Dialogue Classifying

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1 Measures

1.1 Cosine Distance

$$cs(P||Q) = \frac{\sum\limits_{i=1}^{n} p_i q_i}{\sqrt{\sum\limits_{i=1}^{n} p_i^2 \sum\limits_{i=1}^{n} q_i^2}} \tag{1}$$

$$cd(P||Q) = 1 - cs(P, Q) \tag{2}$$

1.2 Kullback-Leibler Divergence

Pre-condition: $\sum\limits_{i=1}^{n} p_i = 1$ and $\sum\limits_{i=1}^{n} q_i = 1$

$$kl(P||Q) = \sum_{i=1}^{n} p_i \ln\left(\frac{p_i}{q_i}\right) \tag{3}$$

1.3 Mean Kullback-Leibler Distance

Pre-condition: $\sum\limits_{i=1}^{n} p_i = 1$ and $\sum\limits_{i=1}^{n} q_i = 1$

$$mkl(P||Q) = \frac{kl(P||Q) + kl(Q||P)}{2} \tag{4}$$

1.4 Symmetric Kullback-Leibler Distance

Pre-condition: $\sum\limits_{i=1}^{n} p_i = 1$ and $\sum\limits_{i=1}^{n} q_i = 1$

$$skl(P||Q) = \sum_{i=1}^{n} (p_i - q_i) \ln\left(\frac{p_i}{q_i}\right) \tag{5}$$

$$skl(P||Q) = skl(Q||P) \tag{6}$$

Proof.

$$
\begin{aligned}
skl(P||Q) &= \sum_{i=1}^{n} (p_i - q_i) \ln \left(\frac{p_i}{q_i} \right) \\
&= \sum_{i=1}^{n} (p_i - q_i)(\ln(p_i) - \ln(q_i)) \\
&= \sum_{i=1}^{n} - (q_i - p_i)(\ln(p_i) - \ln(q_i)) \\
&= \sum_{i=1}^{n} (q_i - p_i)(\ln(q_i) - \ln(p_i)) \\
&= \sum_{i=1}^{n} (q_i - p_i) \ln \left(\frac{q_i}{p_i} \right) \\
&= skl(Q||P)
\end{aligned}
$$

□

1.5 Proportionality of Mean and Symmetric Kullback-Leibler Distance

$$2 * mkl(P||Q) = skl(P||Q) \tag{7}$$

Proof of Equation 7.

$$
\begin{aligned}
2 * mkl((P||Q) &= kl(P||Q) + kl(Q||P) && \text{see Equation 4 and 3} \\
&= \sum_{i=1}^{n} p_i \ln\left(\frac{p_i}{q_i}\right) + \sum_{i=1}^{n} q_i \ln\left(\frac{q_i}{p_i}\right) \\
&= \sum_{i=1}^{n} p_i \ln\left(\frac{p_i}{q_i}\right) + q_i \ln\left(\frac{q_i}{p_i}\right) \\
&= \sum_{i=1}^{n} p_i(\ln(p_i) - \ln(q_i)) + q_i(\ln(q_i) - \ln(p_i)) \\
&= \sum_{i=1}^{n} p_i(\ln(p_i) - \ln(q_i)) - q_i(\ln(p_i) - \ln(q_i)) \\
&= \sum_{i=1}^{n} (p_i - q_i)(\ln(p_i) - ln(q_i)) \\
&= \sum_{i=1}^{n} (p_i - q_i) \ln\left(\frac{p_i}{q_i}\right) \\
&= skl(P||Q) && \text{Equation 5}
\end{aligned}
$$

□

1.6 Jensen Difference Divergence

Pre-condition: $\sum_{i=1}^{n} p_i = 1$ and $\sum_{i=1}^{n} q_i = 1$

$$
j(P||Q) = \sum_{i=1}^{n} \frac{p_i \ln(p_i) + q_i \ln(q_i)}{2} - \frac{p_i + q_i}{2} \ln\left(\frac{p_i + q_i}{2}\right) \tag{8}
$$

2 N-gram model

2.1 Additive Smoothing

$$
p_\lambda(x_i) = \frac{|x_i| + \lambda}{|X| + \lambda N} \tag{9}
$$

In Equitation 9 is $p_\lambda(x_i)$ the probabiloty of n-gram x_i in model m. $|x_i|$ is the number of occurrences of x_i in m and $|X|$ the absolute number of all n-grams in m. Finally, N represents the number of *unique* n-grams in m.