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# Pretraining Sentiment Classifiers with Unlabeled Dialog Data

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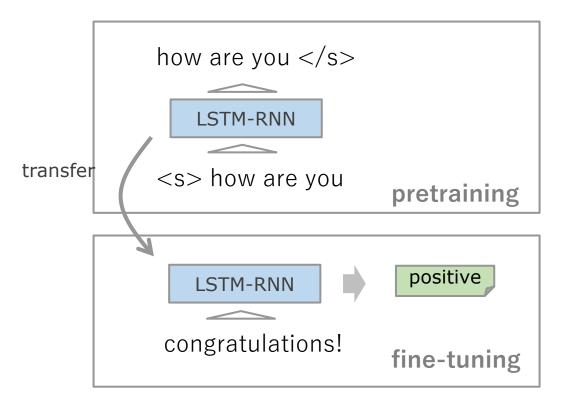
- The amount of labeled training data
  - You will need at least 100k training records to surpass classical approaches (Hu+ 2014, Wu+ 2014)
  - Large-scale labeled datasets of document classification

	training	validation	test	total
Stanford Sentiment Tree Bank	8,544	1,101	2,210	11,855
Large Movie Review Dataset	25,000	-	25,000	50,000
SemEval 2014 Task 9 Subtask B	9,684	1,654	5,666	17,004

### **Previous Work**



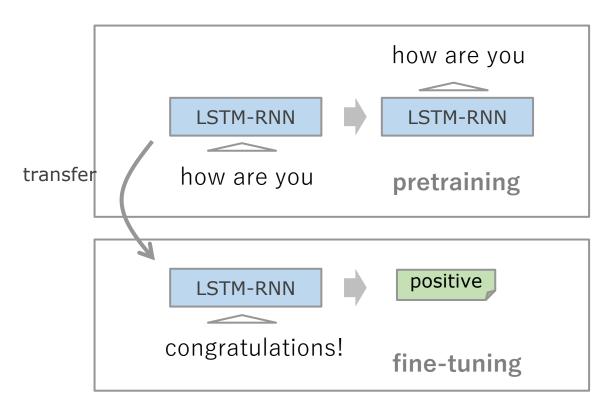
- Semi-supervised approaches
  - Language model



### **Previous Work**



- Semi-supervised approaches
  - Sequence autoencoder (Dai and Le 2015)



## **Our Contributions**



- Pretraining strategy with unlabeled dialog data
  - Pretrain an encoder-decoder model for sentiment classifiers
- Outperform other semi-supervised methods
  - Language model
  - Sequence autoencoder
  - Distant supervision with emoji and emoticons
- Case study based on...
  - Costly labeled sentiment dataset of 99.5K items
  - Large-scale unlabeled dialog dataset of 22.3M utteranceresponse pairs

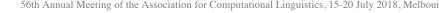


response

Implicitly learn sentiment-handling capabilities through • learning a dialog model

Thank you! Good luck ・°・(ノД`)・° I won't forgive you, (crying emoticon) never 👊 I got home really tired Good job today!





Key Idea

utterance

#### Overview of the Proposed Method



- Datasets
  - Large-scale dialog corpus: a set of a large number of unlabeled utterance-response tweet pairs
  - Labeled dataset: a set of a moderate number of tweets with a sentiment label
- Pretraining
  Istm-RNN
  Istm-RNN
  Istm-RNN
  pretraining
  Istm-RNN
  positive
  congratulations!

### **Data Preparation**



- Dialog data
  - Extract 22.3M pairs of an utterance tweet and its response tweet from Twitter Firehose data

	training	validation	test	total
Dialog data	22,300,000	10,000	50,000	22,360,000

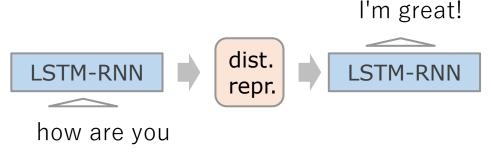
- Sentiment data
  - Positive: 15.0%, Negative: 18.6%, Neutral 66.4%

	training	validation	test	total
Sentiment data	80,591	4,000	15,000	99,591

## Model: Dialog Model



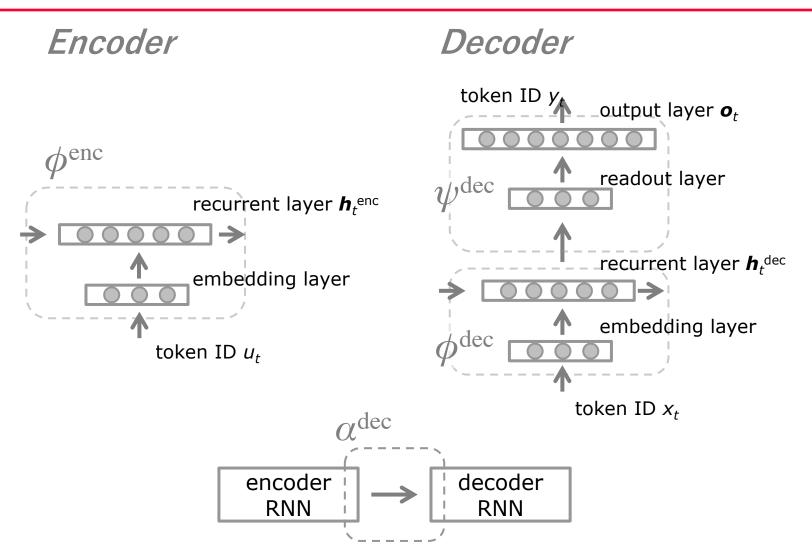
- Dialog model
  - One-layer LSTM-RNN encoder-decoder
  - Embedding layer: 4000 tokens, 256 elements
  - LSTM: 1024 elements
  - Representation which encoder gives: 1024 elements
  - Decoder's readout layer: 256 elements
  - Decoder's output layer: 4000 tokens
  - LSTMs of the encoder and decoder share the parameter



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## Model: Dialog Model

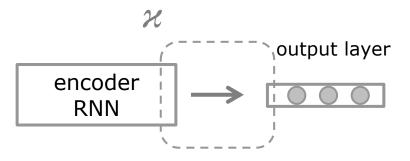




#### Model: Classification Model



- Classification model
  - The architecture of the encoder RNN part is identical to that of the dialog model
  - Produce a probability distribution over sentiment classes by a fully-connected layer and softmax function



#### Training: Dialog Model

- Model pretraining with the dialog data
  - MLE training objective
  - 1 GPU (7 TFLOPS)
  - 5 epochs = 15.9 days
  - Batch size: 64
  - Optimizer: ADADELTA
  - Apply gradient clipping
  - Evaluate validation costs 10 times per epoch and pick up the best model
  - Theano-based implementation



#### Training: Classification Model

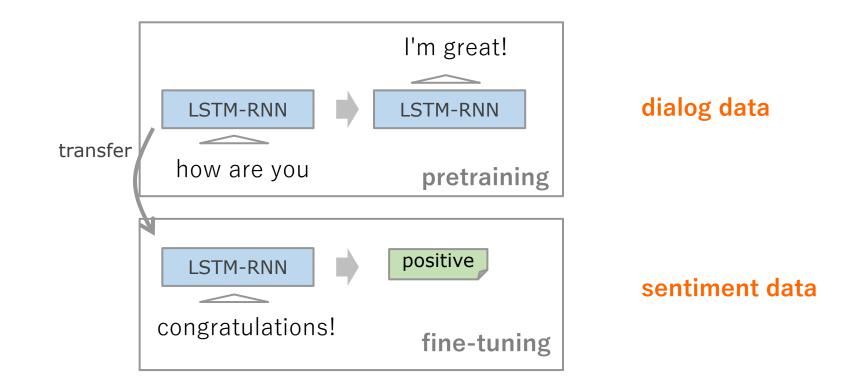


- Classifier model training with the sentiment data
  - Apply 5 different data sizes for each method
    - 5k、10k、20k、40k、80k (all)
  - 5 runs for each method/data size with varying random seeds
  - Evaluate the results by the average of f-measure scores
  - Adjust the duration so that the cost surely converges
    - Pretrained models converge very quickly but those trained from scratch converge slowly
  - The other aspects are the same with pretraining

#### **Proposed Method**



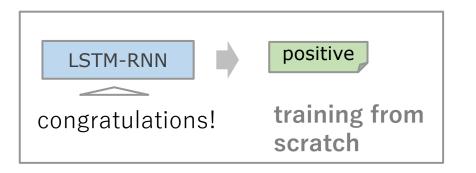
The proposed method: Dial





#### • Default

- No pretraining
- Directly trained by the sentiment data

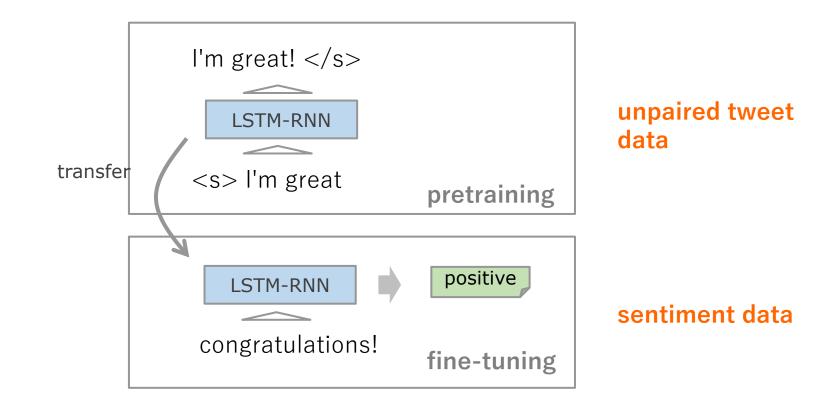


#### sentiment data



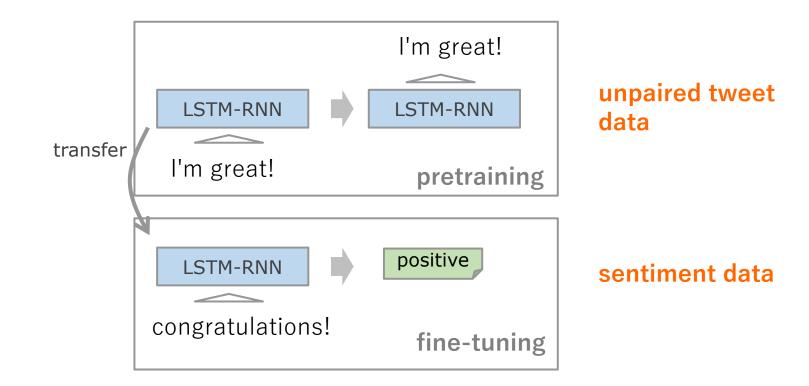
• Lang

- Pretrain an LSTM-RNNs as a language model





- SeqAE
  - Pretrain an LSTM-RNNs as a sequence autoencoder (Dai and Le 2015)

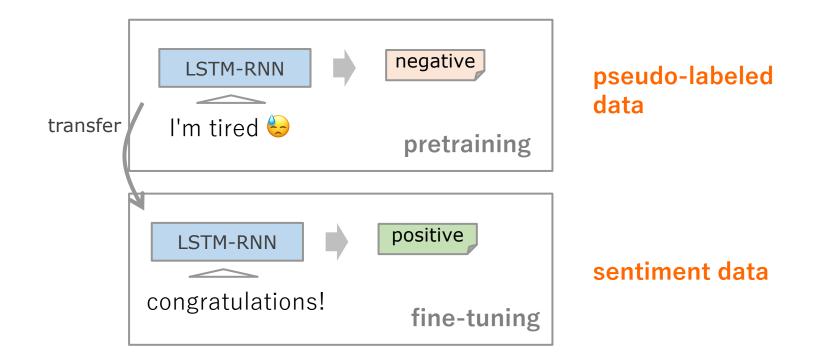




- Emoji and emoticon-based distant supervision
  - Prepare large-scale datasets utilizing emoticons or emoji as pseudo labels (Go+ 2009)
  - Positive emoticon examples
    - 😊 😂 😁 🥶 🤩 💗 👍 💞 🂖 🌟 (^^) (^\_^) ( // ∀ // ) o(^-^)o
  - Negative emoticon examples
    - 😂 💢 🎧 🅺 🥸 🍪 🈓 💔 😰 (ТДТ) (`^´\*) (/--) (、ン、) (´ △`) orz



- Emo2M and Emo6M
  - Pretrain models as classifier models using pseudo-labeled data



## **Baselines with Linear Models**



#### Data

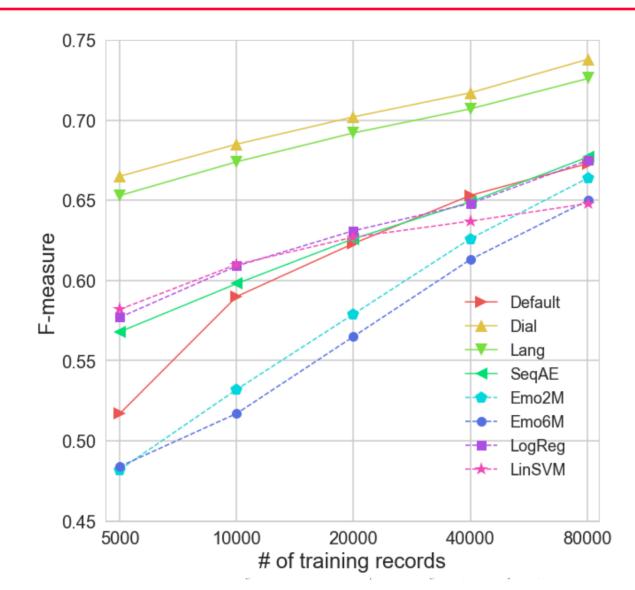
- Use only the sentiment data
- Preprocessing
  - Segment text with a defact-standard morphological analyzer, MeCab
  - 50,000 unigrams and 50,000 bigrams
  - +233 emoji and emoticons

#### • LogReg

- Logistic regression (LIBLINEAR)
- LinSVM
  - Linear SVM (LIBLINEAR)

#### **Results: F-measure**





Original text		English translations		
Source tweet	Generated reply	Source tweet	Generated reply	
明日は待ちに待ったコンサートだ	いいね!	Tomorrow I have a concert I've	That's nice!	
よ		been really looking forward to		
私もっ♪(´∀`)人(´∀`)♪	(*^*)	Me too $\checkmark$ (high five emoticon) $\checkmark$	:)	
残念だったね	(΄ • ω • `)	I'm sorry to hear that	:(	
後でそっちに行くよ	おっけー!	I'm coming later	OK!	
頭痛いよ	うそ、、お大事	I have a headache	Really? Take	
	に…		care of your-	
			self	
アメトーク見たかった~	おもろいよね~	I missed Ame Talk (a TV program)	Watching it is	
			fun	
もう、ごめんじゃ済まされないだ	それはそれで困	Sorry doesn't cut it anymore. I gave	That's too bad	
ろ、呆れる	る。。	up on you.		
大学 合格したよ!	おめでとう!!	I was admitted by the university!	Congratula-	
			tions!!	
もうだめだ	そんなことない	It's all over for me	I don't think so	
	よ(´・ω・')		:(	
嘘つきめ。	ひどい	You liar.	You nasty	
ちょうどいいね	まじかー あり	That's just right	Really?	
	がとう!!!		Thanks!!!	
それ、すごい好き	うん、かっこい	I really like it	Yeah, it's so	
	いよね		cool	

Replies generated by the pretrained encoder-decoder model





- Effectiveness of the pretraining strategy using paired dialog data for sentiment analysis
  - Even more effective in extremely low-resource situations
  - Character-based processing
- Future work
  - Explore combinations of a large-scale unlabeled dataset and a supervised task
  - Exploit other kinds of structures