NTCIR13 MedWeb Task: Multi-label Classification of Tweets using an Ensemble of Neural Networks.

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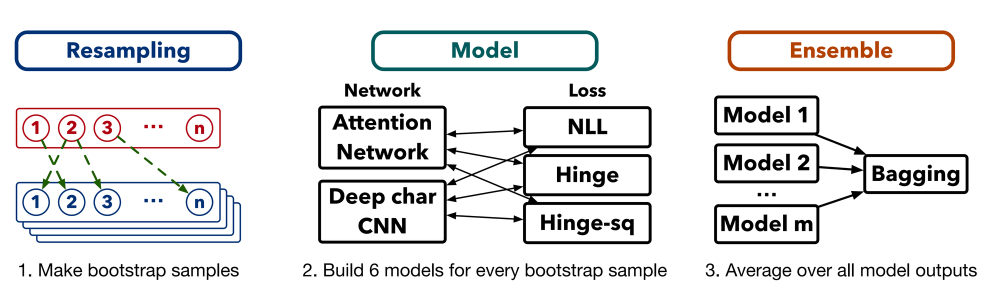
Summary

- Integrate all tasks into a single neural network.
- Two neural networks–HAN and CharCNN–with multi-language learning are combined.
- Ensemble all models with Bagging.
- The ensemble using the NLL and hinge loss produced the best results with **88.0**% accuracy.

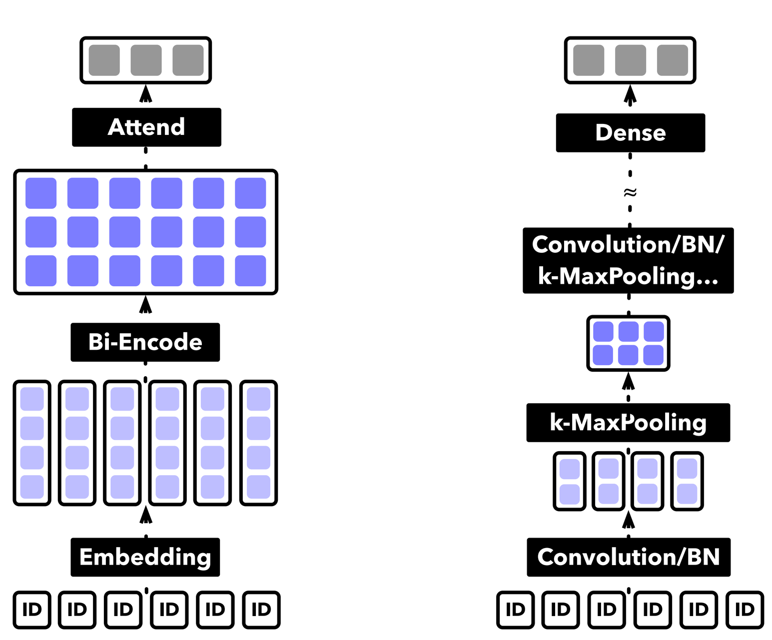
Overview



- Our team tackled the MedWeb using neural networks.

1. Resampling: Create Bootstrap samples.
2. Model: Learn Neural Network with 6 settings.
3. Ensemble: Average over the model outputs.

Features representation



- In this paper, we utilized two neural network models based on both Hierarchical Attention Network (HAN) [1] and Character-level Convolutional Networks (CharCNN) [2].
- The goal is to encode the tweet sentence into a fixed size sentence vector s, which will eventually undergo multi-label classification.

Hierarchical Attention Network

- Given a sentence with words w_t where T is the total number of words in the sentence and embed these words through the embedding matrix $W_e, x_t = W_e w_t$.
- Given the encode bidirectional GRU to encode the tweet sequence $h_t = \mathrm{BiGRU}(x_t)$ [3].
- Compose the tweet vector s with attention mechanism [4]:

$$u_t = \tanh(W_w h_t + b_w),$$
$$\alpha_t = \frac{\exp(u_t^\top u_w)}{\sum_t \exp(u_t^\top u_w)},$$
$$s = \sum_t \alpha_t h_t$$

Character-level Convolutional Network

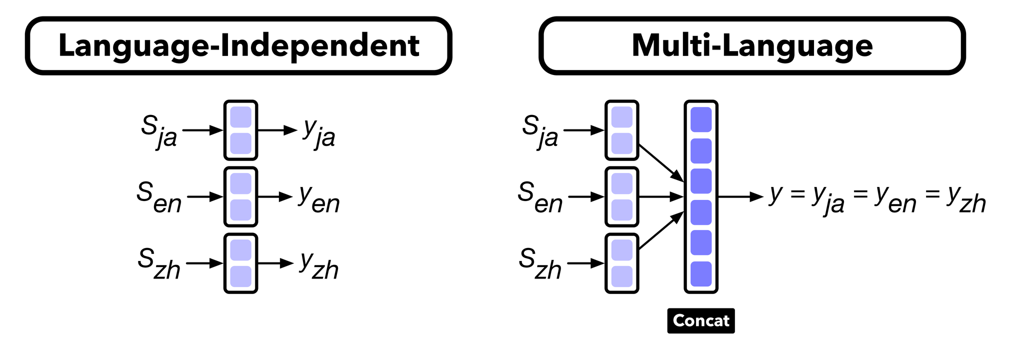
- In contrast to the HAN, the CharCNN is the deep learning method to compose sentence vector from character sequences.
- To accelerate learning procedure, we adapt Batch Normalization [5].
- We define the above procedure as CNN and iterate CNN three times:

$$v_{1,1:T_{v,1}} = \mathrm{CNN}(c_{1:T_c})$$
$$v_{2,1:T_{v,2}} = \mathrm{CNN}(v_{1,1:T_{v,1}})$$
$$v_{3,1:T_{v,3}} = \mathrm{CNN}(v_{2,1:T_{v,2}})$$

- Compose the sentence vector s the linear transformation for hidden features v_3 to compose the sentence vector:

$$s = W_v v_{3,1:T_{v,3}} + b_v.$$

Integrating all three tasks



- Although we generally need to learn the neural network model for each task, the MedWeb task consists of the same label set for the different language datasets.

Language Independent learning

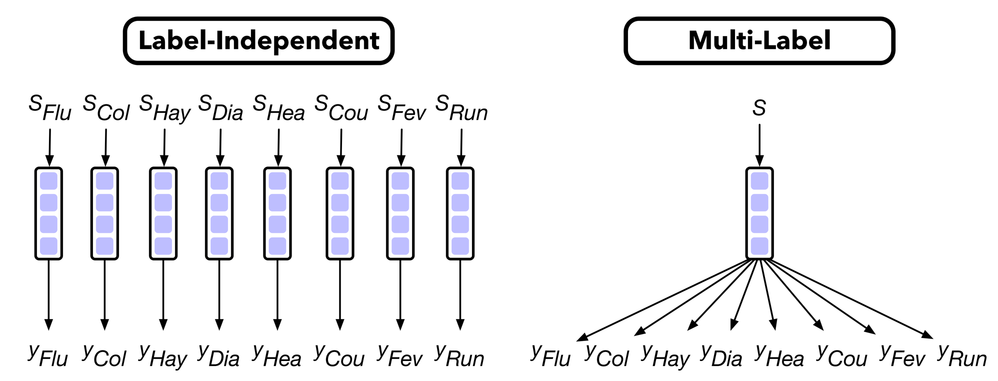
- For each task, we build one neural network model.

Multi-language learning

- Since the English and Chinese tweets are translated from original Japanese tweets, all languages use the same tweet and the same label per line.
- Thus, we represent the three tweets of each language in a single vector for multi-language learning:

$$s^{\mathrm{Multi}} = [s^{\mathrm{ja}}; s^{\mathrm{en}}; s^{\mathrm{zh}}]$$

Multi-label learning



- Since the task is to perform a multi-label classification of 8 diseases or symptoms per tweet, there are two ways to approach this:

Label-Independent learning

- Build the classifier for each label, respectively:

$$\hat{y}_c = w_c^\top s + b'_c \in \mathbb{R}$$

Multi-label learning

- Build one classifier for the 8 labels, simultaneously:

$$\hat{y} = W_c s + b_c \in \mathbb{R}^8$$

- The dimension of outputs $\hat{y}$ equals 8 because each sentence has 8 binary labels: *Influenza, Cold, Hay Fever, Diarrhea, Headache, Cough, Fever* and *Runny nose*.

Loss functions

- To optimize the models, we experimented following three loss functions:

Negative Log-Likelihood

$$\mathcal{L}_{\mathrm{NLL}} = \sum_i^N \sum_{c=1}^8 \ln(1 + \exp(-y_{c,i}\hat{y}_{c,i}))$$

Hinge

$$\mathcal{L}_{\mathrm{Hinge}} = \sum_i^N \sum_{c=1}^8 \max(0, 1 - y_{c,i}\hat{y}_{c,i})$$

Hinge-Square

$$\mathcal{L}_{\mathrm{Hinge\text{-}sq}} = \sum_i^N \sum_{c=1}^8 \max(0, 1 - y_{c,i}\hat{y}_{c,i})^2$$

Bagging ensemble

- Bagging is the ensemble strategy that averages over the outputs learned by resampled dataset.
- We made 20 resampled datasets for this purpose and use each dataset for training the HAN and CharCNN against the 3 loss functions, resulting in 6 methods.

Experiments: Label-independent v.s. Multi-label

Table 1: Comparison between label-independent or multi-label

Target	Exact match accuracy	
	Label-Independent	Multi-Label
Influenza	0.977	**0.988**
Diarrhea	0.973	**0.979**
Hay Fever	0.971	**0.975**
Cough	0.988	**0.991**
Headache	0.979	**0.981**
Fever	**0.931**	0.929
Runny nose	0.948	**0.952**
Cold	0.944	**0.965**
Exact match	0.767	**0.823**

Experiments: Multi-language and Model config

Table 2: Language Independent Learning vs. Multi-language Learning - This table shows that multi-language learning is more accurate than language independent learning in any of the languages and classifiers for this dataset. We also append the other team's results for each language, AKBL-ja-3, UE-en-1, TUA1-zh-3 for benchmark, respectively.

Setting		Exact match accuracy				
Encode	Loss	Language-Independent			Multi-Language	
		ja	en	zh	Single	Ensemble
Attention	NLL	0.823	0.791	0.789	0.823	0.841
	Hinge	0.823	**0.795**	**0.809**	**0.844**	0.841
	Hinge-sq	**0.825**	0.786	0.794	0.822	0.844
CharCNN	NLL	0.800	0.718	0.808	0.831	0.848
	Hinge	0.797	0.686	0.806	0.811	**0.869**
	Hinge-sq	0.772	0.670	0.784	0.811	0.866
Benchmark		0.805	0.789	0.786	-	-

Experiments: Ensemble results

Table 3: This table shows the results of our ensembles. Among the 9 ensembles we created, we submitted the last 3–particularly the ensembles using both HAN and CharCNN. Of the three, the ensemble with loss functions NLL and Hinge produced the highest accuracy: 88.0%.

Ensemble strategy		Exact match
Encode	Loss	
Attention	NLL × Hinge × Hinge-sq	0.842
	NLL × Hinge	0.836
	NLL × Hinge-sq	0.844
CNN	NLL × Hinge × Hinge-sq	0.861
	NLL × Hinge	0.861
	NLL × Hinge-sq	0.859
Attention × CNN	NLL × Hinge × Hinge-sq	0.877
	NLL × Hinge	**0.880**
	NLL × Hinge-sq	0.878

References

[1] Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alexander J Smola, and Eduard H Hovy. Hierarchical attention networks for document classification. In *Proceedings of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (HLT-NAACL)*, pages 1480–1489, 2016.

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[3] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

[4] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2015.

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