**关系分类国内外综述**

关系分类是将具有两个标记实体的句子分配给预定关系集合的任务[1]。例如，“We poured the <e1>milk</e1> into the <e2>pumpkin mixture</e2>.”描述了Entity-Destination关系(e1,e2)。关系分类是一个基本任务，可以作为一个预先存在的系统为信息提取，自然语言理解，信息检索等提供先验知识[2]。

最近的研究通常在监督的角度提出关系分类的任务，传统的监督方法可以分为基于特征的方法和内核方法。

基于特征的方法集中于提取和选择用于关系分类的相关特征。Kambhatla（2004）[3]利用词汇，句法和语义特征，将它们提供给最大熵模型。Hendrickx等人（2010）[4]的研究表明，SemEval-2010任务8的获胜者在所有参与者中使用最多类型的特征和资源。然而，采用基于特征的方法难以找到最佳特征集，因为遍历特征的所有组合对于基于特征的方法是耗时的。

为了解决上述特征选择的问题，内核方法根据精心设计的内核计算句子之间的结构共性来表示输入数据.Mooney和Bunescu（2005）[5]将句子分割为子序列并使用提出的子序列核来计算相似性。Bunescu和Mooney（2005）提出了依赖树内核，并从标记实体之间的最短依赖路径（SDP）中提取信息。由于内核方法需要在输入样本之间进行相似性计算，因此当面对大规模数据集时，它们的计算成本相对较高。

之后，机器学习的相关算法被引入用于解决关系分类问题，研究主要集中在**支持向量机（SVM）或最大熵分类器**。Rink和Harabagiu（2010a）[6]采用的是SVM结合特征捕获语境、语义角色关系和可能存在的关系。这种方法的F1得分是82.19％，精度为77.92％。Tratz和Hovy（2010）[7]使用大量布尔特征训练的最大熵分类器实现分类。

如今，基于深度神经网络的方法已经成为关系分类的主要解决方案。这些方案主要集中在四个方面：**（一）CNN模型的优化。**Socher等人（2012）[8]等人提出的MV-RNN模型试图通过利用句法树来捕捉句子语义的组成方面。Zeng等人（2014）[9]提出了一个具有softmax分类的CNN模型，提取词汇和句子层次的特征。然而，这些方法仍然依赖于词汇资源和NLP工具包的附加特征。Yu等人（2014）[10]提出了基于因子的组合嵌入模型（FCM），该模型使用句法依赖树及句子级嵌入。dos Santos等人 （2015）[11]提出了一个带有类嵌入矩阵的排名CNN（CR-CNN）模型。**（二）RNN模型的优化。**Miwa和Bansal（2016）[12]的研究表明，由于在网络架构中捕获的语言结构有限，基于LSTM的RNN模型的性能优于CNN模型。目前已经提出了一些更负责的模型来解决这个问题，包括双向LSTM模型（Zhang等人，2015）[13]，深度循环神经网络（Xu等人，2016）[14]和双向树结构的LSTM-RNN模型（Miwa和Bansal，2016）[12]。**（三）基于依赖树的模型。**例如，基于句法树的RNN模型（Hashimoto等人，2013）[15]，基于最短依赖路径的CNN模型（Xu等人，2015a）[16]和SDP-LSTM模型（Xu等人，2015b）[17]。**（四）CNN模型和RNN模型的结合。**最后，Nguyen和Grishman（2015）[18]同时训练CNN模型和RNN模型，并使用投票，堆栈或对数线性建模来综合其输出。

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