Local System Voting Feature for Machine Translation System Combination

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1 System Combination

- combine the output of multiple strong systems to one hypothesis

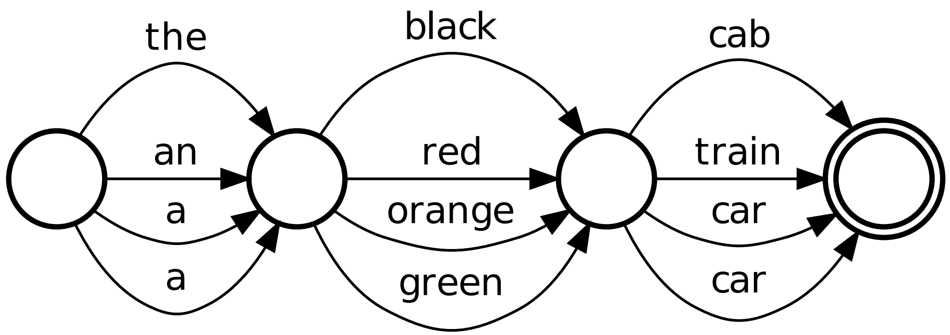
- combination confusion network approach (used by e.g. BBN, IBM, JHU)
  - combine confusion networks built from the individual system outputs
  - confusion network scored by several models
  - decoding similar phrase-based machine translation decoders

- Successfully applied in several evaluation campaigns
  e.g. WMT [Freitag & Peitz^{+} 14], IWSLT [Freitag & Peitz^{+} 13],
  NTCIR [Feng & Freitag^{+} 13], WMT [Peitz & Mansour^{+} 13], WMT [Freitag & Peitz^{+} 12]

- Part of open source statistical machine translation toolkit `Jane`

Confusion Network Generation

- Select one of the input hypotheses as primary hypothesis
- Primary hypothesis determines the word order
  - All remaining hypotheses are word-to-word aligned
- Pairwise alignments generated via GIZA++
- The confusion network can be constructed with the calculated alignment



Decoding

- Do not stick to one primary hypothesis
- Final network is a union of all m (= amount individual systems) confusion networks (each having a different system as primary system)
- Final Network is scored by M models in a log-linear framework
  - $\sum_{i=1}^{M} \boldsymbol{\lambda}_i \boldsymbol{h}_i$
- Scaling factors optimized with MERT on n-best lists
- Shortest path algorithm to extract final hypothesis
- All graph operations are conducted with openFST [Allauzen & Riley$^+$ 07]

Features

- m binary system voting features
  - For each word the voting feature for system i ($1 \leq i \leq m$) is 1 iff the word is from system i, otherwise 0
- Binary primary system feature
  - Feature that marks the primary hypothesis
- LM feature
  - 3-gram language model trained on the input hypotheses
- Word penalty
  - Counts the number of words

2 Local System Voting Feature

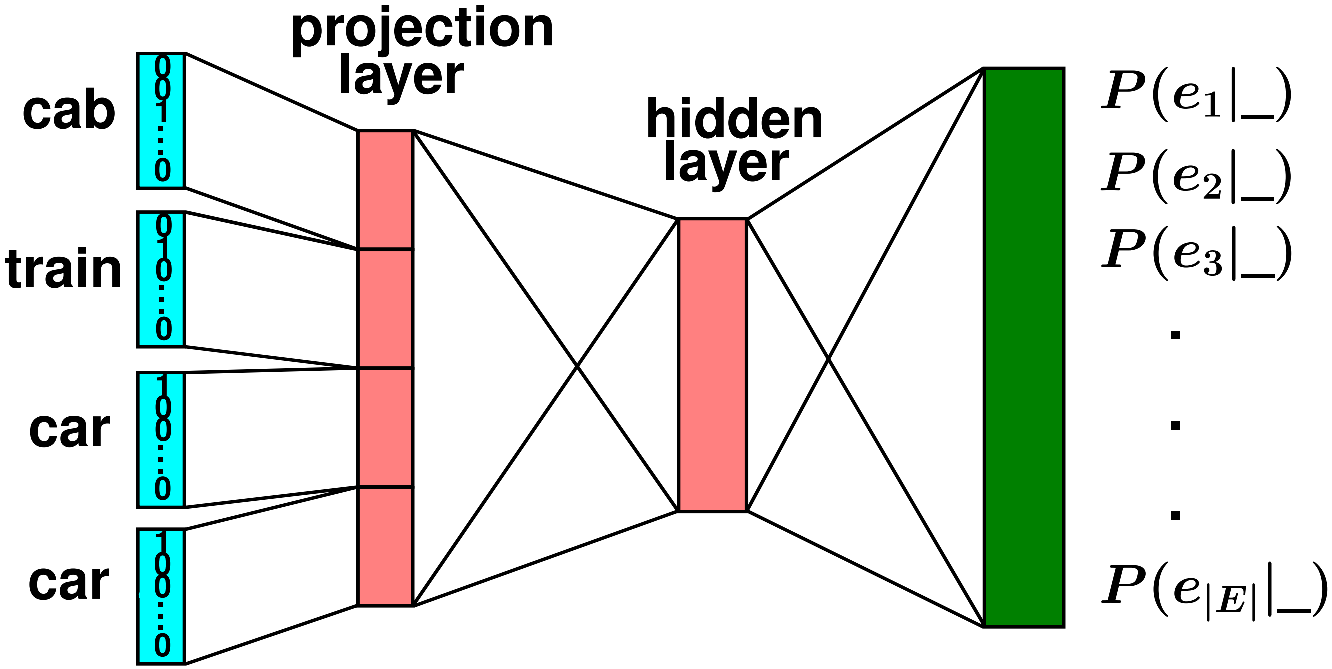
Motivation:

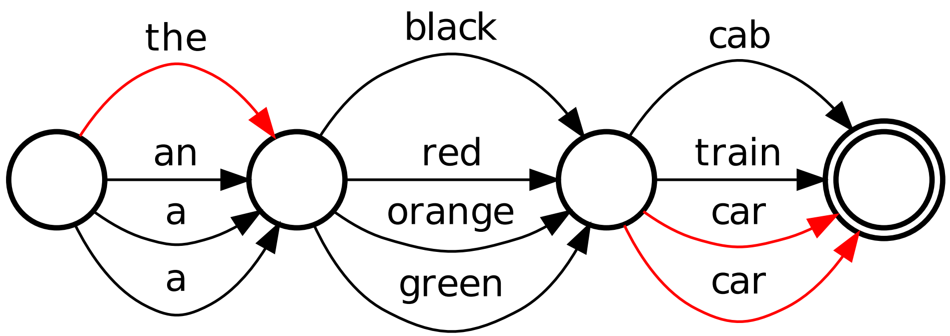
- Binary voting features give preference to one or few individual systems
- Hypotheses with low voting feature weights have no effect on the final output

Idea:

- Define a local voting feature which give a score based on the current sentence/words
- Train model by a feed-forward neural network (NN) to give also unseen events a reliable score
- Related work from speech recognition: [Hillard & Hoffmeister$^+$ 07] trained a classifier to learn which word should be selected

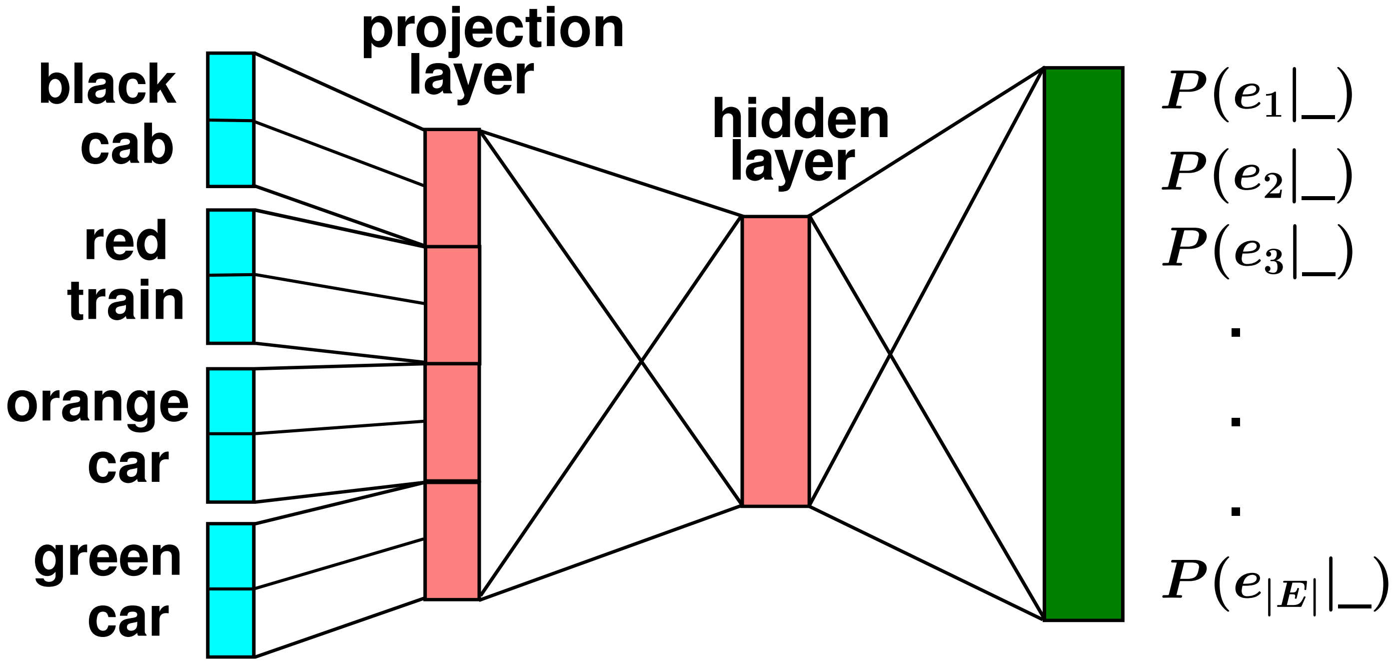
Neural Network Unigram Input Example

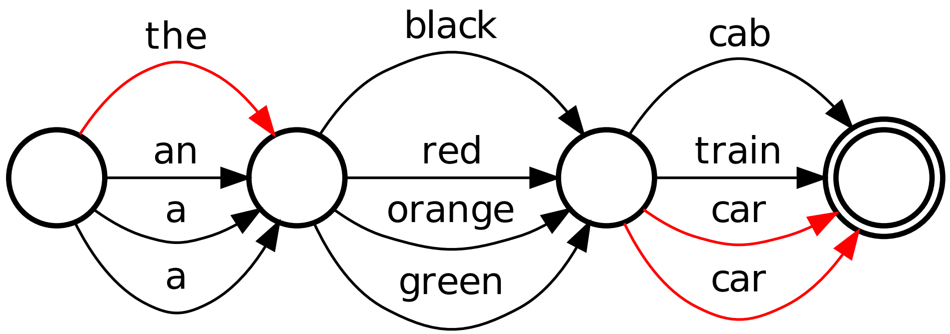




- Best sBLEU path is labeled red
- 1-of-n encoding was applied to map words to a suitable NN input

Neural Network Bigram Input Example





- Taking history of the individual hypotheses into account
- 1-of-n encoding was applied to map words to a suitable NN input

Neural Networks in System Combination

- Add one additional model based to the log-linear framework

- Training data:
  - Split tuning set into 2 sets (one for NN training, one for MERT)
  - Training samples cover only limited vocabulary
    $\Rightarrow$ Use word classes

- Trainied using NPLM [Vaswani & Zhao^{+} 13]

BOLT Arabic→English Results

system combination	word classes	tune BLEU	tune TER	test BLEU	test TER
baseline		30.1	51.2	27.6	55.8
+unigram neural network model	no	31.4	51.2	28.5	56.0
	yes	31.1	51.1	28.3	55.7
+bigram neural network model	no	31.3	51.1	28.4	55.8
	yes	31.4	51.2	28.7	56.0

- 5 Systems
- 1510 sentences result in 6.5M training samples
- Test set has a OOV rate of 43.25%
- MERT tune set has a OOV rate of 43.24%

BOLT Chinese→English Results

system combination	word classes	tune BLEU	tune TER	test BLEU	test TER
baseline		17.9	61.5	18.3	60.9
+unigram neural network model	no	18.1	61.2	18.3	60.3
	yes	18.4	61.5	19.0	60.3
+bigram neural network model	no	18.1	61.3	18.6	60.3
	yes	18.1	61.2	18.7	59.9

- 9 Systems
- 1844 sentences result in 15M training samples
- Test set has a OOV rate of 40.73%
- MERT tune set has a OOV rate of 40.91%

BOLT Chinese→English Analysis

#	baseline		+bigram wcNN	
1	120/14072	(0.9%)	214/14072	(1.5%)
2	592/ 6129	(9.7%)	764/ 6129	(12.5%)
3	1141/ 4159	(27.4%)	1319/ 4159	(31.7%)
4	1573/ 3241	(48.5%)	1669/ 3241	(51.5%)
5	2051/ 2881	(71.2%)	1993/ 2881	(69.2%)
6	2381/ 2744	(86.8%)	2332/ 2744	(85.0%)
7	2817/ 2965	(95.0%)	2820/ 2965	(95.1%)
8	3818/ 3860	(98.9%)	3815/ 3860	(98.8%)
9	11008/11008	(100.0%)	11008/11008	(100.0%)

- More words created by a single or a few systems are used

3 Conclusion

- Proposed novel local system voting model
- Using feedforward neural network models
- Allow confusion network to prefer other systems even in the same sentence
- Improved likelihood to select words created by only few systems
- Use word classes to avoid sparsity problem
- Improvements of 0.7% for Ch-En and 1.1% for Ar-En

Thank you for your attention

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BOLT Arabic→English System

	Arabic	English
Sentences	8M	
Running words	189M	186M
Vocabulary	608K	519K
Tune sentences	1510 (NN), 1080 (MERT)	
Test sentences	1137	

5 Systems
1510 sentences result in 6.5M training samples
Test set has a OOV rate of 43.25% MERT tune set has a OOV rate of 43.24%

BOLT Chinese→English Systems

	Chinese	English
Sentences	13M	
Running words	255M	279M
Vocabulary	370K	833K
Tune sentences	1844 (NN), 985 (MERT)	
Test sentences	1124	

9 Systems

1844 sentences result in 15M training samples
Test set has a OOV rate of 40.73% MERT tune set has a OOV rate of 40.91%