the rest: s,t,u,v,w,x,y,z

$$H(p) = 2.5 bits = H(p')(\underline{barb})$$

- Other data: <u>probable</u>: $(\frac{1}{8})(6+6+6+1+2+1+6+6) = 4.25$

$$H(p) < 4.25 bits = H(p')(\underline{probable})$$

- And finally: <u>abba</u>: $(\frac{1}{4})(2+1+1+2) = 1.5$

$$H(p) > 1.5 bits = H(p')(\underline{abba})$$

- But what about: <u>baby</u> $-p'(`y`)\log_2 p(`y`) = -.25\log_2 0 = \infty$ (??)

Cross Entropy: Usage

- Comparing data??
  - NO! (we believe that we test on **real** data!)
- Rather: comparing distributions (**vs.** real data)
- Have (got) 2 distributions: p and q (on some Ω, X)
  - which is better?
  - better: has lower cross-entropy (perplexity) on real data S
- "Real" data: S

$$H_S(p) = -1/|S| \sum_{i=1..|S|} log_2 p(y_i|x_i) \;\; ?? \;\; H_S(q) = -1/|S| \sum_{i=1..|S|} log_2 q(y_i|x_i)$$

Comparing Distributions

- $p(.)$ from previous example: $\boxed{H_S(p) = 4.25}$

  p(a) = .25, p(b) = .5, p(α) = $\frac{1}{64}$ for $\alpha \in \{c..r\}$, = 0 for the rest: s,t,u,v,w,x,y,z

- $q(.|.)$ (conditional; defined by a table):

q(.|.)→ ↓	a	b	e	l	o	p	r	other
a	0	.5	0	0	0	.125	0	0
b	1	0	0	0	1	.125	0	0
e	0	0	0	1	0	.125	0	0
l	0	.5	0	0	0	.125	0	0
o	0	0	0	0	0	.125	1	0
p	0	0	0	0	0	.125	0	1
r	0	0	0	0	0	.125	0	0
other	0	0	1	0	0	.125	0	0

ex.: q(o|r) = 1

q(r|p) = .125

(1/8) (log(p|oth.)+log(r|p)+log(o|r)+log(b|o)+log(a|b)+log(b|a)+log(l|b)+log(e|l))

(1/8) (0 + 3 + 0 + 0 + 1 + 0 + 1 + 0)

$\boxed{H_S(q) = .625}$