

# A Joint Graph Model for Pinyin-to-Chinese Conversion with Typo Correction\*

Zhongye Jia and Hai Zhao<sup>†</sup>

MOE-Microsoft Key Laboratory for Intelligent Computing and Intelligent Systems,  
Center for Brain-Like Computing and Machine Intelligence  
Department of Computer Science and Engineering, Shanghai Jiao Tong University  
800 Dongchuan Road, Shanghai 200240, China  
jia.zhongye@gmail.com, zhaohai@cs.sjtu.edu.cn

## Abstract

It is very important for Chinese language processing with the aid of an efficient input method engine (IME), of which pinyin-to-Chinese (PTC) conversion is the core part. Meanwhile, though typos are inevitable during user pinyin inputting, existing IMEs paid little attention to such big inconvenience. In this paper, motivated by a key equivalence of two decoding algorithms, we propose a joint graph model to globally optimize PTC and typo correction for IME. The evaluation results show that the proposed method outperforms both existing academic and commercial IMEs.

## 1 Introduction

### 1.1 Chinese Input Method

The daily life of Chinese people heavily depends on Chinese input method engine (IME), no matter whether one is composing an E-mail, writing an article, or sending a text message. However, every Chinese word inputted into computer or cell-phone cannot be typed through one-to-one mapping of key-to-letter inputting directly, but has to go through an IME as there are thousands of Chinese characters for inputting while only 26 letter keys are available in the keyboard. An IME is an essential software interface that maps Chinese characters into English letter combinations. An ef-

ficient IME will largely improve the user experience of Chinese information processing.

Nowadays most of Chinese IMEs are pinyin based. Pinyin is originally designed as the phonetic symbol of a Chinese character (based on the standard modern Chinese, mandarin), using Latin letters as its syllable notation. For example, the pinyin of the Chinese character “爱”(love) is “ài”. Most characters usually have unique pinyin representations, while a few Chinese characters may be pronounced in several different ways, so they may have multiple pinyin representations. The advantage of pinyin IME is that it only adopts the pronunciation perspective of Chinese characters so that it is simple and easy to learn. But there are only less than 500 pinyin syllables in standard modern Chinese, compared with over 6,000 commonly used Chinese characters, which leads to serious ambiguities for pinyin-to-character mapping. Modern pinyin IMEs mostly use a “*sentence-based*” decoding technique (Chen and Lee, 2000) to alleviate the ambiguities. “*Sentence based*” means that IME generates a sequence of Chinese characters upon a sequence of pinyin inputs with respect to certain statistical criteria.

### 1.2 Typos and Chinese Spell Checking

Written in Chinese characters but not alphabets, spell checking for Chinese language is quite different from the same task for other languages. Since Chinese characters are entered via IME, those user-made typos do not immediately lead to spelling errors. When a user types a wrong letter, IME will be very likely to fail to generate the expected Chinese character sequence. Normally, the user may immediately notice the inputting error and then make corrections, which usually means doing a bunch of extra operations like cursor

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<sup>†</sup>Corresponding author

movement, deletion and re-typing. Thus there are two separated sub-tasks for Chinese spell checking: 1. *typo checking* for user typed pinyin sequences which should be a built-in module in IME, and 2. *spell checking* for Chinese texts in its narrow sense, which is typically a module of word processing applications (Yang et al., 2012b). These two terms are often confused especially in IME related works such as (Chen and Lee, 2000) and (Wu et al., 2009).

Pinyin typos have always been a serious problem for Chinese pinyin IMEs. The user may fail to input the completely right pinyin simply because he/she is a dialect speaker and does not know the exact pronunciation for the expected character. This may be a very common situation since there are about seven quite different dialects in Chinese, among which being spoken languages, six are far different from the standard modern Chinese, mandarin. With the boom of smart-phones, pinyin typos worsen due to the limited size of soft keyboard, and the lack of physical feedback on the touch screen. However, existing practical IMEs only provide small patches to deal with typos such as *Fuzzy Pinyin* (Wu and Chen, 2004) and other language specific errors (Zheng et al., 2011b).

Typo checking and correction has an important impact on IME performance. When IME fails to correct a typo and generate the expected sentence, the user will have to take much extra effort to move the cursor back to the mistyped letter and correct it, which leads to very poor user experience (Jia and Zhao, 2013).

## 2 Related Works

The very first approach for Chinese input with typo correction was made by (Chen and Lee, 2000), which was also the initial attempt of “sentence-based” IME. The idea of “statistical input method” was proposed by modeling PTC conversion as a hidden Markov model (HMM), and using Viterbi (Viterbi, 1967) algorithm to decode the sequence. They solved the typo correction problem by decomposing the conditional probability  $P(H|P)$  of Chinese character sequence  $H$  given pinyin sequence  $P$  into a language model  $P(w_i|w_{i-1})$  and a typing model  $P(p_i|w_i)$ . The typing model that was estimated on real user input data was for typo correction. However, real user input data can be very noisy and not very convenient to obtain. As we will propose a joint model

in this paper, such an individual typing model is not necessarily built in our approach.

(Zheng et al., 2011a) developed an IME system with typo correction called CHIME using noisy channel error model and language-specific features. However their model depended on a very strong assumption that input pinyin sequence should have been segmented into pinyin words by the user. This assumption does not really hold in modern “sentence-based” IMEs. We release this assumption since our model solves segmentation, typo correction and PTC conversion jointly.

Besides the common HMM approach for PTC conversion, there are also various methods such as: support vector machine (Jiang et al., 2007), maximum entropy (ME) model (Wang et al., 2006), conditional random field (CRF) (Li et al., 2009) and statistical machine translation (SMT) (Yang et al., 2012a; Wang et al., 2013c; Zhang and Zhao, 2013), etc.

Spell checking or typo checking was first proposed for English (Peterson, 1980). (Mays et al., 1991) addressed that spell checking should be done within a context, i.e., a sentence or a long phrase with a certain meaning, instead of only in one word. A recent spell correction work is (Li et al., 2006), where a distributional similarity was introduced for spell correction of web queries.

Early attempts for Chinese spelling checking could date back to (Chang, 1994) where character tables for similar shape, pronunciation, meaning, and input-method-code characters were proposed. More recently, the 7th SIGHAN Workshop on Chinese Language Processing (Yu et al., 2013) held a shared task on Chinese spell checking. Various approaches were made for the task including language model (LM) based methods (Chen et al., 2013), ME model (Han and Chang, 2013), CRF (Wang et al., 2013d; Wang et al., 2013a), SMT (Chiu et al., 2013; Liu et al., 2013), and graph model (Jia et al., 2013), etc.

## 3 Pinyin Input Method Model

### 3.1 From English Letter to Chinese Sentence

It is a rather long journey from the first English letter typed on the keyboard to finally a completed Chinese sentence generated by IME. We will first take an overview of the entire process.

The average length of pinyin syllables is about 3 letters. There are about 410 pinyin syllables used in the current pinyin system. Each pinyin syllable

ble has a bunch of corresponding Chinese characters which share the same pronunciation represented by the syllable. The number of those homophones ranges from 1 to over 300. Chinese characters then form words. But word in Chinese is a rather vague concept. Without word delimiters, linguists have argued on what a Chinese word really is for a long time and that is why there is always a primary word segmentation treatment in most Chinese language processing tasks (Zhao et al., 2006; Huang and Zhao, 2007; Zhao and Kit, 2008; Zhao et al., 2010; Zhao and Kit, 2011; Zhao et al., 2013). A Chinese word may contain from 1 to over 10 characters due to different word segmentation conventions. Figure 1 demonstrates the relationship of pinyin and word, from pinyin letters “nihao” to the word “你好 (hello)”. Typically, an IME takes the pinyin input, segments it into syllables, looks up corresponding words in a dictionary and generates a sentence with the candidate words.

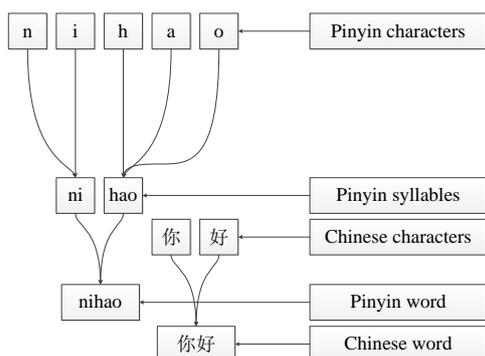


Figure 1: Relationship of pinyin and words

### 3.2 Pinyin Segmentation and Typo Correction

Non-Chinese users may feel confused or even surprised if they know that when typing pinyin through an IME, Chinese IME users will never enter delimiters such as “Space” key to segment either pinyin syllables or pinyin words, but just input the entire un-segmented pinyin sequence. For example, if one wants to input “你好世界 (Hello world)”, he will just type “nihaoshijie” instead of segmented pinyin sequence “ni hao shi jie”. Nevertheless, pinyin syllable segmentation is a much easier problem compared to Chinese word segmentation. Since pinyin syllables have a very limited vocabulary and follow a set of regularities strictly, it is convenient to perform pinyin syllable

segmentation by using rules. But as the pinyin input is not segmented, it is nearly impossible to adopt previous spell checking methods for English to pinyin typo checking, although techniques for English spell checking have been well developed. A bit confusing but interesting, pinyin typo correction and segmentation come as two sides of one problem: when a pinyin sequence is mistyped, it is unlikely to be correctly segmented; when it is segmented in an awkward way, it is likely to be mistyped.

Inspired by (Yang et al., 2012b) and (Jia et al., 2013), we adopt the graph model for Chinese spell checking for pinyin segmentation and typo correction, which is based on the shortest path word segmentation algorithm (Casey and Lecolinet, 1996). The model has two major steps: segmentation and correction.

#### 3.2.1 Pinyin Segmentation

The shortest path segmentation algorithm is based on the idea that a reasonable segmentation should minimize the number of segmented units. For a pinyin sequence  $p_1p_2 \dots p_L$ , where  $p_i$  is a letter, first a directed acyclic graph (DAG)  $G_S = (\mathbb{V}, \mathbb{E})$  is built for pinyin segmentation step. The vertex set  $\mathbb{V}$  consists of the following parts:

- Virtual start vertex  $S_0$  and end vertex  $S_E$ ;
- Possible legal syllables fetched from dictionary  $\mathbb{D}_p$  according to the input pinyin sequence:

$$\{S_{i,j} | S_{i,j} = p_i \dots p_j \in \mathbb{D}_p\};$$

- The letter itself as a fallback no matter if it is a legal pinyin syllable or not:

$$\{S_i | S_i = p_i\}.$$

The vertex weights  $w_S$  are all set to 0. The edges are from a syllable to all syllables next to it:

$$\mathbb{E} = \{E(S_{i,j} \rightarrow S_{j+1,k}) | S_{i,j}, S_{j+1,k} \in \mathbb{V}\}.$$

The edge weight the negative logarithm of conditional probability  $P(S_{j+1,k} | S_{i,j})$  that a syllable  $S_{i,j}$  is followed by  $S_{j+1,k}$ , which is give by a bigram language model of pinyin syllables:

$$W_{E(S_{i,j} \rightarrow S_{j+1,k})} = -\log P(S_{j+1,k} | S_{i,j})$$

The shortest path  $P^*$  on the graph is the path  $P$  with the least sum of weights:

$$P^* = \arg \min_{(v,E) \in G \wedge (v,E) \in P} \sum_v w_v + \sum_E W_E.$$



In the HMM for pinyin IME, observation states are pinyin syllables, hidden states are Chinese words, emission probability is  $P(s_i|w_i)$ , and transition probability is  $P(w_i|w_{i-1})$ . Note the transition probability is the conditional probability between words instead of characters. PTC conversion is to decode the Chinese word sequence from the pinyin sequence. The Viterbi algorithm (Viterbi, 1967) is used for the decoding.

The shortest path algorithm for typo correction and Viterbi algorithm for PTC conversion are very closely related. It has been strictly proven by (Forney, 1973) that the sequence decoding problem on HMM is formally identical to finding a shortest path on a certain graph, which can be constructed in the following manner.

Consider a first order HMM with all possible observations  $\mathbb{O} = \{o_1, o_2, \dots, o_M\}$ , hidden states  $\mathbb{S} = \{s_1, s_2, \dots, s_N\}$ , a special start state  $s_0$ , emission probabilities  $(\mathcal{E}_{s_i, o_k}) = P(o_k|s_i)$ , transition probabilities  $(\mathcal{T}_{s_i, s_j}) = P(s_j|s_i)$ , and start probabilities  $(\mathcal{S}_{s_i}) = P(s_i|s_0)$ . For an observation sequence of  $T$  time periods  $Y = \{y_1, y_2, \dots, y_T | y_t \in \mathbb{O}, t = 1, \dots, T\}$ , the decoding problem is to find the best corresponding hidden state sequence  $X^*$  with the highest probability, i.e.,

$$X^* = \arg \max_{x_1, x_t \in \mathbb{S}} \mathcal{S}_{x_1} \mathcal{E}_{x_1, y_1} \prod_{t=2}^T \mathcal{E}_{x_t, y_t} \mathcal{T}_{x_{t-1}, x_t}. \quad (1)$$

Then we will construct a DAG  $G = (\mathbb{V}, \mathbb{E})$  upon the HMM. The vertex set  $\mathbb{V}$  includes:

- Virtual start vertex  $v_0$  and end vertex  $v_E$  with vertex weight of 0;
- Normal vertices  $v_{x_t}$ , where  $t = 1, \dots, T$ , and  $\forall x_t \in \mathbb{S}$ . The vertex weight is the negative logarithm of emission probability:

$$w_{v_{x_t}} = -\log \mathcal{E}_{x_t, y_t}.$$

The edge set  $\mathbb{E}$  includes:

- Edges from the start vertex  $E(v_0 \rightarrow v_{x_1})$  with edge weight

$$W_{E(v_0 \rightarrow v_{x_1})} = -\log \mathcal{S}_{x_1},$$

where  $\forall x_1 \in \mathbb{S}$ ;

- Edges to the end vertex  $E(v_{x_T} \rightarrow v_E)$  with vertex weights of 0;

- Edges between adjacent time periods  $E(v_{x_{t-1}} \rightarrow v_{x_t})$  with edge weight

$$W_{E(v_{x_{t-1}} \rightarrow v_{x_t})} = -\log \mathcal{T}_{x_{t-1}, x_t},$$

where  $t = 2, \dots, T$ , and  $\forall x_t, x_{t-1} \in \mathbb{S}$ .

The shortest path  $P^*$  from  $v_0$  to  $v_E$  is the one with the least sum of vertex and edge weights, i.e.,

$$\begin{aligned} P^* &= \arg \min_{v_{x_t} \in \mathbb{V}} \sum_{t=1}^T (w_{v_{x_t}} + W_{E(v_{x_{t-1}} \rightarrow v_{x_t})}) \\ &= \arg \min_{v_{x_1}, v_{x_t} \in \mathbb{V}} \{-\log \mathcal{S}_{x_1} - \log \mathcal{E}_{x_1, y_1} \\ &\quad + \sum_{t=2}^T (-\log \mathcal{E}_{x_t, y_t} - \log \mathcal{T}_{x_{t-1}, x_t})\} \\ &= \arg \max_{v_{x_1}, v_{x_t} \in \mathbb{V}} \mathcal{S}_{x_1} \mathcal{E}_{x_1, y_1} \prod_{t=2}^T \mathcal{E}_{x_t, y_t} \mathcal{T}_{x_{t-1}, x_t}. \quad (2) \end{aligned}$$

The optimization goal of  $P^*$  in Equation (2) is identical to that of  $X^*$  in Equation (1).

### 3.4 Joint Graph Model For Pinyin IME

Given HMM decoding problem is identical to SSSP problem on DAG, we propose a joint graph model for PTC conversion with typo correction. The joint graph model aims to find the global optimal for both PTC conversion and typo correction on the entire input pinyin sequence. The graph  $G = (\mathbb{V}, \mathbb{E})$  is constructed based on graph  $G_c$  for typo correction in Section 3.2. The vertex set  $\mathbb{V}$  consists of the following parts:

- Virtual start vertex  $V_0$  and end vertex  $V_E$  with vertex weight of 0;
- Adjacent pinyin syllables in  $G_c$  are merged into pinyin words. Corresponding Chinese words are fetched from a PTC dictionary  $\mathbb{D}_c$ , which is a dictionary maps pinyin words to Chinese words, and added as vertices:

$$\{V_{i,j} | \forall V_{i,j} \in \mathbb{D}_c[S'_i \dots S'_j], i \leq j\};$$

The vertex weight consists of two parts: 1. the vertex weights of syllables in  $G_c$ , and 2. the emission probability:

$$\begin{aligned} w_{V_{i,j}} &= \beta \sum_{k=i}^j \mathcal{L}(S'_k, S_k) \\ &\quad - \gamma \log P(S'_i \dots S'_j | V_{i,j}); \end{aligned}$$



vocabulary  $\mathcal{V}$  with pinyin. The emission probabilities are estimated using the lexical translation module of MOSES (Koehn et al., 2007) as “translation probability” from pinyin to Chinese.

## 4.2 Evaluation Metrics

We will use conventional sequence labeling evaluation metrics such as sequence accuracy and character accuracy<sup>2</sup>.

Chinese characters in a sentence may be separated by digits, punctuation and alphabets which are directly inputted without the IME. We follow the so-called term *Max Input Unit* (MIU), the longest consecutive Chinese character sequence proposed by (Jia and Zhao, 2013). We will mainly consider MIU accuracy (MIU-Acc) which is the ratio of the number of completely corrected generated MIUs over the number of all MIUs, and character accuracy (Ch-Acc), but the sentence accuracy (S-Acc) will also be reported in evaluation results.

We will also report the conversion error rate (ConvER) proposed by (Zheng et al., 2011a), which is the ratio of the number of mistyped pinyin word that is not converted to the right Chinese word over the total number of mistyped pinyin words<sup>3</sup>.

## 4.3 Baseline System without Typo Correction

Firstly we build a baseline system without typo correction which is a pipeline of pinyin syllable segmentation and PTC conversion. The baseline system takes a pinyin input sequence, segments it into syllables, and then converts it to Chinese character sequence.

The pinyin syllable segmentation already has very high (over 98%) accuracy with a trigram LM using improved Kneser-Ney smoothing. According to our empirical observation, emission probabilities are mostly 1 since most Chinese words have unique pronunciation. So in this step we set  $\gamma = 0$ . We consider different LM smoothing methods including Kneser-Ney (KN), improved Kneser-Ney (IKN), and Witten-Bell (WB). All of the three smoothing methods for bigram and trigram LMs are examined both using back-off mod-

els and interpolated models. The number of  $N$ -best candidates for PTC conversion is set to 10. The results on **DEV** are shown in Figure 7 in which the “-i” suffix indicates using interpolated model. According to the results, we then choose the trigram LM using Kneser-Ney smoothing with interpolation.

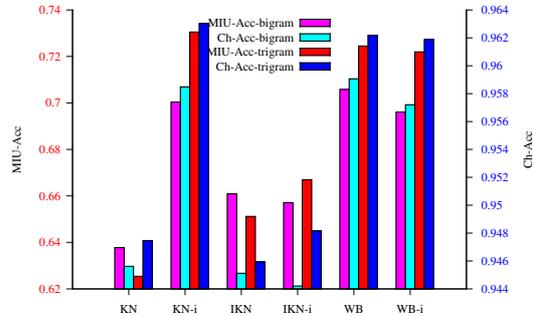


Figure 7: MIU-Acc and Ch-Acc with different LM smoothing

The choice of the number of  $N$ -best candidates for PTC conversion also has a strong impact on the results. Figure 8 shows the results on **DEV** with different  $N$ s, of which the  $N$  axis is drawn in logarithmic scale. We can observe that MIU-Acc slightly decreases while  $N$  goes up, but Ch-Acc largely increases. We therefore choose  $N = 10$  as trade-off.

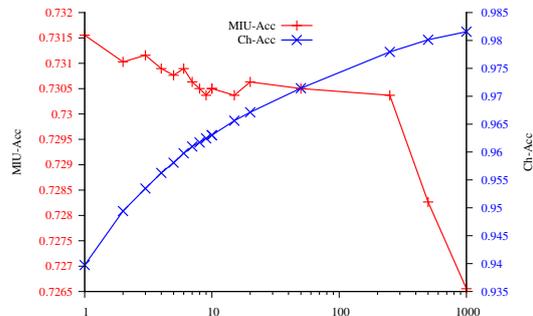


Figure 8: MIU-Acc and Ch-Acc with different  $N$ s

The parameter  $\gamma$  determines emission probability. Results with different  $\gamma$  on **DEV** is shown in Figure 9, of which the  $\gamma$  axis is drawn in logarithmic scale.  $\gamma = 0.03$  is chosen at last.

We compare our baseline system with several practical pinyin IMEs including *sunpinyin* and *Google Input Tools* (Online version)<sup>4</sup>. The results on **DEV** are shown in Table 2.

<sup>2</sup>We only work on the PTC conversion part of IME, thus we are unable to use existing evaluation systems (Jia and Zhao, 2013) for full Chinese IME functions.

<sup>3</sup>Other evaluation metrics are also proposed by (Zheng et al., 2011a) which is only suitable for their system since our system uses a joint model

<sup>4</sup><http://www.google.com/inputtools/try/>

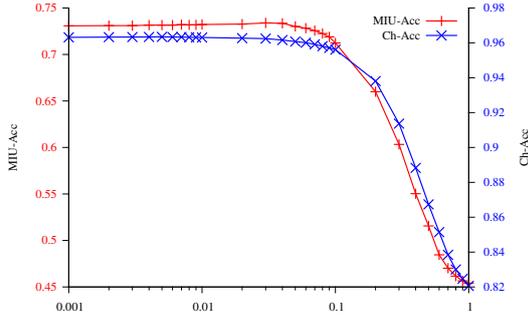


Figure 9: MIU-Acc and Ch-Acc with different  $\gamma$

|           | MIU-Acc | Ch-Acc | S-Acc |
|-----------|---------|--------|-------|
| Baseline  | 73.39   | 96.24  | 38.00 |
| sunpinyin | 52.37   | 87.51  | 13.95 |
| Google    | 74.74   | 94.81  | 40.2  |
| Yang-ME   | -       | 93.3   | 30.2  |
| Yang-MT   | -       | 95.5   | 45.4  |

Table 2: Baseline system compared to other IMEs (%)

#### 4.4 PTC Conversion with Typo Correction

Based upon the baseline system, we build the joint system of PTC conversion with typo correction.

We simulate user typos by randomly generating errors automatically on the corpus. The typo rate is set according to previous Human-Computer Interaction (HCI) studies. Due to few works have been done on modeling Chinese text entry, we have to refer to those corresponding results on English (Wobbrock and Myers, 2006; MacKenzie and Soukoreff, 2002; Clarkson et al., 2005), which show that the average typo rate is about 2%. (Zheng et al., 2011a) performed an experiment that 2,000 sentences of 11,968 Chinese words were entered by 5 native speakers. The collected data consists of 775 mistyped pinyin words caused by one edit operation, and 85 caused by two edit operations. As we observe on **TRAIN** that the average pinyin word length is 5.24, then typo rate in the experiment of (Zheng et al., 2011a) can be roughly estimated as:

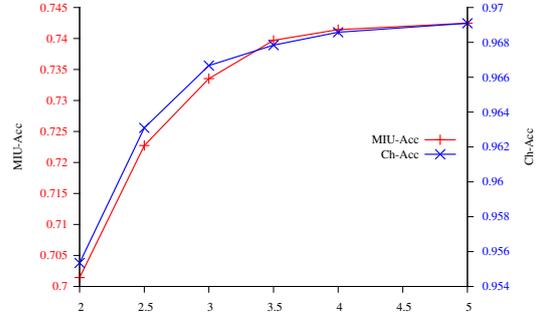
$$\frac{775 + 85 \times 2}{11968 \times 5.24} = 1.51\%,$$

which is similar to the conclusion on English. Thus we generate corpora from **DEV** with typo rate of 0% (**0-P**), 2% (**2-P**), and 5% (**5-P**) to evaluate the system.

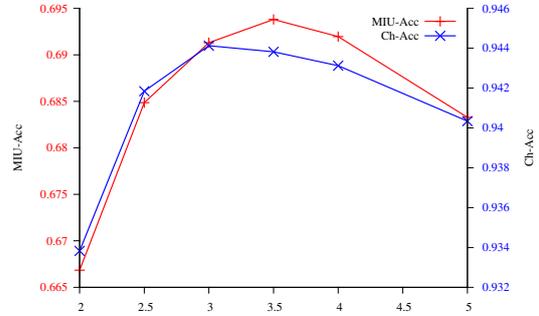
According to (Zheng et al., 2011a) most mistyped pinyin words are caused by one edit operation. Since pinyin syllable is much shorter than

pinyin word, this ratio can be higher for pinyin syllables. From our statistics on **TRAIN**, with 2% randomly generated typos,  $Pr(\mathcal{L}(S', S) < 2) = 99.86\%$ . Thus we set the threshold  $T$  for  $\mathcal{L}$  to 2.

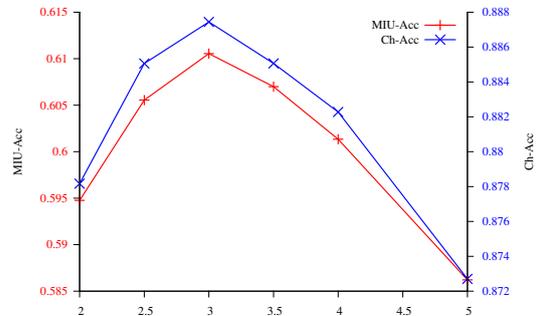
We first set  $K$ -shortest paths filter to  $K = 10$  and tune  $\beta$ . Results with different  $\beta$  are shown in Figure 10. With  $\beta = 3.5$ , we select  $K$ . Re-



(a) **0-P**



(b) **2-P**



(c) **5-P**

Figure 10: MIU-Acc and Ch-Acc with different  $\beta$

sults with different  $K$  are shown in Figure 11. We choose  $K = 20$  since there is no significant improvement when  $K > 20$ .

The selection of  $K$  also directly guarantees the running time of the joint model. With  $K = 20$ , on a normal PC with Intel Pentium Dual-Core E6700 CPU, the PTC conversion rate is over 2000 characters-per-minute (*cpm*), which is much faster than the normal typing rate of 200 *cpm*.

With all parameters optimized, results on **TEST**

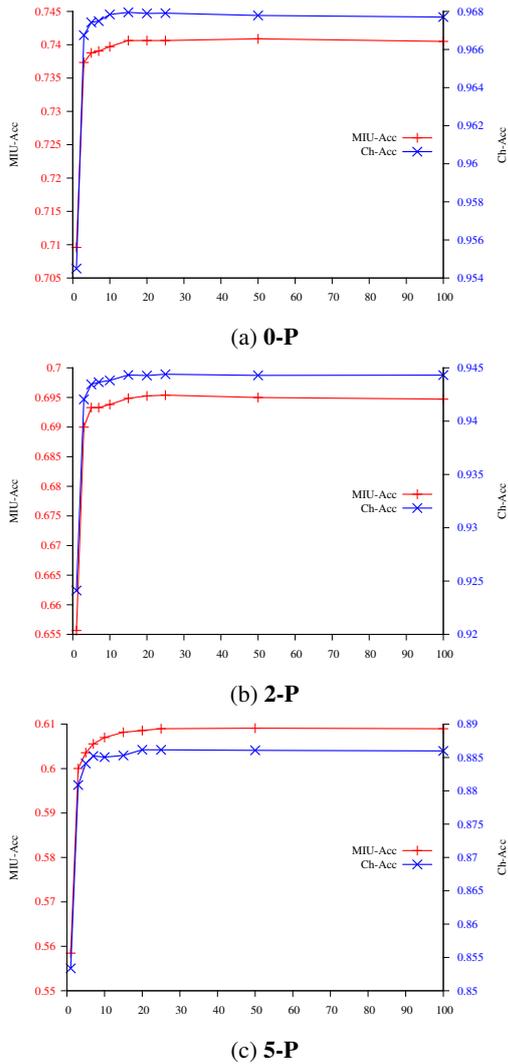


Figure 11: MIU-Acc and Ch-Acc with different  $K$

using the proposed joint model are shown in Table 3 and Table 4. Our results are compared to the baseline system without typo correction and *Google Input Tool*. Since *sunpinyin* does not have typo correction module and performs much poorer than our baseline system, we do not include it in the comparison. Though no direct proofs can be found to indicate if *Google Input Tool* has an independent typo correction component, its outputs show that such a component is unlikely available.

Since *Google Input Tool* has to be accessed through a web interface and the network connection cannot be guaranteed, we only take a subset of 10K sentences of **TEST** to perform the experiments, and the results are shown in Table 3.

The scores reported in (Zheng et al., 2011a) are not listed in Table 4 since the data set is different. They reported a ConvER of 53.56%, which is given here for reference.

Additionally, to further inspect the robustness of our model, performance with typo rate ranges from 0% to 5% is shown in Figure 12. Although the performance decreases while typo rate goes up, it is still quite satisfying around typo rate of 2% which is assumed to be the real world situation.

|                     | MIU-Acc | Ch-Acc | S-Acc | ConvER |
|---------------------|---------|--------|-------|--------|
| Baseline <b>0-P</b> | 79.90   | 97.47  | 48.87 | -      |
| Baseline <b>2-P</b> | 50.47   | 90.53  | 11.12 | 99.95  |
| Baseline <b>5-P</b> | 30.26   | 82.83  | 3.32  | 99.99  |
| Google <b>0-P</b>   | 79.08   | 95.26  | 46.83 | -      |
| Google <b>2-P</b>   | 49.47   | 61.50  | 11.08 | 91.70  |
| Google <b>5-P</b>   | 29.18   | 36.20  | 3.29  | 94.64  |
| Joint <b>0-P</b>    | 79.90   | 97.52  | 49.27 | -      |
| Joint <b>2-P</b>    | 75.55   | 95.40  | 40.69 | 18.45  |
| Joint <b>5-P</b>    | 67.76   | 90.17  | 27.86 | 24.68  |

Table 3: Test results on 10K sentences from **TEST** (%)

|                     | MIU-Acc | Ch-Acc | S-Acc | ConvER |
|---------------------|---------|--------|-------|--------|
| Baseline <b>0-P</b> | 74.46   | 96.42  | 40.50 | -      |
| Baseline <b>2-P</b> | 47.25   | 89.50  | 9.62  | 99.95  |
| Baseline <b>5-P</b> | 28.28   | 81.74  | 2.63  | 99.98  |
| Joint <b>2-P</b>    | 74.22   | 96.39  | 40.34 | -      |
| Joint <b>2-P</b>    | 69.91   | 94.14  | 33.11 | 21.35  |
| Joint <b>5-P</b>    | 62.14   | 88.49  | 22.62 | 27.79  |

Table 4: Test results on **TEST** (%)

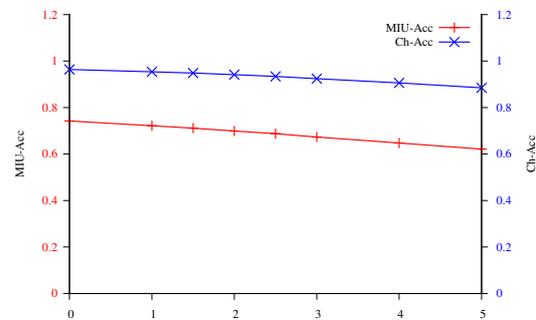


Figure 12: MIU-Acc and Ch-Acc with different typo rate (%)

## 5 Conclusion

In this paper, we have developed a joint graph model for pinyin-to-Chinese conversion with typo correction. This model finds a joint global optimal for typo correction and PTC conversion on the entire input pinyin sequence. The evaluation results show that our model outperforms both previous academic systems and existing commercial products. In addition, the joint model is efficient enough for practical use.

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