CSE6328.3
Speech & Language Processing

HTK and the Project two

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HTK: A Toolkit for HMM-based Speech Recognition

- HTK: software toolkit for HMM-based speech recognition
- Originally built in Cambridge Univ. (UK); Acquired and released by Microsoft Inc..
- HTK provides a set of tools to process speech data, transcription, grammar network, HMM training, HMM decoding, ASR evaluation, …
- Unix-style of command-line:

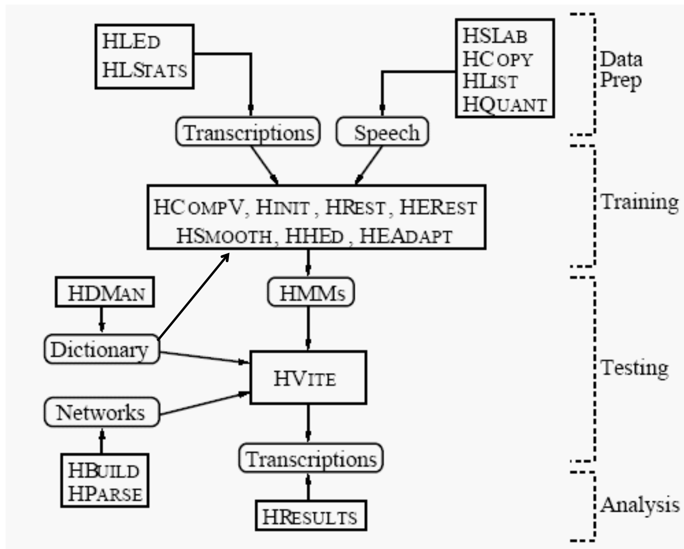
  tool-name [options] mandatory_arguments
- Easy to write shell scripts to perform large-scale experiments.
- A Linux version of HTK is available at:

  /cs/course/6328/project2/HTK34
- Also sample and tutorial directories:

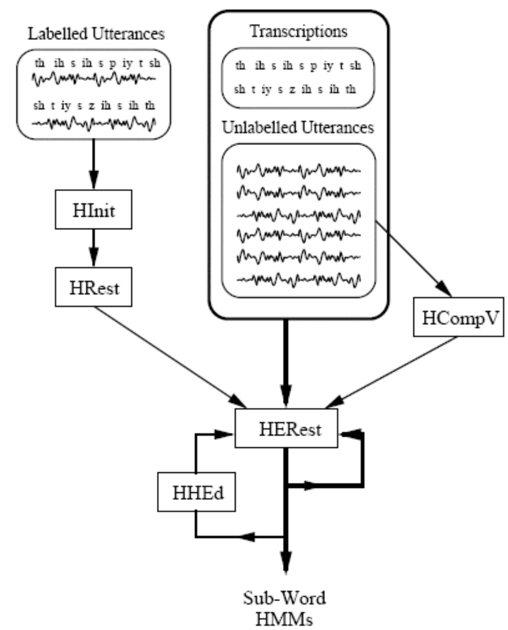
  /cs/course/6328/…/HTK-samples/HTKDemo

  /cs/course/6328/…/HTK-samples/HTKTutorial
- Use Linux machines: *indigo, navy, cherry, hickory, hemlock, willow*, etc..

HTK Tools Overview



HMM Training in HTK



HMM Training in HTK

- HMM Training in HTK:
  1. Get initial segmentation of data (uniform, hand labels, or forced alignment)
  2. Train monophone HMMs on segments (*HInit*, *HRest, HCompV*)
  3. Train monophone HMMs using embedded training (*HERest*)
  4. Create triphones from monophones by cloning (HHEd)
  5. Train triphone HMMs using embedded training (*HERest*)
  6. Create context clustering for tying parameters using decision tree (HHEd)
  7. Tie all logical states in triphones to form state-tied triphone HMMs (HHEd)
  8. Run embedded training (HERest); split mixtures (HHEd); repeat.

Important Tools for the project

- *HSLab*: view and play voice data.
- *HCopy*: feature extraction
- *HList*: list data files
- *HCompV*: flat initialization of HMMs
- *HInit*: initialize HMMs from uniform segmentation
- *HRest*: training HMMs based on the Baum-Welch algorithm.
- *HParse/HBuild*: building recognition network.
- *HVite*: Viterbi decoding with 2-gram LM.
- HDecode: Viterbi decoding (more efficient) with 2- or 3-gram LM.
- *HHEd*: change HMM model structure, decision tree based parameter tying
- *HResults*: measure recognition performance.

General Info of the project (1)

- Use HTK to build an ASR system from training data.
- Do experiments to improve your system.
- Evaluate your systems on test data and report the best.
- Requirements:
  – Use mixture Gaussian CDHMM.
  – Use mono-phone and state-tied tri-phone models
  – Can’t use any test data in HMM training.
- Progressive model training procedure:
  – Simple models → complex models
  – Single Gaussian → more mixtures
  – Mono-phone → tri-phone

General Info of the project (2)

- Project key issues: be careful on data formats
  – Use a given 3-gram LM
  – Acoustic modeling: speech unit selection → model estimation (initialization, refining, etc.)
  – Dictionary is provided
  – No need to record data (use the provided database)

General Info of the project (3)

- The expected strategy:
  1) Properly initialize HMM's from scratch.
  2) Evaluate HMM's on test set.
  3) Think about ideas to improve models.
  4) Retrain/update/enhance HMM's.
  5) Evaluate the enhanced HMM's again.
  6) Goto 3) to repeat until find your best HMM setting.
- You need to hand in the following electronic files:
  – A report (max 8 pages), *report_X.xxx*, to describe all conducted experiments; why you did them; your methods to improve the system; your best system setting and the best performance you achieved; others.
  – A training script, *train_X.script*, to get your best HMMs from scratch.
  – A test script, *test_X.script,* to evaluate your HMMs on test data.
  – A *readme_X.txt* file to explain how to run your scripts.

General Info of the project (3)

- My marking scheme:
  – The methodology you adopt in building the system.
  – Whether you follow the project specification.
  – What ideas you come up with for improving the system.
  – A full course from scratch to your best system.
  – Your best recognition performance.
  – The best systems will get bonus marks.
  – How well you do in your project presentation
- Deadlines and presentation dates

Hints for the Project

- Focus on:
  - How to initialize models ?
    - HTK provides two solutions
  - How to choose modeling unit ?
    - mono-phone
    - Consider context-dependent phone, such as left and/or right bi-phone and tri-phone.
  - How to decide the optimal Gaussian mixture number per HMM state?
  - Other ideas you come up with …
- Get your version 1.0 ASAP.

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YORK UNIVERSITY redefine THE POSSIBLE.

No.8

Statistical Language Modeling

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Automatic Speech Recognition (II): Language Modeling (LM)

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ASR Solution

$$\hat{W} = \arg\max_{W \in \Gamma} p(W \mid X) = \arg\max_{W \in \Gamma} P(W) \cdot p(X \mid W)$$

$$= \arg\max_{W \in \Gamma} \overline{P}_\Gamma(W) \cdot \overline{p}_\Lambda(X \mid W)$$

- $\overline{p}_\Lambda(X \mid W)$ — ***Acoustic Model (AM)***: gives the probability of generating feature ***X*** when ***W*** is uttered.
  - Need a model for every ***W*** to model all speech signals (features) from ***W*** → HMM is an ideal model for speech
  - Speech unit selection: what speech unit is modeled by each HMM? (phoneme, syllable, word, phrase, sentence, etc.)
    - Sub-word unit is more flexible (better)
- $\overline{P}_\Gamma(W)$ — ***Language Model (LM)***: gives the probability of W (word, phrase, sentence) is chosen to say.
  - ***Need a flexible model to calculate the probability for all kinds of W → Markov Chain model (n-gram)***

ASR Problems

- **Training Stage:**
  - ***Acoustic modeling***: how to select speech unit and estimate HMMs reliably and efficiently from available training data.
  - ***Language modeling***: how to estimate n-gram model from text training data; handle data sparseness problem.
- **Test Stage:**
  - ***Search***: given HMM's and n-gram model, how to efficiently search for the optimal path from a huge grammar network.
    - Search space is extremely large
    - Call for an efficient pruning strategy

N-gram Language Model (LM)

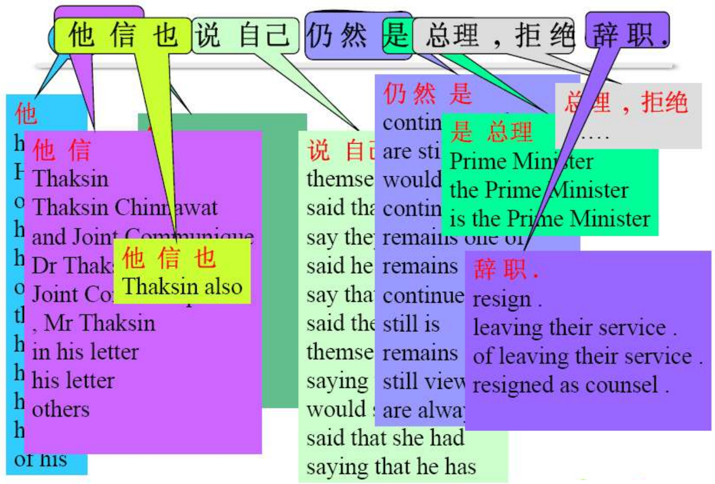
- **N-gram Language model (LM) essentially is a Markov Chain model, which is composed of a set of multinomial distributions.**
- **Given $W=w_1,w_2,\ldots,w_M$, LM probability $Pr(W)$ is expressed as**

$$\Pr(W) = \Pr(w_1, w_2, \cdots, w_M) = \prod_{i=1}^{M} p(w_i \mid h_i)$$

  - where $h_t=w_{t-n+1},\ldots,w_{t-1}$ is history of w_t.
  - In unigram, $h_t=null$ (parameters ~|V|, |V| vocabulary size)
  - In bigram, $h_t=w_{t-1}$ (parameters ~|V|*|V|)
  - In trigram, $h_t=w_{t-2}w_{t-1}$ (parameters ~|V|*|V|*|V|)
  - In 4-gram, $h_t=w_{t-3}w_{t-2}w_{t-1}$ (parameters ~|V|*|V|*|V|*|V|)
- **How to evaluate performance of LM?**

N-gram LM: Applications

- N-gram LM has many applications in speech recognition, OCR, machine translation, etc..
- N-gram LM for statistical machine translation:



Perplexity of LM

- Perplexity: the most widely used performance measure for LM.
- Given an LM { *Pr(.)* } with vocabulary size |V|, and a sufficiently long test word sequence $W=w_1,w_2,\ldots,w_M$:
  - Calculate a negative log-prob quantity per word:

$$LP = -\frac{1}{M}\log_2 \Pr(W)$$

  - Perplexity of LM is computed as

$$PP = 2^{LP}$$

- Perplexity: indicates the prediction of the LM is about as difficult as guessing a word among PP equally likely words.
- Perplexity: the smaller PP value, the better LM prediction capability.
- Training-set perplexity: how much LM fits or explain the data
- Test-set perplexity: generalization capability of the LM to predict new text data.

LM: vocabulary selection

- Large vocabulary size
  - ➔ exponential growth of various n-grams
  - ➔ exponential increasement of LM model parameters
  - ➔ much more training data and computing resources
- Need to control vocabulary size in LM.
- Given the training text data,
  - limit vocabulary of LM to the most frequent words occurring in the training corpus, e.g., the top N words.
  - All other words are mapped as unknown word, *<UNK>.*
  - This gives the lowest rate of out-of-vocabulary (OOV) words for the same vocabulary size.
- Example: English newspaper WSJ (Wall Street Journal)
  - Training corpus: 37 million words (full 3-year archive)
  - Vocabulary: 20,000 words
  - OOV rate: 4%
  - 2-gram PP: 114
  - 3-gram PP: 76

LM Training (1)

- Collect text corpus: need > tens of millions of words for 3-gram
- Corpus preprocessing: (*very time-consuming*)
  - Text clean-up: remove punctuation and other symbols
  - Normalization: 0.1% → (zero) point one percent
    6:00 → six o' clock; 1/2 → one half, …
  - Surrounding each sentence with TAGS <s> and </s>
  - Language-specific processing: e.g., for some oriental languages (Chinese, Japanese, etc.) do tokenization → find word boundaries from a stream of characters.
  - Output: clean text

<s> w1 w2 w3 w4 w5 </s>
<s> w11 w21 w32 w41 w52 w12 w22 w33 w44 w54 w16 w26 w36 w43 w56 </s>
<s> w12 w23 w31 w42 w51 w11 w23 w34 w44 w5 </s>
….

LM Training (2)

- LM parameter estimation from clean text:
  - The entire training text can be mapped into an ordered sample of n-grams without loss of information:

    $S=h_1w_1, h_2w_2, \ldots h_Tw_T$

    (assume we have T words in training corpus)
  - Group together all n-grams with the same history h :

    $S_h=hw_{x1}, hw_{x2}, \ldots , hw_{xn}$
  - S_h can be viewed as an i.i.d. sample from $Pr(w|h)$.
  - We denote $p_{hw}=p(w|h)$ for all possible w's and h's.
  - So probability of S_h follows a multinomial distribution:

$$\Pr(S_h) \propto \prod_{w \in V} [p(w \mid h)]^{N(hw)}$$

where $N(hw)$ is frequency of n-gram hw occurring in S_h.

LM Training (3): ML estimation

- Maximum Likelihood (ML) estimation of multinomial distribution is easy to derive.
- The ML estimate of n-gram LM is:

$$\arg\max_{p(w|h)} \sum_{w \in V} N(hw) \cdot \ln p(w \mid h) = \arg\max_{p_{hw}} \sum_{w \in V} N(hw) \cdot \ln p_{hw}$$

$$\text{subject to constrants } \sum_{w \in V} p_{hw} = 1 \text{ for all } h.$$

$$\Rightarrow p_{hw}^{(ML)} = \frac{N(hw)}{\sum_{w \in V} N(hw)} = \frac{N(hw)}{N(h)}$$

LM Training (3): MAP estimation

- The natural conjugate prior of multinomial distribution is the Dirichlet distribution.
- Choose Dirichlet distribution as priors:

$$p(\{p_{hw}\}) \propto \prod_{w \in V} [p_{hw}]^{K(hw)}$$

  - where { *K(hw)}* are hyper-parameters to specify the prior.
- Derive posterior p.d.f. from Bayesian learning:

$$p(\{p_{hw}\} | S_h) \propto \prod_{w \in V} [p_{hw}]^{K(hw)+N(hw)}$$

- Maximization of posteriori p.d.f. → the MAP estimate:

$$p_{hw}^{(MAP)} = \frac{N(hw)+K(hw)}{\sum_{w \in V}[N(hw)+K(hw)]}$$

- MAP estimates of n-gram LM can be used for smoothing.

Data Sparseness in LM estimation

- ML estimation never works due to data sparseness.
- Example: in 1.2 million words English text (vocabulary 1000 words)
  - 20% bigrams and 60% trigrams occur only once.
  - 85% of trigrams occur less than five times.
  - After observing the whole 1.2 Mw data, the expected chance of seeing a new bi-gram is 22%, a new tri-gram 65%.
- In ML estimation: zero-frequency → zero probability
- Data sparseness problem can not be solved by collecting more data.
  - Extremely uneven distribution of n-grams in natural language.
  - After amount of data reaches a certain point, the speed of reducing OOV rate or rate of new n-grams by adding more data becomes extremely slow.
- Call for a better estimation strategy: ***smoothing ML estimates***
  - ***Back-off scheme: discounting + redistributing***
  - ***Linear interpolation scheme***

Statistical Estimators

Example:

Corpus: five Jane Austen novels

N = 617,091 words

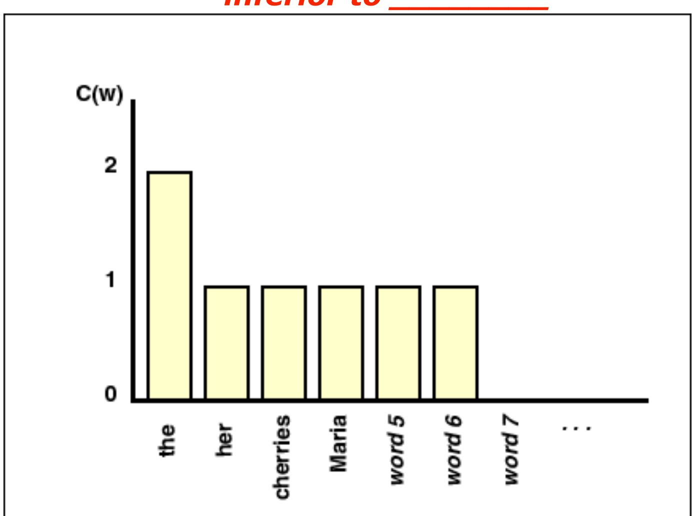
V = 14,585 unique words

Task: predict the next word of the trigram "inferior to ________"

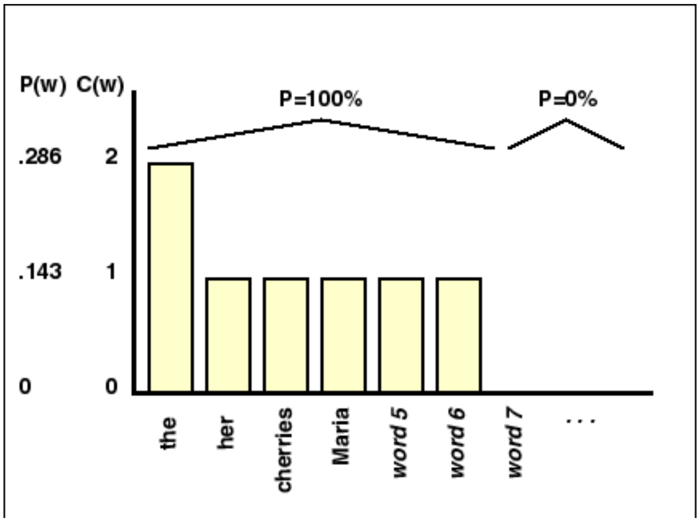
from test data: "[In person, she was] inferior to *both* [sisters.]"

Instances in the Training Corpus:

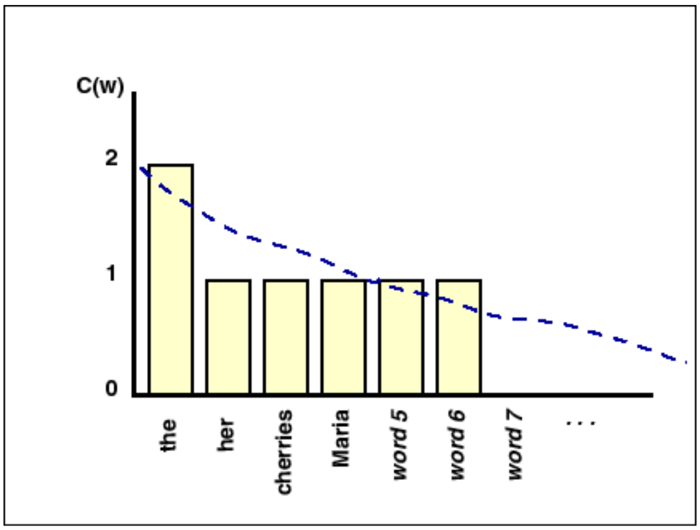
"inferior to ________"



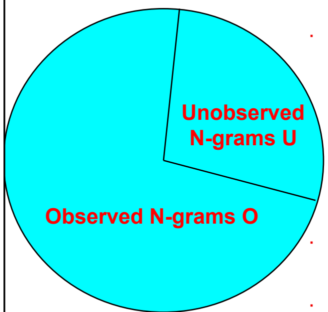
Maximum Likelihood Estimate:



Actual Probability Distribution:



Back-off Scheme(1): discounting



- How to estimate probability of an n-gram never observed ?

$$\text{For O set}: \; p(w|h) = \frac{N(hw)}{N(h)}$$

$$\text{For U set}: \; p(w|h) = 0$$

- Discounting is related to the zero-frequency estimation problem
- Discounting: discount probability mass in set O, and re-distribute to set U.
  - For set O: discounted probability

Q1: how much to discount ?

$$p^*(w|h) \quad (0 \le p^*(w|h) \le p(w|h))$$

- Total discounted mass: the zero-frequency probability

Q2: how to distribute the total discounted mass among all unobserved n-grams?

$$\lambda(h) = 1 - \sum_w p^*(w|h) \quad (\text{note} \sum_w p(w|h) = 1)$$

Back-off Scheme(1): discounting based on MAP Estimation

- Laplace's law (Floor discounting)
  - MAP estimation when setting uniform priors:

$$p_{FL}(w|h) = \frac{N(hw)+1}{N(h)+|V|}$$

  - Total discounted mass:

$$\lambda(h) = 1 - \sum_w p_{FL}(w|h) = \frac{N_0(h)}{N(h)+|V|}$$

total number of unobserved n-grams with the history h

  - Laplace's law usually over-discounts in LM estimation

- Lidstone's law

$$p_{lid}(w|h) = \frac{N(hw)+\varepsilon}{N(h)+|V|\cdot\varepsilon}$$

$$\lambda_{lid}(h) = 1 - \sum_w p_{lid}(w|h) = \frac{N_0(h)\cdot\varepsilon}{N(h)+|V|\cdot\varepsilon}$$

Back-off Scheme(1): Good-Turing Discounting (I)

- Good-Turing discounting: discount n-gram counts directly.
- *r*: frequency (occurring r times)
- *N_r*: total number of distinct n-grams occurring exactly *r* times.
- Good-Turing discounting rule:

$$r^* = (r+1)\frac{E(N_{r+1})}{E(N_r)} \quad (< r)$$

- Total probability mass reserved for unseen n-grams:

$$\lambda(h) = \frac{E(N_1)}{N(h)}$$

- How to calculate expectation *$E(N_r)$*?

r	*N_r*
0	212,522,973
1	138,741
2	25,413
3	10,531
4	5,997
5	3,565
6	2,486
7	1,754
8	1,342
…	…
1366	1
1917	1
2233	1
2507	1

Back-off Scheme(1): Good-Turing Discounting (II)

- How to get *$E(N_r)$?*
  - Directly use N_r to approximate the expectation.
    - Only adjust low frequency words (to say, r<=10)
    - No need to adjust high frequency words (r>10)
  - Fit all observed *(r,Nr)* to a function *S*, then use the smoothed value *S(r) as* the expectation*.*
    - Usually use hyperbolic function

$$E(N_r) = S(r) = a \cdot b^r \, (\text{with b} < \text{-1})$$

- Good-Turing estimate is *r*/N(h).*
- Re-normalize to a proper prob dist

r	r*	N_r
0	0.0007	212,522,973
1	0.3663	138,741
2	1.228	25,413
3	2.122	10,531
4	3.058	5,997
5	4.015	3,565
6	4.984	2,486
7	5.96	1,754
8	6.942	1,342
…	…	…
1366	1366	1
1917	1917	1
2233	2233	1
2507	2507	1

Back-off Scheme(2): Re-distributing methods

- Uniform re-distributing: the total discounted mass (a.k.a. the zero-frequency probability) *λ(h)* is uniformly distributed to all unseen ngrams.

- Katz's recursive re-distributing: the total discounted mass *λ(h)* is distributed over all unobserved events proportionally to a less specific distribution *p(w|h')*.
  - Build unigram *p(w)*, distribute *λ(h)* uniformly.
  - Build bi-gram *p(w|w')*, distribute *λ(h)* over all unseen *w* proportionally to *p(w).*
  - Build tri-gram *p(w|w'w''), distribute λ(h)* proportional to *p(w|w").*
  - So on so forth.

Katz's Back-off LM Scheme

- Recursively build from unigram → bi-gram → tri-gram →…
- Use Good-Turing method to discount low frequency events ONLY, say r≤k (k=6). No discounting for high frequency events, say, r>k.
- The total discounted probability mass is re-distributed to all unseen events proportional to their probabilities calculated from 1 level lower n-gram LM.

$$p_{Katz}(w\,|\,h) = \begin{cases} r / N(h) & \text{if } r > k, r = N(hw) \\ d_r \cdot r / N(h) & \text{if } 0 < r \le k \\ \alpha_h \cdot p(w\,|\,h') & \text{if } r = 0 \end{cases}$$

where $d_r = \dfrac{\frac{r^*}{r} - \frac{(k+1)N_{k+1}}{N_1}}{1 - \frac{(k+1)N_{k+1}}{N_1}}$ and $\alpha_h = \dfrac{1 - \sum_{w:r>0} p_{Katz}(w\,|\,h)}{1 - \sum_{w:r>0} p(w\,|\,h')}$

Back-off Scheme(3): Other Simple Discounting methods

- **Absolute discounting: all non-zero frequencies are discounted by a small constant, the total discounted mass is uniformly distributed over unseen events:**

$$p_{abs} = \begin{cases} (r-\delta)/N(h) & \text{if } r>0 \\ (|V|-N_0)\delta/N_0 N(h) & \text{otherwise} \end{cases}$$

- **Linear discounting: all non-zero frequencies are scaled by a constant slightly less than one, uniformly re-distribute.**

$$p_{ld} = \begin{cases} (1-\alpha)\cdot r/N(h) & \text{if } r>0 \\ C\cdot\alpha/N_0 N(h) & \text{otherwise} \end{cases}$$

Interpolation Scheme

- **Simple linear interpolation of several ML n-grams:**

$$p(w\,|\,w'w'') = \varepsilon_1\cdot p^{ML}(w) + \varepsilon_2\cdot p^{ML}(w\,|\,w'') + \varepsilon_3\cdot p^{ML}(w\,|\,w'w'')$$
$$\text{with } 0\le\varepsilon_1,\varepsilon_2,\varepsilon_3\le 1 \text{ and } \varepsilon_1+\varepsilon_2+\varepsilon_3=1.$$

- **General linear interpolation: weights are a function of history.**

$$p(w\,|\,h) = \sum_{i=1}^{K}\lambda_i(h)\cdot p_i(w\,|\,h)$$
$$\text{with } 0\le\lambda_i(h)\le 1 \text{ and } \sum_{i=1}^{K}\lambda_i(h)=1.$$

  - **Weights must be tied based on equivalence classes of *h*.**
- **How to estimate interpolation weights?**
  - **Held-out method: split training data to two parts; one for LMs and the other for weights.**
  - **Cross-Validation: split data into *N* parts; estimate LM's from any (N-1) parts, estimate weight from the other; rotate N times; average all estimates for the final results.**

Interpolation Weights Estimation

- All interpolation weights are estimated from the held-out training sample $W_h=\{w_1,w_2,\ldots,w_T\}$ by means of the EM algorithm.
- For simple interpolation:

$$\lambda_i^{(n+1)} = \frac{1}{T}\cdot\sum_{t=1}^{T}\frac{\lambda_i^{(n)}\cdot p_i(w_t)}{\sum_j \lambda_j^{(n)}\cdot p_j(w_t)}$$

- For general linear interpolation:

$$\lambda_i^{(n+1)}(h) = \frac{1}{T}\cdot\sum_{t=1}^{T}\frac{\delta(h_t=h)\cdot\lambda_i^{(n)}(h)\cdot p_i(w_t\mid h)}{\sum_j \lambda_j^{(n)}(h)\cdot p_j(w_t\mid h)}$$

where

$$\delta(x)=\begin{cases}0 & \mathrm{x}\neq 0\\ 1 & \mathrm{x}=0\end{cases}$$

Class-based N-Gram LM

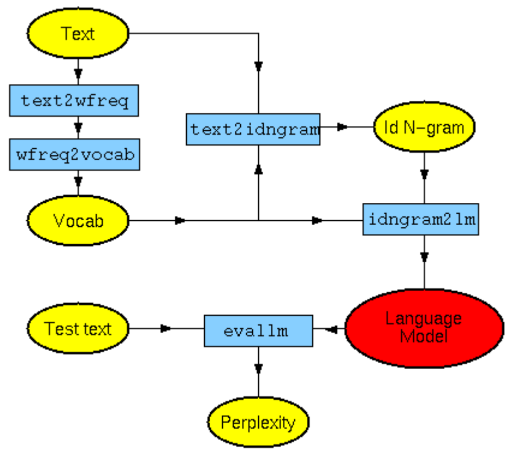
- To reduce LM parameters, group words into classes:
  - Based on morphology, e.g. part-of-speech, etc.
  - Based on semantic meaning: city name, time, number, etc.
- There exist many automatic word clustering algorithms.
- In class-based n-gram LM, each Markov state is a word class, conditional probabilities all depend on word classes rather than individual words.
- Greatly reduce parameter # → require less training data.
- Class-based trigram model:

$$p(w_i\mid w_{i-2}w_{i-1}) = \Pr(w_i\mid C(w_i))\cdot p(C(w_i)\mid C(w_{i-2})C(w_{i-1}))$$

where $C(w_i)$ means the class w_i belongs to.

N-gram LM Toolkit

- No need to write your own program to do all above-mentioned n-gram LM computation.



- A free Statistical Language Model Toolkit is available:

http://mi.eng.cam.ac.uk/~prc14/toolkit.html

Other Issues

- LM Interpolation
  - Task-independent (TI) text data:
    - Purchasing, Web Crawling, etc.
  - Task-dependent (TD) text data: collecting.
- Rapid LM Adaptation
  - Topic adaptation
- Discriminative Training of LM
  - Convex Optimization: Linear programming (LP)
  - Discriminative Adaptation:
    - Constrained optimization → LP

Text Categorization

- Each category is modeled by a mixture of multinomial model (MMM).

$$p(X_t \mid C_i) = c_t \sum_k \omega_{ik} \prod_d u_{ikd}^{m_{td}}$$

- Maximum likelihood Estimation:
  - EM Algorithm
- Discriminative Learning – Large Margin Estimation:
  - AM algorithm:
    - M-approx and E-approx

Discriminative Training

- Convex Optimization: Linear Programming

$$\begin{aligned}
&\min\ -\rho \\
&s.\,t. \\
&c_{tij} + \sum_d d^{u}_{ikd}\psi^{u}_{ikd} + d^{\omega}_{ik}\psi^{\omega}_{ik} - \sum_d d^{u}_{jk'd}\psi^{u}_{jk'd} - d^{\omega}_{jk'}\psi^{\omega}_{jk'} \succ \rho \quad (t_s) \\
&\sum_d e^{\psi^{u(0)}_{ikd}}\psi^{u}_{ikd} \le \sum_d e^{\psi^{u(0)}_{ikd}}\psi^{u(0)}_{ikd} \quad (ik_s) \\
&\psi^{u}_{ikd} \le \psi^{u(0)}_{ikd} + \xi \quad (ikd_s) \\
&\psi^{u}_{ikd} \ge \psi^{u(0)}_{ikd} - \xi \quad (ikd_s) \\
&\sum_k e^{\psi^{\omega(0)}_{ik}}\psi^{\omega}_{ik} \le \sum_k e^{\psi^{\omega(0)}_{ik}}\psi^{(0)}_{ik} \quad (i_s) \\
&\psi^{\omega}_{ik} \le \psi^{\omega(0)}_{ik} + \xi \quad (ik_s) \\
&\psi^{\omega}_{ik} \ge \psi^{\omega(0)}_{ik} - \xi \quad (ik_s)
\end{aligned}$$

Experimental Results: Text Classification Error Rate

- The USAA corpus:

Method	*Bank-HT*	*Bank-ASR*
Vector-based	06.84%	09.10%
NBCv1+DT	05.86%	09.09%
NBCv2+DT	05.54%	09.42%
soft margin LS MAM	***05.54%***	***08.82%***

- The RCV1 corpus:

		Training set	Test set
Multinomial (m=1)	MLE	n/a	7.5%
Mix of multinomial (m=6)	MLE-EM	n/a	5.5%
Mix of multinomial (m=6)	LME-AM	0.71%	3.9%