



Figure 2: Our proposed architecture for multi-task medical concept normalization. Two tasks have their own matching tensor and multi-view CNN to extract features. Shared structure is used to reinforce the normalization result of both tasks.

Chinese words	translation	Chinese words	translation
C1a 胆总管结石	胆总管结石	C6a 胆总管结石	胆总管结石
C1b 胆总管结石	胆总管结石	C6b 胆总管结石	胆总管结石
C1c 胆总管结石	胆总管结石	C6c 胆总管结石	胆总管结石
C1d 胆总管结石	胆总管结石	C6d 胆总管结石	胆总管结石
C1e 胆总管结石	胆总管结石	C6e 胆总管结石	胆总管结石
C1f 胆总管结石	胆总管结石	C6f 胆总管结石	胆总管结石
C1g 胆总管结石	胆总管结石	C6g 胆总管结石	胆总管结石
C1h 胆总管结石	胆总管结石	C6h 胆总管结石	胆总管结石
C1i 胆总管结石	胆总管结石	C6i 胆总管结石	胆总管结石
C1j 胆总管结石	胆总管结石	C6j 胆总管结石	胆总管结石
C1k 胆总管结石	胆总管结石	C6k 胆总管结石	胆总管结石
C1l 胆总管结石	胆总管结石	C6l 胆总管结石	胆总管结石
C1m 胆总管结石	胆总管结石	C6m 胆总管结石	胆总管结石
C1n 胆总管结石	胆总管结石	C6n 胆总管结石	胆总管结石
C1o 胆总管结石	胆总管结石	C6o 胆总管结石	胆总管结石
C1p 胆总管结石	胆总管结石	C6p 胆总管结石	胆总管结石
C1q 胆总管结石	胆总管结石	C6q 胆总管结石	胆总管结石
C1r 胆总管结石	胆总管结石	C6r 胆总管结石	胆总管结石
C1s 胆总管结石	胆总管结石	C6s 胆总管结石	胆总管结石
C1t 胆总管结石	胆总管结石	C6t 胆总管结石	胆总管结石
C1u 胆总管结石	胆总管结石	C6u 胆总管结石	胆总管结石
C1v 胆总管结石	胆总管结石	C6v 胆总管结石	胆总管结石
C1w 胆总管结石	胆总管结石	C6w 胆总管结石	胆总管结石
C1x 胆总管结石	胆总管结石	C6x 胆总管结石	胆总管结石
C1y 胆总管结石	胆总管结石	C6y 胆总管结石	胆总管结石
C1z 胆总管结石	胆总管结石	C6z 胆总管结石	胆总管结石

Table 1: Chinese words and translations in our paper

Model Formulation

The main idea of this work is based on introducing a tensor generator, and then embedding the multi-view architecture and the multi-task framework to a deep network. Given two mention-entity pairs for disease and procedure, the tensor generator yields two matching tensors separately. Then for each task, interaction representation vector is produced by multi-view CNN. Finally a matching score for normalization is generated in the multi-task module utilizing both shared information and task-specific features. The proposed framework is shown in Figure 2 and all the Chinese words in this paper are translated in Table 1. The details of the model are shown as follows:

- **Matching Tensor.** To tackle short-text problem, for both

tasks, a matching tensor is formulated to model interaction between mention-entity pair from both string and semantic aspects in character, word and sentence levels. Particularly, to incorporate context information and solve word-order problem, Bi-LSTM is utilized to integrate sentence level semantics into character vectors.

- **Multi-view CNN model.** We aim to do semantic matching to address non-standard expression problem. CNN is capable of capturing higher level of meaningful matching patterns such as n-grams when convolving across matching matrix (Pang et al. 2016). In our model, four matrices in matching tensor represent different views of matching patterns rather than channels of a picture, where a single CNN can hardly capture all the information sufficiently. Therefore, we adopt multi-view CNN idea to first extract and then effectively aggregate matching signals from four views with a view-pooling strategy.
- **Multi-task learning framework.** Disease and corresponding procedure name for each patient could provide useful information such as body parts to the two related tasks which single task learning may fail to capture. To gain insights from heterogeneous data sources, we design multi-task architecture with constraints to combine the commonalities and differences between medical names in the clinical record.

Matching tensor

The design of matching tensor aims to enrich short-text comparison into string and semantic matching. It resembles human judgement when matching text pairs. Intuitively string matching relying on morphological features is the first to consider. Besides, in Chinese, the meaning of a word is correlated with its composing characters and for unknown token, we may even infer its meaning from the meanings of its