

$$P_c(t) = (1-\gamma) \cdot P_{\text{mix}}(t) + \gamma \cdot \frac{1}{|V|}$$

$P_c(t)$ serves as collection prior

$$P_{\text{mix}}(t) \text{ is similar to linear smoothing} \rightarrow P_{\text{mix}}(t) = (1-\alpha_{df}) \cdot P_r(t) + \alpha_{df} P_{df}(t)$$

$P_r(t)$ is like the collection LM, and it looks like a softmax function, \uparrow is like temperature, controlling how peaked the background LM.

$$P_r(t) = \frac{P(t|c)}{\sum_{t \in V} P(t|c)}$$

$P_{df}(t)$ is new, it's like a document-presence LM

$$P_{df}(t) = \frac{df(t)}{N}$$

S_{base} in \tilde{S} would be negative if $tf(t, d)^{\beta_{df}(t)} \leq |d| \cdot P_c(t)$

meaning the term is present in the document, but at a lower rate than the collection model would have predicted for a document of that length

$$\frac{P_{df}(t)}{P_c(t)}$$

if a term appears in many documents but has low total frequency, it is more informative.

if a term has low document frequency but has a lot of term frequency, it is concentrated in a few documents

$$g(t) = 1 + \lambda_{\text{edr}} \cdot \text{clip}\left(\log \frac{P_{df}(t)}{P_c(t)}, -C_{\text{edr}}, C_{\text{edr}}\right) \rightarrow \text{this modifies each term's weight}$$

$m(t, d)$ is always negative, it's a penalty for if the query term is not in the document

$\text{AND}(q, d)$ rewards the document if it has more distinct query terms, tanh is almost like a binary func

$LP(d)$ is the length penalty for documents longer than average on a log scale

corpus