NLP 1 - Assignment 4

Selene Baez Santamaria

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Exercise 1. PMI

- (a) For each example, explain what P(x,y) represents.
 - P(x,y) represents the probability of the bi-gram "eat pizza".
 - P(x,y) represents the probability of a Tweet containing "happy" and "pizza".
- (b) What do negative, zero and positive PMI's mean? Defining PMI as $\log_2(r)$ where $r = \frac{P(x,y)}{P(x)P(y)} = \frac{P(x|y)}{P(x)} = \frac{P(y|x)}{P(y)}$
 - If PMI $< 0 \rightarrow r < 1 \rightarrow P(x,y) < P(x)P(y)$. This means that the actual co-occurrence probability is less than their predicted co-occurrence probability if they were independent. Therefore, lower PMIs correspond to co-occurrences that are less likely. Example: "he you" has a low association and is very unlikely to co-occur.
 - If PMI = $0 \to r = 1 \to P(x, y) = P(x)P(y)$. This means that the two events are statistically independent.
 - If PMI > $0 \to r > 1 \to P(x,y) > P(x)P(y)$. This means that the actual co-occurrence probability is higher than their predicted co-occurrence probability if they were independent. Therefore, higher PMIs correspond to co-occurrences that are more likely. Example: "New York" has a high association and is very likely to co-occur.

Exercise 2. MaxEnt

(a) Simplified expression for $\log P(y|\vec{x})$

$$\log P(y|\vec{x}) = \log \frac{exp(\sum_{1} w_{i} f_{i}(\vec{x}, y))}{\sum_{y'} exp(\sum_{1} w_{i} f_{i}(\vec{x}, y')))}$$

$$= \log exp(\sum_{1} w_{i} f_{i}(\vec{x}, y)) - \log \sum_{y'} exp(\sum_{1} w_{i} f_{i}(\vec{x}, y')))$$

$$= \sum_{1} w_{i} f_{i}(\vec{x}, y) - C = \vec{w} \cdot \vec{f} - C$$

The end result is a linear function of the feature vector.

(b) Which sense is the most probable?

For y = 1, features 1 and 7 are active

$$p(y=1|\vec{x}) = \frac{\exp(2.0 - 0.1)}{\exp(2.0 - 0.1) + \exp(1.8 + 1.1) + \exp(0.3 + 2.7)}$$
(1)

$$= \frac{\exp(1.9)}{\exp(1.9) + \exp(2.9) + \exp(3)} \tag{2}$$

$$=\frac{6.685}{44.945} = 0.149\tag{3}$$

For y = 2, features 2 and 8 are active

$$p(y=1|\vec{x}) = \frac{\exp(2.9)}{\exp(1.9) + \exp(2.9) + \exp(3)} \tag{4}$$

$$=\frac{18.174}{44.945} = 0.404\tag{5}$$

For y = 3, features 3 and 9 are active

$$p(y=1|\vec{x}) = \frac{\exp(3)}{\exp(1.9) + \exp(2.9) + \exp(3)}$$
 (6)

$$=\frac{20.085}{44.945} = 0.447\tag{7}$$

Hence, y=3 = Noun: a factory is the most probable.

Exercise 3. FOL to Natural language

- (a) "Every bear is furry."
- (b) "Jan helps Joost"
- (c) "Sergii eats pizza"
- (d) "Sergii eats pizza with a fork"
- (e) "Every student lifts Marie, but not necessarily together"
- (f) "All students lift Marie, together"

Exercise 4. Natural language to FOL

- (a) $\exists e.x. \ hating(e) \land pasta(x) \land hater(e, Juan) \land hatee(e, x)$
- (b) $\exists x. \; Student(x) \land \forall (y) Class(y) \land \exists e. \; liking(e) \land liker(e, x) \land likee(e, y)$
- (c) $\exists e.x. \ seeing(e) \land seer(e, Marie) \land seen(e, Marie)$

Exercise 5. Grammar with semantic attachments

(a) Whiskers likes Sam

Rule applied	Result
$S \to NPVP$	VP.sem(NP.sem)
$VP \rightarrow V_t NP$	$V_t.sem(NP.sem)(NP.sem)$
$NP \to N$	$V_t.sem(N.sem)(NP.sem)$
$NP \to N$	$V_t.sem(N.sem)(N.sem)$
$V_t \to likes$	$\lambda x. \lambda y. (\exists e. \ Liking(e) \land Liker(e, y) \land Likee(e, x)) (N.sem)(N.sem)$
$N \to Sam$	$\lambda x. \lambda y. (\exists e. \ Liking(e) \land Liker(e, y) \land Likee(e, x)) (Sam)(N.sem)$
$N \rightarrow Whiskers$	$\lambda x. \lambda y. (\exists e. \ Liking(e) \land Liker(e, y) \land Likee(e, x)) (Sam)(Whiskers)$

(b) A cat meows

The MR is: $\lambda x. (\exists e. Meowing(e) \land Meower(e, x))$

We face the problem that we cannot specify that x must be a cat. We solve it by adding these rules:

• $NP \to DetN$ $\lambda x. (\exists x. Cat(x))$ • $N \to Cat$ $\lambda x. Cat(x)$ • $V_i \to meows$ $\lambda x. (\exists (e) Meowing(e) \land Meower(e, x) \land Cat(x))$

Exercise 6. IBM Model

- (a) Assumptions:
 - Independence?