## NLP Formula Sheet

## 04 - Language Modeling

### **Perplexity Formula:**

$$PP(W) = P(w_1, w_2, \dots, w_N)^{-rac{1}{N}} = \left(\prod_{i=1}^N rac{1}{P(w_i|w_1, w_2, \dots, w_{i-1})}
ight)^{rac{1}{N}}$$

### **Unigram Model:**

$$P(w_i \mid w_{i-1}) = rac{C(w_{i-1}, w_i) + 1}{C(w_{i-1}) + V}$$

### **Good-Turing Estimation:**

$$P_{GT}(w) = rac{\stackrel{\smile}{(C(w)+1)N_{C(w)+1}}}{N_{C(w)}N}$$

### 05 - Spell Correction

### **Maximum Likelihood Estimation:**

$$\operatorname{argmax}_{c \in \mathcal{C}} P(c \mid w) = \operatorname{argmax}_{c \in \mathcal{C}} P(w \mid c) P(c)$$

### Minimum Edit Distance:

$$D[i,j] = \min egin{cases} D(i-1,j) + 1 \ D(i,j-1) + 1 \ D(i-1,j-1) + \delta(a_i,b_j) \end{cases}$$

### **Cost Function:**

$$\delta(a_i,b_j) = egin{cases} 0 & ext{if } a_i = b_j \ 2 & ext{if } a_i 
eq b_j \end{cases}$$

### 06 - Word Embedding

Term Frequency (TF): 
$$TF(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

Inverse Document Frequency (IDF): 
$$IDF(t,D) = \log_{10}\left(\frac{\text{Total number of documents }|D|}{\text{Number of documents containing term }t}\right)$$

#### **TF-IDF:**

$$TF$$
- $IDF(t, d, D) = TF(t, d) \times IDF(t, D)$ 

### **Pointwise Mutual Information (PMI):**

$$PMI(w,c) = \log_{10}\left(rac{P(w,c)}{P(w)\cdot P(c)}
ight)$$

#### **Positive Pointwise Mutual Information (PPMI):**

$$PPMI(w, c) = \max(PMI(w, c), 0)$$

### Skip-gram Objective:

Maximize 
$$\sum \log_{10} P(w_t \mid w_{t-k}, \dots, w_{t+k})$$

### Continuous Bag of Words (CBOW) Objective:

Maximize 
$$\sum \log_{10} P(w_{t-k}, \dots, w_{t+k} \mid w_t)$$

### **Cosine Similarity:**

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

#### **GloVe Loss Function:**

$$J = \sum_{i,j=1}^V f(P_{ij}) (w_i^T ilde{w}_j + b_i + ilde{b}_j - \log_{10}(X_{ij}))^2$$

# 07 - Sequence Modeling

### **LSTM Hidden State Calculation:**

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h)$$

$$y_t = \sigma(W_y h_t + b_y)$$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

### 08 - Transformers

### **Scaled Dot-Product Attention:**

$$\operatorname{Attention}(Q,K,V) = \operatorname{softmax}\left(rac{QK^T}{\sqrt{d_k}}
ight)V$$

#### **Multi-Head Attention:**

$$MultiHead(Q, K, V) = Concat(head_1, ..., head_h)W^O$$

$$\text{where head}_i = \operatorname{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

### **Positional Encoding:**

$$PE_{(pos,2i)} = \sin\left(rac{pos}{10000^{2i/d_{
m model}}}
ight)$$

$$PE_{(pos,2i+1)} = \cos\left(rac{pos}{10000^{2i/d_{ ext{model}}}}
ight)$$

### Word Probability Given Tag:

$$P(w_i \mid t_i)$$

### **Tag Transition Probability:**

$$P(t_i \mid t_{i-1})$$

### **CRF** Formula:

$$P(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp\left(\sum_{i=1}^{n} \sum_{j=1}^{m} \lambda_{j} f_{j}(y_{i-1}, y_{i}, \mathbf{x}, i)\right)$$

### **Linear CRF Formula:**

$$P(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp\left(\sum_{i=1}^{n} \sum_{k=1}^{K} \theta_k \cdot g_k(y_{i-1}, y_i, \mathbf{x}, i)\right)$$

### 11 - Machine Translation

### **Encoder Hidden State Calculation:**

$$h_t = f(h_{t-1}, x_t)$$

### **Decoder Hidden State Calculation:**

$$s_t = f(s_{t-1}, y_{t-1}, c_t)$$

# Attention Weight Calculation: $lpha_{ij} = rac{\exp(e_{ij})}{\sum_{k=1}^n \exp(e_{ik})}$

$$lpha_{ij} = rac{\exp(e_{ij})}{\sum_{k=1}^n \exp(e_{ik})}$$

### **Decoder Output Calculation:**

$$P(y_t \mid y_{< t}, x) = \text{softmax}(Vs_t)$$

### **Cross-Entropy Loss:**

$$ext{CE}(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

### **BLEU Score:**

$$\mathrm{BLEU} = \mathrm{BP} imes \exp\left(\sum_{n=1}^N w_n \log p_n\right)$$