System Combination with Log-linear Models

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1 Introduction

- The commonly used system combination approaches:
  - Hypothesis combination:
    - * Recogniser output voting error reduction (ROVER).
    - * Confusion network combination (CNC).

      Need Multiple passes of decoding.
  - Log-likelihood combination:
    - * Joint decoding.

      Need single pass of decoding.

2 Joint Decoding

- The systems to be combined have the same HMM topology.
- Log-likelihoods are combined at frame level.
  - Combine hybrid and tandem systems:

$$\mathcal{L}(\boldsymbol{o}_t|s_i) \propto \eta_{\mathrm{H}} \underbrace{\log p_{\mathrm{H}}(\boldsymbol{o}_t|s_i)}_{\text{hybrid log-likelihood}} + \eta_{\mathrm{T}} \underbrace{\log p_{\mathrm{T}}(\boldsymbol{o}_t|s_i)}_{\text{tandem log-likelihood}}$$

  $\eta_{\mathrm{H}} = 1.0$ and $\eta_{\mathrm{T}} = 0.25$: combination weights used for hybrid and tandem systems.
- The combined log-likelihoods are un-normalised.
- Decoding:
  - Viterbi decoding is used.
  - Generated lattices are suitable for lattice rescoring.
- Related to log-linear models (LLMs).
  - Cache arc likelihoods in lattice for efficient rescoring.

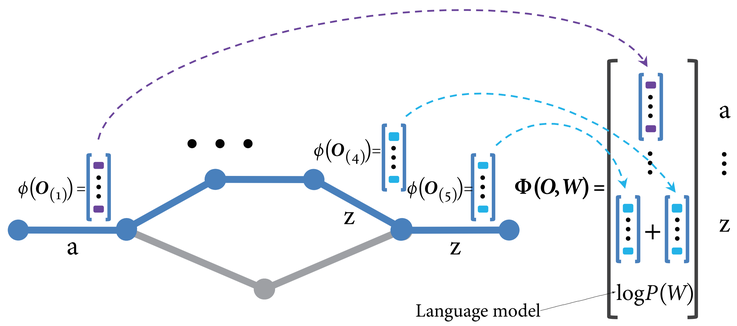
3 Structured Log-linear Models

- Systems can be combined at segment level.
- Relax the frame level Markov assumption to segment level.
- Capture long-span dependencies within the segment.
- The conditional distribution of the word sequence W given the observations $\boldsymbol{O}$ is modelled:

$$P(W|\boldsymbol{O}, \boldsymbol{\eta}) \propto \exp\left(\boldsymbol{\eta}^{\mathrm{T}} \Phi(\boldsymbol{O}, W)\right)$$

$\boldsymbol{\eta}$: model parameters (weights); $\Phi(\boldsymbol{O}, W)$: feature vector.

- The form of the feature vector $\Phi(\boldsymbol{O}, W)$:

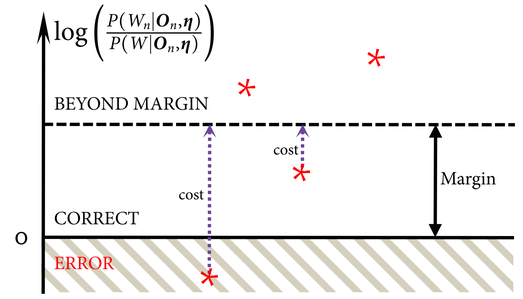


- Features for segment $\boldsymbol{O}_{(i)}$ with (tri-phone) hypothesis w_i:

$$\phi(\boldsymbol{O}_{(i)}) = \begin{bmatrix} \log p_{\mathrm{H}}(\boldsymbol{O}_{(i)}|w_i) \\ \log p_{\mathrm{T}}(\boldsymbol{O}_{(i)}|w_i) \end{bmatrix} \begin{matrix} \text{hybrid log-likelihood} \\ \text{tandem log-likelihood} \end{matrix}$$

4 Training and Decoding

- Large margin (LM):



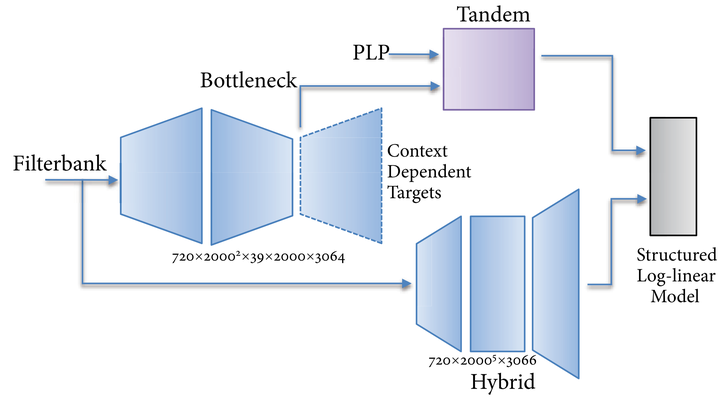
  - Margin: log-posterior ratio.
  - Introduce loss — minimise $\mathcal{F}_{\mathrm{LM}}(\boldsymbol{\eta})$:

$$\mathcal{F}_{\mathrm{LM}}(\boldsymbol{\eta}) = \sum_{n=1}^{N} \left[\max_{W \neq W_n} \left\{ \mathcal{L}(W, W_n) - \log\left(\frac{P(W_n|\boldsymbol{O}_n, \boldsymbol{\eta})}{P(W|\boldsymbol{O}_n, \boldsymbol{\eta})}\right)\right\}\right]_+$$

- Decoding:
  - Lattice rescoring, i.e. Viterbi algorithm applied to lattices.

5 Experiments

- The system framework:



  - Use 13d PLP and 40d log-Mel filter bank coefficients, and their first and higher order delta coefficients.
  - Use the standard bigram configuration.
- Results on the AURORA 4 dataset:

System	Criterion	Test Set WER(%)				Avg.
		Set A	Set B	Set C	Set D	
Tandem	MPE	4.78	7.63	8.93	19.14	12.45
Hybrid		3.75	6.70	7.68	17.62	11.24
CNC	–	3.87	6.76	7.45	17.17	11.06
Joint	Empirical	3.79	6.47	7.86	17.34	11.04
LLM	Empirical	3.74	6.57	7.88	17.12	10.98
	Large Margin	3.64	6.56	7.04	16.83	10.79

6 Conclusions

- Structured log-linear models
  - Relax the Markov assumption to segment level.
  - Use features from multiple systems.
    - * The combination weights are trained.

7 Acknowledgement

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