Multi-Specialty Domain Adaptation for Chinese Medical Named Entity Recognition

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医疗命名实体识别面临的重要挑战：医疗领域标注数据缺乏

医疗数据难以获取

医疗数据标注难度大

医疗领域标注数据缺乏

领域自适应

联邦学习

主动学习

……

为什么需要领域自适应？

当为了在某个领域(Target Domain)训练一个数据驱动的机器学习模型时，我们如果缺少这个Target Domain的标注数据，可以利用其他领域(Source Domain)已有数据进行训练。但是由于现在的模型归纳能力有限，通常在out-of-domain的数据上的性能会出现非常明显的下降。

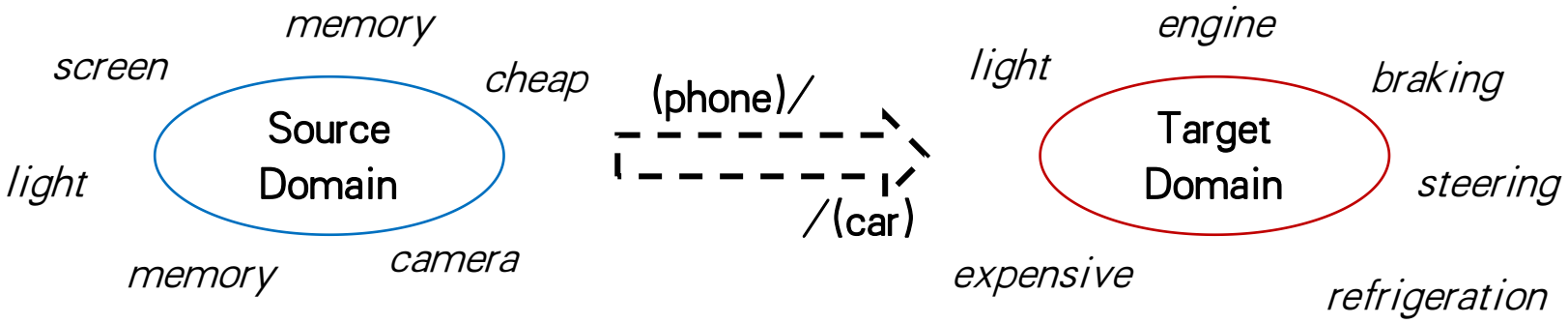
背景

例子

由于不同领域数据的分布不同，特性不同等等，模型在跨领域测试时往往会因为领域差异，使得数据驱动模型的能力被削弱。比如评论情感分析任务中(积极/消极)，同一个词在不同领域可能有不同的情感极性。

a（soruce domain==phone)：这部手机的重量很*轻* （``*轻*''是积极）

b（target domain==car)：这辆车的重量很*轻* （``*轻*''是消极）



背景

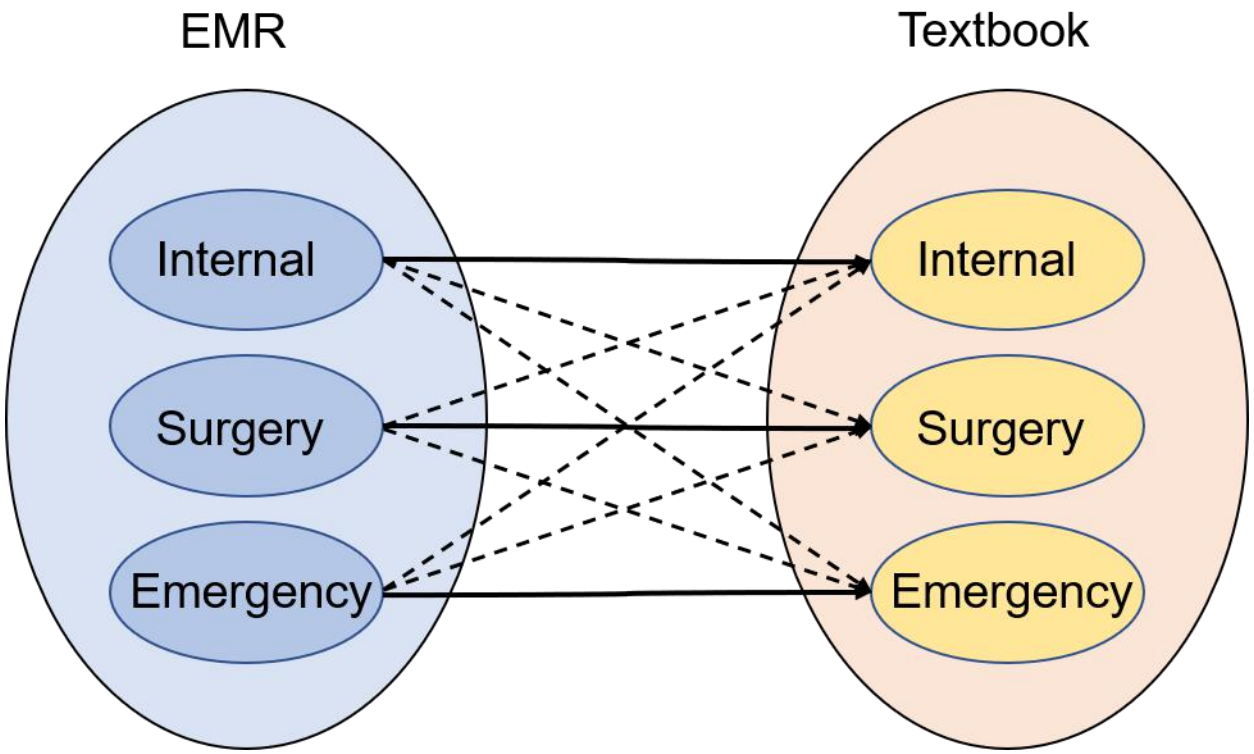
领域自适应标准范式

- **Single-Domain to Single-Domain adaptation**
- **Multi-Domain to Single-Domain adaptation**
- **Single-Domain to Multi-Domain adaptation**

背景

Internal Medicine	病人 病理 改变 显示 弥漫性肺泡损伤 (Disease) Patient's pathological changes show Diffuse alveolar damage, 和 炎症细胞浸润, (Disease) 早期的 特征 是 and inflammatory cell infiltration, the early feature is 肺水肿。 (Disease) pneumonedema.
Surgery	术前 心电图检查, (Check) 全麻下 Before surgery, ECG examination, under general anesthesia 行 动脉导管结扎术。 (Check) conduct ligation of patent ductus arteriosus.
Emergency	体检 发现 血压下降, (Sign) Physical examination reveals a drop in blood pressure, 膀胱占位, (Symptom) 排尿困难, (Symptom) 肉眼血尿。 (Symptom) bladder occupying, dysuria, gross hematuria.

Multi-domain to Multi-domain Adaptation

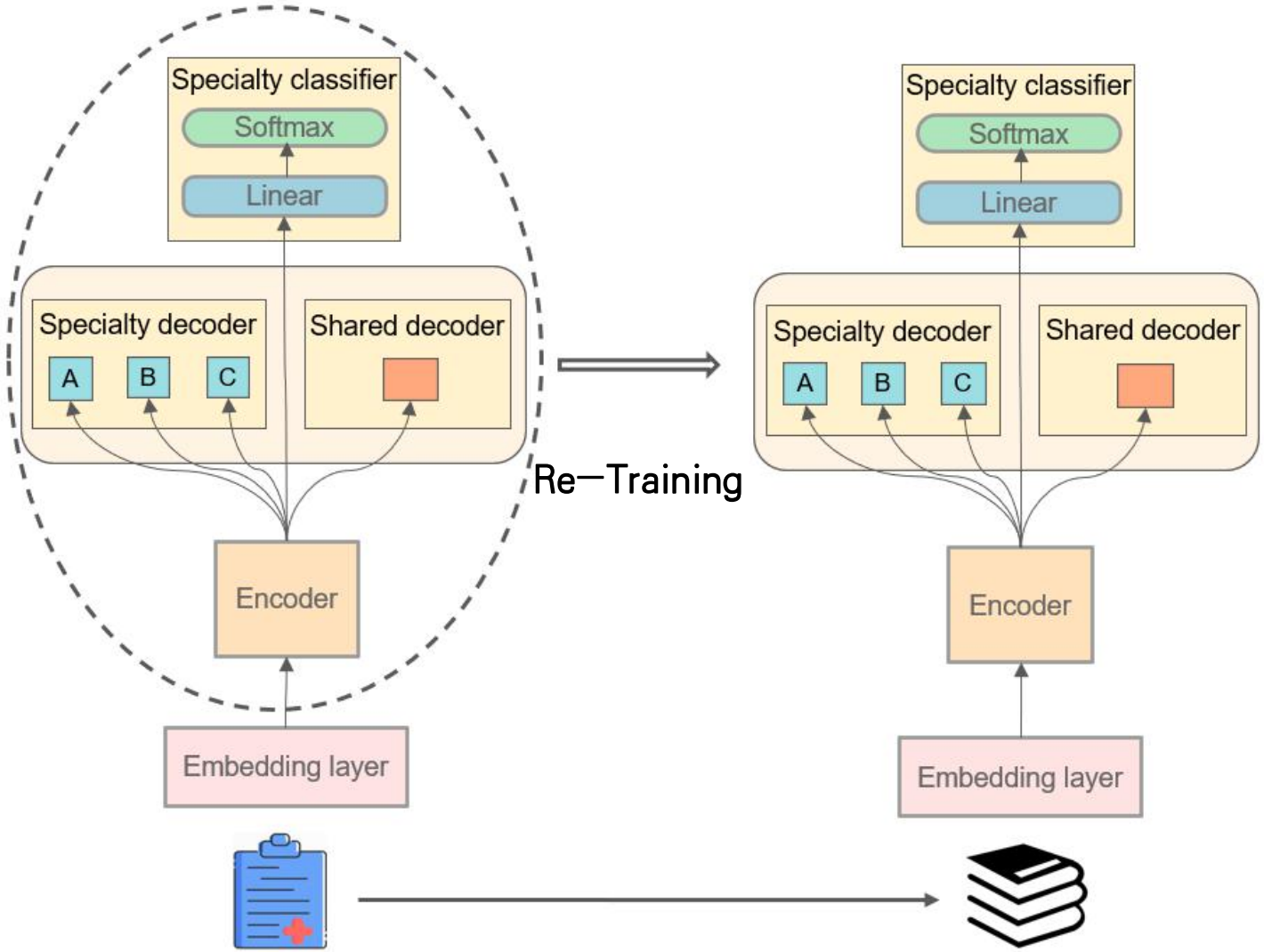


Specialty	EMR	Textbook
Internal Medicine	4521	492
Surgery	1782	18
Emergency	1856	227
Sum	8159	737

方法

Multi—Task ： MT

Multi—Specialty ： MS



实验设计

Without Domain adaptation （BBC/Target-Only、BBC/Mix、Lattice/Mix)

Single-Domain to Single-Domain adaptation **(**DANN、BBC/Re-Training)

Multi-Domain to Multi-Domain adaptation **(**BBC/Re-Training/MT、**MSADA**)

结果及消融实验

Method	Disease	Symptom	Sign	Operation	Drug	Check	F1-micro
BBC/Target-Only	83.94	76.24	59.01	22.00	83.72	55.13	73.92
BBC/Mix	87.31	83.12	45.05	47.33	73.44	61.82	76.17
Lattice/Mix [15]	**87.34**	81.68	50.79	64.24	75.49	72.78	78.51
DANN [16]	78.76	69.87	52.91	22.47	64.20	50.34	66.76
BBC/Re-Training	86.46	81.28	58.52	**72.29**	**85.61**	70.09	78.83
BBC/Re-Training/MT	86.86	82.92	**64.55**	45.67	83.52	69.06	79.23
MSADA	84.06	**86.51**	48.43	68.63	80.53	**80.11**	**80.84**

Method	Disease	Symptom	Sign	Operation	Drug	Check	F1-micro
MSADA	84.06	**86.51**	48.43	68.63	80.53	**80.11**	**80.84**
-MS	86.86	82.92	**64.55**	45.67	83.52	69.06	79.23
-MT	**87.28**	82.83	48.00	77.91	80.30	72.40	79.12
-BERT	82.00	75.35	27.51	47.20	53.94	56.13	68.64
-MT/MS	86.46	81.28	58.52	**72.29**	**85.61**	70.09	78.83
-MT/MS/BERT	78.34	72.64	48.23	20.41	57.93	54.76	66.25

总 结

In summary, this paper makes the following contributions:

1) We propose a novel multi-to-multi domain adaptation paradigm for Chinese MER, constructed a corresponding dataset, and explored the effect of various methods on the proposed dataset.

2) To solve the unique challenge of multi-to-multi domain adaptation from EMR to medical textbook, we propose a method named MSADA with adaptive specialty alignment mechanism to capture multi-specialty information.

3) On the dataset we constructed, MSADA significantly outperforms all other competitive methods, with improvements ranging between +1.61 to +14.08 F1-micro.

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Thanks!