



Multi-channel Reverse Dictionary Model 多通道反向词典模型

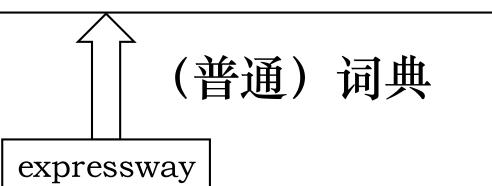
THUNLP

岂凡超

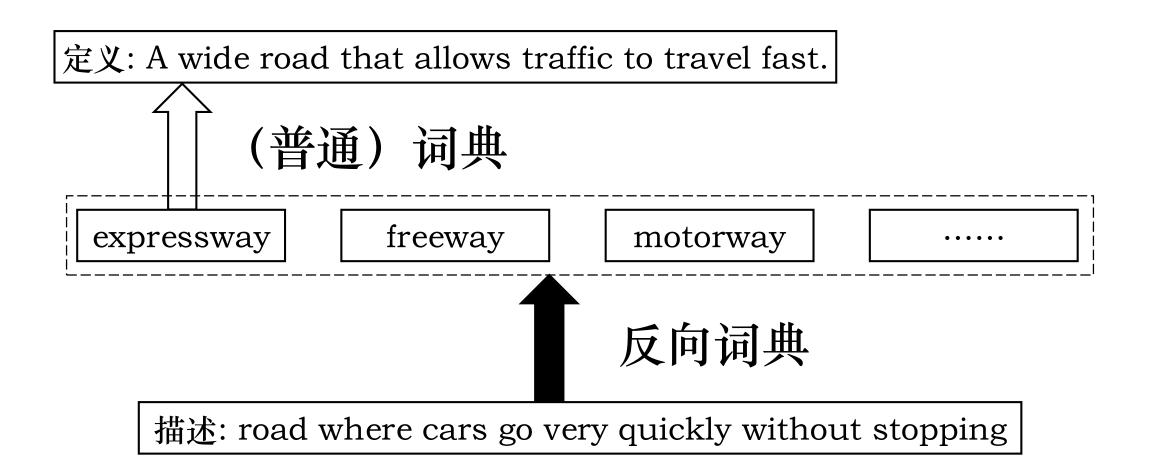
qfc17@mails.tsinghua.edu.cn 2019/12/22

研究背景一反向词典

定义: A wide road that allows traffic to travel fast.



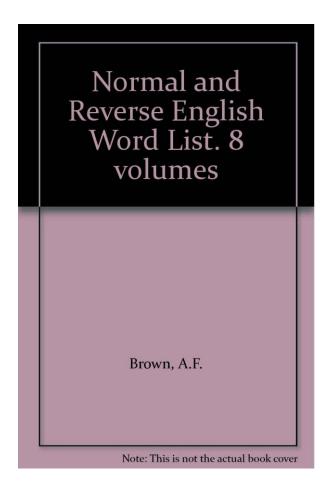
研究背景一反向词典

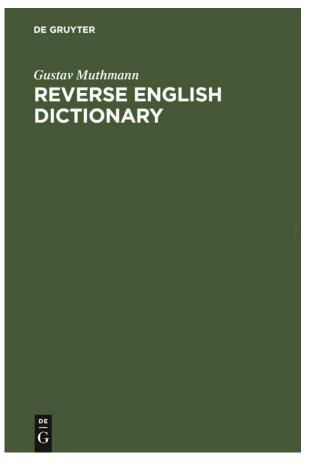


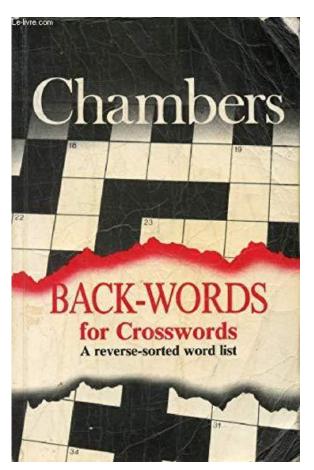
研究背景一反向词典

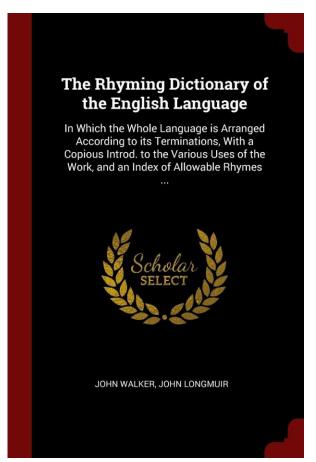
- 反向词典具有重要实用价值
 - ·解决舌尖现象(Tip of the tongue,话到嘴边说不出来)
 - 为新语言学习者提供帮助
 - •帮助选词性命名不能(word selection anomia)患者
- 反向词典同样具有自然语言处理研究价值
 - •用于评测句子表示学习质量 [Hill et al. 2016]
 - •有助于包含文本到实体映射的任务,如问答、信息检索 [Kartsaklis et al. 2018]

研究背景一现有反向词典







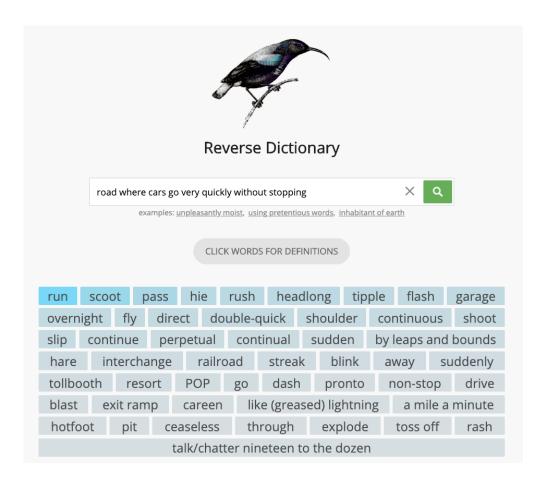


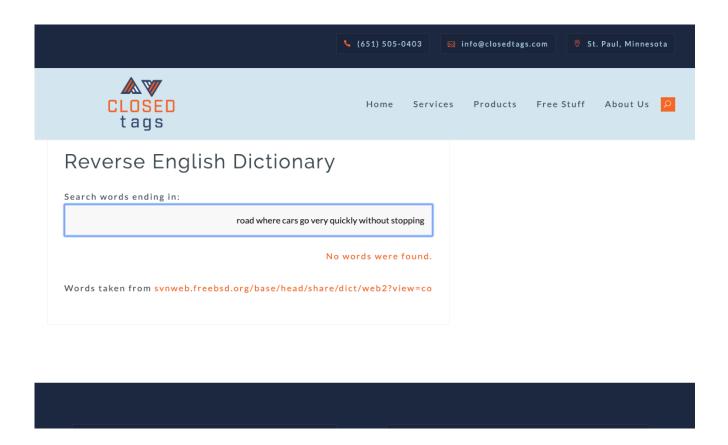
研究背景一现有反向词典



https://www.onelook.com/thesaurus/

研究背景一现有反向词典





https://reversedictionary.org/

https://closedtags.com/reverse-english-dictionary/

研究背景一现有反向词典研究

- •基于句子匹配的方法 [Bilac et al. 2004, Zock and Bilac 2004, Méndez et al. 2013, Shaw et al. 2013]
 - 在数据库中存储足够多的词语及其定义
 - 返回与输入描述最相似的词典定义所对应的词语
 - 使用特征工程衡量相似度

反向词典查询输入非常多变,可能与已存储的词典定义有巨大差别!

Bilac, S.; Watanabe, W.; Hashimoto, T.; Tokunaga, T.; and Tanaka, H. 2004. Dictionary search based on the target word description. In Proceedings of NLP. Zock, M., and Bilac, S. 2004. Word lookup on the basis of associations: from an idea to a roadmap. In Proceedings of the Workshop on Enhancing and Using Electronic Dictionaries.

Méndez, O.; Calvo, H.; and Moreno-Armend´ariz, M. A. 2013. A reverse dictionary based on semantic analysis using wordnet. In Proceedings of MICAI. Shaw, R.; Datta, A.; VanderMeer, D. E.; and Dutta, K. 2013. Building a scalable database-driven reverse dictionary. IEEE Transactions on Knowledge and Data Engineering 25:528540.

研究背景一现有反向词典研究

- •基于神经语言模型的方法[Hill et al. 2016, Morinaga and Yamaguchi 2018, Kartsaklis et al. 2018, Hedderich et al. 2019, Pilehvar 2019]
 - 使用神经语言模型将输入描述编码到词向量空间
 - •返回与输入描述的句子表示最近的词向量对应的词语

存在大量低频词,其词向量效果较差!

Hill, F.; Cho, K.; Korhonen, A.; and Bengio, Y. 2016. Learning to understand phrases by embedding the dictionary. TACL 4:17 – 30.

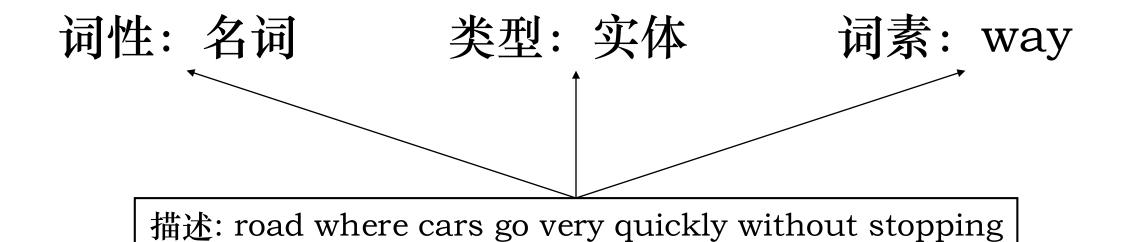
Morinaga, Y., and Yamaguchi, K. 2018. Improvement of reverse dictionary by tuning word vectors and category inference. In Proceedings of ICIST.

Kartsaklis, D.; Pilehvar, M. T.; and Collier, N. 2018. Mapping text to knowledge graph entities using multi-sense LSTMs. In Proceedings of EMNLP.

Hedderich, M. A.; Yates, A.; Klakow, D.; and de Melo, G. 2019. Using multi-sense vector embeddings for reverse dictionaries. In Proceedings of IWCS.

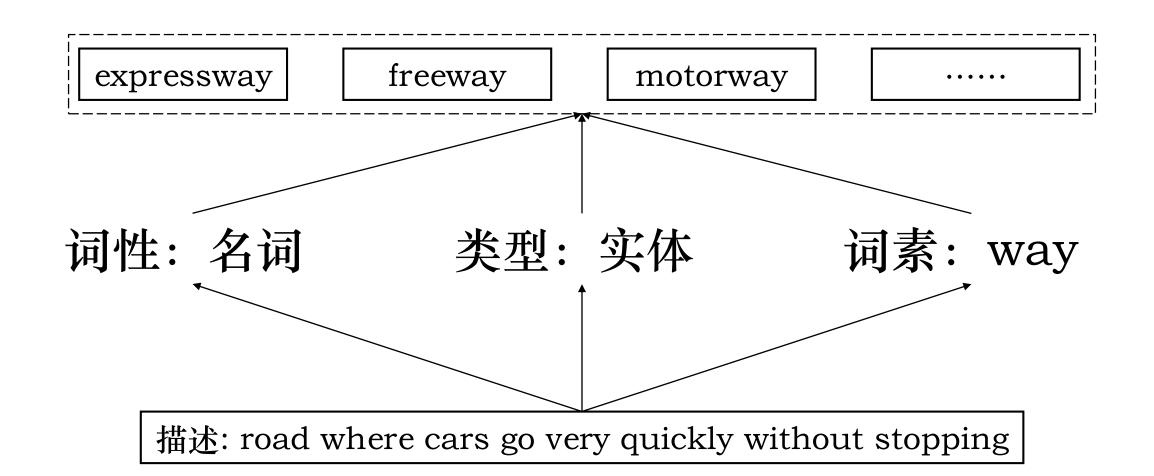
Pilehvar, M. T. 2019. On the importance of distinguishing word meaning representations: A case study on reverse dictionary mapping. In Proceedings of NAACL.

研究动机一人的推断过程

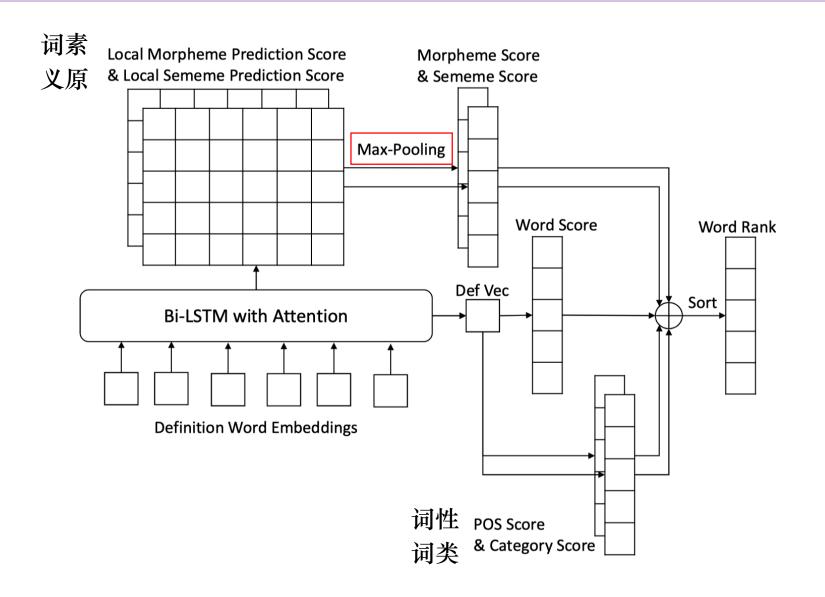


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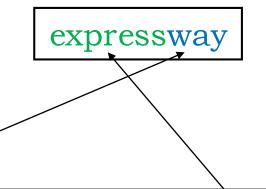
研究动机一人的推断过程



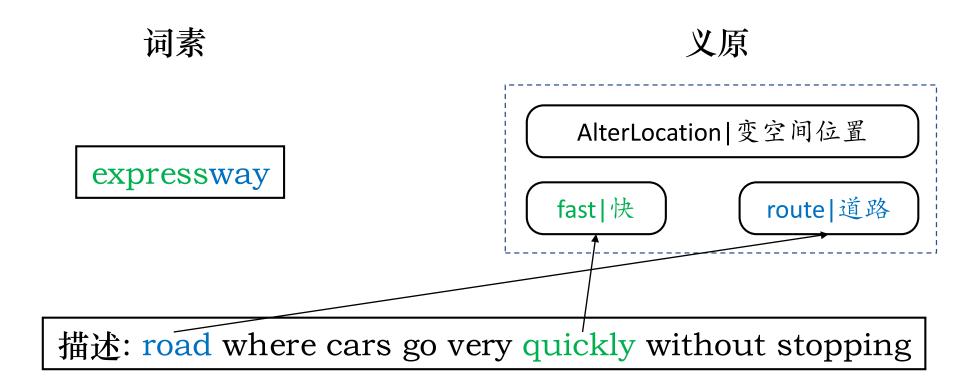
- •多通道反向词典模型——包含多个特征预测器
 - •内部通道——词本身的特征
 - •词性 (Part-of-speech)
 - 词素 (Morpheme)
 - 外部通道——外部知识库提供的特征
 - 词类 (Word Category) ——借助WordNet/同义词词林
 - 义原 (Sememe) ——借助HowNet



词素



描述: road where cars go very quickly without stopping



•英文数据集

	Model	S	Seen Definition	n	Un	seen Definitio	n	Description			
	OneLook	0 .66/.94/.95 200		200	-			5.5	.33 /.54/.76	332	
	BOW	172	.03/.16/.43	414	248	.03/.13/.39	424	22	.13/.41/.69	308	
	RNN	134	.03/.16/.44	375	171	.03/.15/.42	404	17	.14/.40/.73 .14/.41/.74	274	
	RDWECI	121	.06/.20/.44	420	170	.05/.19/.43	420	16		306	
	SuperSense		.03/.15/.36	462	465	.02/.11/.31	454	115	.03/.15/.47	396	
SOTA	MS-LSTM	0	.92/.98/.99	65	276	.03/.14/.37	426	1000	.01/.04/.18	404	
	BiLSTM	25	.18/.39/.63	363	101	.07/.24/.49	401	5	.25/.60/.83	214	
	+Mor	24	.19/.41/.63	345	80	.08/.26/.52	399	4	.26/.62/.85	198	
	+Cat	19	.19/.42/.68	309	68	.08/.28/.54	362	4	.30/.62/.85	206	
	+Sem	19	.19/.43/.66	349	80	.08/.26/.53	393	4	.30/ .64 /.87	218	
	Multi-channel	16	.20/.44/.71	310	54	.09/.29/.58	358	2	.32/ .64/.88	203	

median rank accuracy@1/10/100 rank variance

•中文数据集

Model		Seen Definition	n	Useen Definition				Description			Question	
BOW	59	.08/.28/.56	403	65	.08/.28/.53	411	40	.07/.30/.60	357	42	.10/.28/.63	362
RNN	69	.05/.23/.55	379	103	.05/.21/.49	405	79	.04/.26/.53	361	56	.07/.27/.60	346
RDWECI	56	.09/.31/.56	423	83	.08/.28/.52	436	32	.09/.32/.59	376	45	.12/.32/.61	384
BiLSTM	4	.28/.58/.78	302	14	.15/.45/.71	343	13	.14/.44/.78	233	4	.30/.61/.82	243
+POS	4	.28/.58/.78	309	14	.16/.45/.71	346	13	.14/.44/.79	255	5	.25/.59/.79	271
+Mor	1	.43/.73/.87	260	11	.19 /.47/.73	332	8	.22/.52/ .83	251	1	.42/.73/.86	227
+Cat	4	.29/.58/.78	319	16	.14/.43/.70	356	13	.16/.45/.77	289	3	.33/.62/.82	246
+Sem	4	.29/.60/.80	298	14	.16/.45/.72	340	12	.15/.45/.75	244	4	.34/.61/.83	231
Multi-channel	1	.49/.78/.90	220	10	.18/ .49/.76	310	5	.24/.56/ .82	260	0	.50/.73/.90	223

median rank accuracy@1/10/100 rank variance

•给定先验知识

• 英文

Prior Knowlege		Seen Definition	n	Un	nseen Definitio	Description			
None	16	.20/.44/.71	310	54	.09/.29/.58	358	2.5	.32/.64/.88	203
POS Tag	13	.21/.45/.72	290	45	.10/.31/.60	348	3	.35/.65/.91	174
Initial Letter	1	.39/.73/.90	270	4	.26/.63/.85	348	0	.62/.90/.97	160
Word Length	1	.40/.71/.90	269	6	.25/.56/.84	346	0	.55/.85/.95	163

median rank

accuracy@1/10/100

rank variance

• 中文

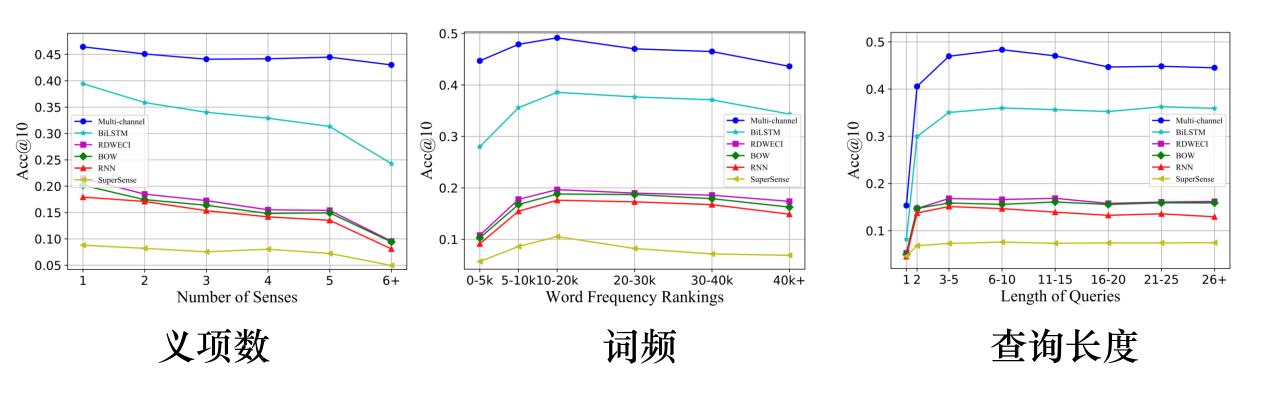
Prior Knowledge	Seen Definition			Useen Definition			Description			Question		
None	1	.49/.78/.90	220	10	.18/.49/.76	310	5	.24/.56/.82	260	0	.50/.73/.90	223
POS Tag	1	.50/.79/.90	222	9	.18/.51/.77	307	4	.24/.61/.85	252	0	.50/.74/.90	223
Initial Char	0	.74/.89/.92	220	0	.55/.82/.86	304	0	.61/.88/.93	239	0	.84/.95/.95	213
Word Length	0	.54/.82/.91	217	6	.23/.57/.81	297	3	.32/.68/88	242	0	.62/.85/.94	212

median rank

accuracy@1/10/100

rank variance

•模型鲁棒性



结论

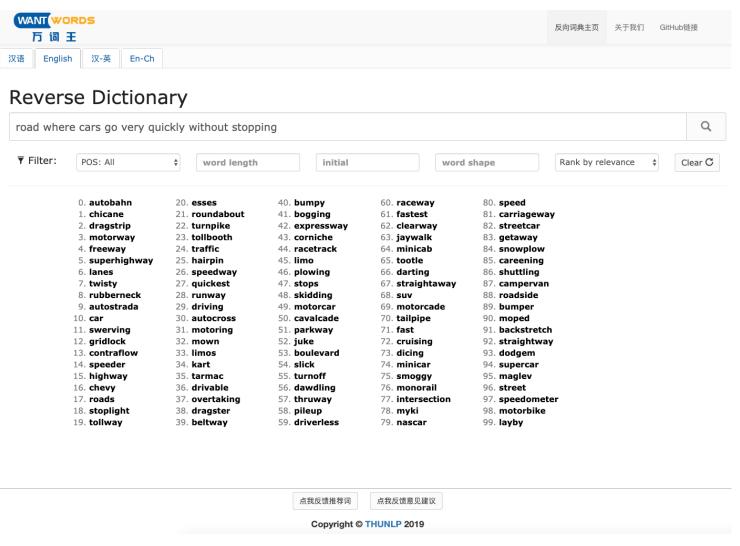
- •主要贡献
 - •基于人的描述-词的推断过程,提出多通道反向词典模型,包含内部通道:词性、词素,和外部通道:词类、义原
 - •在真实场景数据集实现了当前最佳性能(state-of-the-art)
- •未来工作
 - •和基于文本匹配的方法相结合,更好的解决极端情况(如输入只有单个词)
 - 迁移到其他任务





论文地址

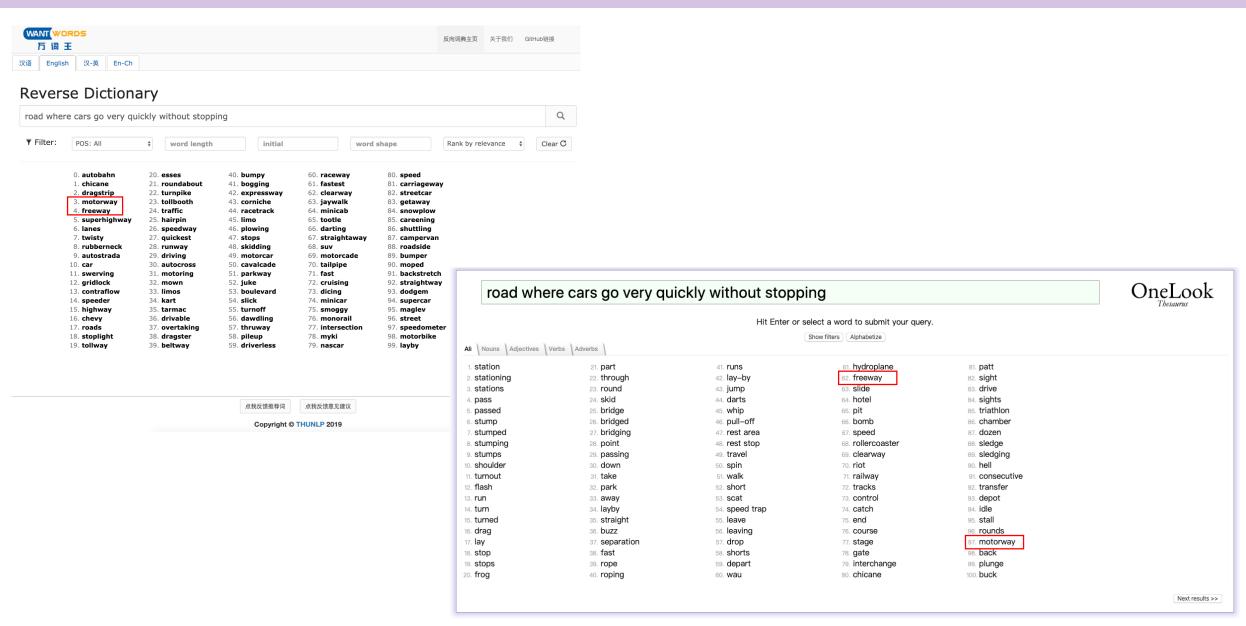
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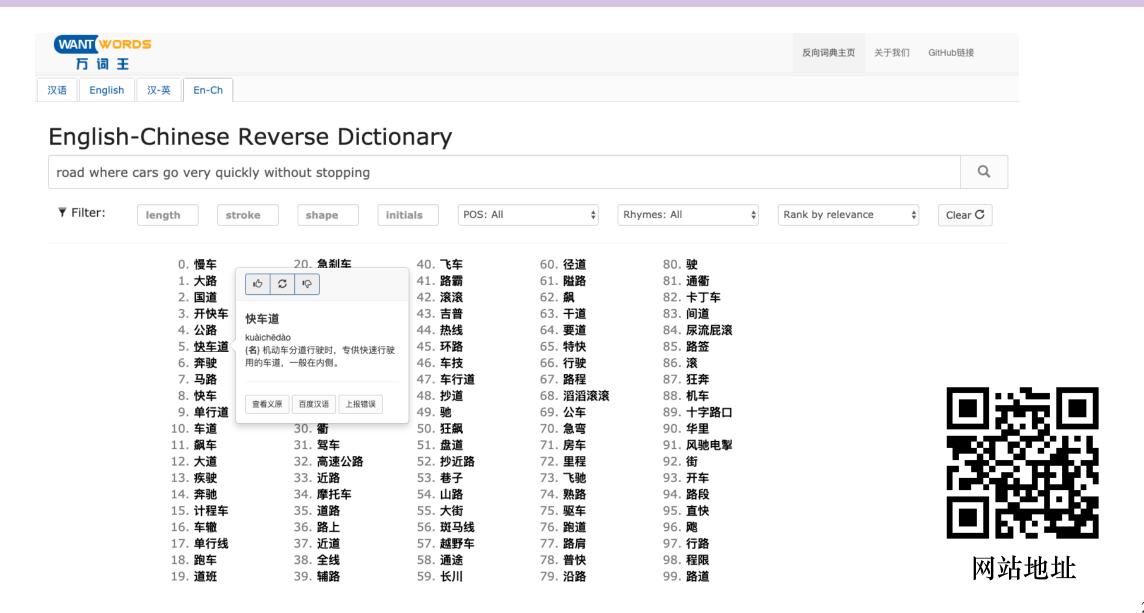




网站地址

https://wantwords.thunlp.org/







感谢聆听,欢迎指教!



论文地址



项目地址



网站地址