

## 第七章：语言模型 作业讲评



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- 第一部分：SRILM
- 第二部分：插值语言模型公式推导
- 第三部分：哥大E6870

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- Kaldi中包含了SRILM工具，无需额外下载
  - 使用-help查看工具提供的各个可选参数

## ●数据准备

## ●生成ARPA语言模型（参考实现）：

`ngram-count -text 训练文本 -order 3 -limit-vocab -vocab 词典 -unk  
-map-unk "<SPOKEN_NOISE>" -wbdiscout -interpolate -lm 语言模型文件`

## ●计算PPL（参考实现）：

`Ngram -ppl 测试文本 -order 3 -lm 语言模型文件`

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# 插值语言模型公式推导

插值平滑的递归形式:

递归至一元  $P(w_i) \xrightarrow{ML}$   
uniform

$$P_{interp}(w_i | w_{i-N+1}^{i-1}) = \lambda_{w_{i-N+1}^{i-1}} P_{ML}(w_i | w_{i-N+1}^{i-1}) + (1 - \lambda_{w_{i-N+1}^{i-1}}) P_{interp}(w_i | w_{i-N+2}^{i-1})$$

$\lambda_{w_{i-N+1}^{i-1}}$   $N$ 元       $P_{ML}(w_i | w_{i-N+1}^{i-1})$   $N$ 元       $P_{interp}(w_i | w_{i-N+2}^{i-1})$   $N-1$ 元

更新公式: held-out 集合上更新  $\lambda$ . train

① E步: expected count

$$E(\lambda_{w_{i-N+1}^{i-1}}) = \sum_{w_i} c(w_i | w_{i-N+1}^{i-1}) \frac{\lambda_{w_{i-N+1}^{i-1}} * P_{ML}(w_i | w_{i-N+1}^{i-1})}{\lambda_{w_{i-N+1}^{i-1}} P_{ML}(w_i | w_{i-N+1}^{i-1}) + (1 - \lambda_{w_{i-N+1}^{i-1}}) P_{interp}(w_i | w_{i-N+2}^{i-1})}$$

$c(w_i | w_{i-N+1}^{i-1})$  长为  $N$  的字符串在 dev 出现的次数

② M步

$$\lambda_{w_{i-N+1}^{i-1}} = \frac{E(\lambda_{w_{i-N+1}^{i-1}})}{\sum_{j=1}^N E(\lambda_{w_{i-N+j}^{i-1}})} \quad \sum \lambda = 1$$

更新至  $|\lambda - \tilde{\lambda}| < \epsilon$  或 steps 数  $> n$ . stop.

# 插值语言模型公式推导

设Held-Samuel S,  $w \in S$  为句法,  $w_i$  为词Tword.  
 为符号方便起, 记为  $w_i, i=1 \dots N$  包含S中所有词  
 简记历史信息为  $h_i$   
 插值模型  $P(w_i | h_i; \lambda) = \sum_{k=1}^K \lambda_k P_k(w_i | h_i)$   
 $\lambda$  表示参数,  $P_k$  为  $P_k(w_i | h_i)$  即  $k$  的概率  
 $L(\lambda; S) = \prod_{w_i \in S} P(w_i | h_i; \lambda)$   
 记  $y_{ik} = \begin{cases} 1, & \text{第 } i \text{ 词来自第 } k \text{ 模型} \\ 0, & \text{otherwise} \end{cases}$   
 $P(S, \gamma | \lambda) = \prod_{i=1}^N P(w_i, y_{i1} \dots y_{iK} | h_i, \lambda)$   
 $= \prod_{i=1}^N \prod_{k=1}^K [\lambda_k P_k(w_i | h_i)]^{y_{ik}}$   
 $= \prod_{k=1}^K \lambda_k^{\sum_{i=1}^N y_{ik}} \prod_{i=1}^N [P_k(w_i | h_i)]^{y_{ik}}$   
 $\log P(S, \gamma | \lambda) = \sum_{k=1}^K (\sum_{i=1}^N y_{ik}) \log \lambda_k + \sum_{i=1}^N \sum_{k=1}^K y_{ik} \log P_k(w_i | h_i)$   
 $\theta(\lambda, \lambda^{(0)}) = E[\log P(S, \gamma | \lambda) | S, \lambda^{(0)}]$   
 $= \sum_{k=1}^K \sum_{i=1}^N E[y_{ik}] \log \lambda_k + \dots (\text{与 } \lambda \text{ 无关})$   
 $E[y_{ik} | w_i, \lambda^{(0)}] = P(y_{ik}=1 | w_i, \lambda^{(0)})$   
 $= \frac{P(w_i | y_{ik}=1, \lambda^{(0)}) P(y_{ik}=1 | \lambda^{(0)})}{\sum_{k=1}^K P(w_i | y_{ik}=1, \lambda^{(0)}) P(y_{ik}=1 | \lambda^{(0)})}$   
 $= \frac{\lambda_k P_k(w_i | h_i)}{\sum_{k=1}^K \lambda_k P_k(w_i | h_i)}$

$$\theta^{(1)} = \arg \max_{\theta} Q(\theta, \theta^{(0)})$$

$$\frac{\partial \theta(\lambda, \lambda^{(0)})}{\partial \lambda_k} = \frac{\sum_{i=1}^N y_{ik}}{N}$$

$$= \frac{1}{N} \sum_{w \in S} \sum_{i=1}^N \frac{\lambda_k P_k(w_i | h_i)}{\sum_{k=1}^K \lambda_k P_k(w_i | h_i)}$$

有  $\sum_{k=1}^K \lambda_k = 1$  的约束下, 最大化  $Q(\lambda, \lambda^{(0)})$   
 使用拉格朗日乘子法  
 $F = Q(\lambda, \lambda^{(0)}) - P(\sum_{k=1}^K \lambda_k - 1)$   
 $\begin{cases} \frac{\partial F}{\partial \lambda_k} = \frac{\sum_{i=1}^N E[y_{ik}]}{\lambda_k} + P = 0 \\ \frac{\partial F}{\partial P} = \sum_{k=1}^K \lambda_k - 1 = 0 \end{cases}$   
 $\Rightarrow \begin{cases} \lambda_k = -\frac{\sum_{i=1}^N E[y_{ik}]}{P} \quad \text{同理 } \lambda_1 = -\frac{\sum_{i=1}^N E[y_{i1}]}{P} \dots \\ \sum_{k=1}^K \lambda_k = 1 \end{cases}$   
 $\Rightarrow -\frac{\sum_{i=1}^N \sum_{k=1}^K E[y_{ik}]}{P} = 1 \Rightarrow P = -N$   
 $\Rightarrow \lambda_k = \frac{\sum_{i=1}^N E[y_{ik}]}{N} = \frac{1}{N} \sum_{i=1}^N \frac{\lambda_k P_k(w_i | h_i)}{\sum_{k=1}^K \lambda_k P_k(w_i | h_i)}$

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## NGramCounter Class Reference

Class for storing counts for a set of n-grams. [More...](#)

```
#include <util.H>
```

[List of all members.](#)

### Public Member Functions

	<b>NGramCounter</b> () <i>Ctor; initializes object to be empty.</i>
void	<b>write</b> (ostream &outStrm, const <b>SymbolTable</b> &symTable= <b>SymbolTable</b> ()) const <i>Writes all counts to stream outStrm in a text format.</i>
void	<b>clear</b> () <i>Clears object; deletes all n-grams in table.</i>
unsigned	<b>size</b> () const <i>Returns number of n-grams in table.</i>
bool	<b>empty</b> () const <i>Returns whether object is empty.</i>
unsigned	<b>incr_count</b> (const vector< int > &ngram) <i>Increments count of an n-gram; returns new count.</i>
void	<b>set_count</b> (const vector< int > &ngram, unsigned val) <i>Sets count of an n-gram to val.</i>
unsigned	<b>get_count</b> (const vector< int > &ngram) const <i>Returns count of an n-gram, or 0 if not present.</i>

## ● 实现ngram计数

对lang\_model.c 中的  
count\_sentence\_ngrams 进行  
补全。

```
// static map<vector<int>, set<int> > histOnePlusMap;
for (int wordIdx = m_n - 1; wordIdx < wordCnt; ++wordIdx) {
    // process from n-gram to 1-gram
    for (int n = 1; n <= m_n; ++n) {
        // process m_predCounts
        vector<int> ngram(wordList.begin() + wordIdx - (m_n - n),
                           wordList.begin() + wordIdx + 1);
        int count = m_predCounts.incr_count(ngram);
        // process m_histCounts
        vector<int> histNgram(ngram.begin(), ngram.end() - 1);
        m_histCounts.incr_count(histNgram);
        if (count == 1) {
            m_histOnePlusCounts.incr_count(histNgram);
        }
    }
}
```

## ● 实现Witten-Bell平滑算法

$$P_{\text{WB}}(w_i|w_{i-1}) = \frac{c_h(w_{i-1})}{c_h(w_{i-1}) + N_{1+}(w_{i-1})} P_{\text{MLE}}(w_i|w_{i-1}) + \frac{N_{1+}(w_{i-1})}{c_h(w_{i-1}) + N_{1+}(w_{i-1})} P_{\text{backoff}}(w_i)$$

$$P_{\text{backoff}}(w_i) = P_{\text{WB}}(w_i) = \frac{c_h(\epsilon)}{c_h(\epsilon) + N_{1+}(\epsilon)} P_{\text{MLE}}(w_i) + \frac{N_{1+}(\epsilon)}{c_h(\epsilon) + N_{1+}(\epsilon)} \frac{1}{|V|}$$

```
vector<int> histNgram(ngram.begin(), ngram.end() - 1);
int predCnt = m_predCounts.get_count(ngram);
int histCnt = m_histCounts.get_count(histNgram);
int histOnePlusCnt = m_histOnePlusCounts.get_count(histNgram);

double lambda = 0.0, PMle = 0.0, beta = 1.0, PBackoff;
if (histCnt > 0) {
    lambda = 1.0 * histCnt / (histCnt + histOnePlusCnt);
    PMle = 1.0 * predCnt / histCnt;
    beta = 1.0 * histOnePlusCnt / (histCnt + histOnePlusCnt);
}
if (ngram.size() == 1) {
    // recursive terminate
    PBackoff = 1.0 / vocSize;
} else {
    // recursive
    PBackoff =
        get_prob_witten_bell(vector<int>(ngram.begin() + 1, ngram.end()));
}
retProb = lambda * PMle + beta * PBackoff;
```

感谢各位聆听 !

Thanks for Listening

