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A comprehensive review of conditional random fields: variants, hybrids and applications

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Abstract

The conditional random fields (CRFs) model plays an important role in the machine learning field. Driven by the development of the artificial intelligence, the CRF models have enjoyed great advancement. To analyze the recent development of the CRFs, this paper presents a comprehensive review of different versions of the CRF models and their applications. On the basis of elaborating on the background and definition of the CRFs, it analyzes three basic problems faced by the CRF models and reviews their latest improvements. Based on that, it presents the applications of the CRFs in the natural language processing, computer vision, biomedicine, Internet intelligence and other relevant fields. At last, specific analysis and future directions of the CRFs are discussed.

Keywords Conditional random fields · Probabilistic graphical models · Machine learning · Artificial intelligence

1 Introduction

With the development of the artificial intelligence, the machine learning field has received wide and profound progress. The CRFs, as an important type of the machine learning models developed on the basis of the Maximum Entropy Markov Model (MEMM) (Mccallum et al. 2000), have also attracted attention from the scholars. In fact, the past few years have witnessed an endless emergence of studies on the CRFs, some of which have been devoted to the improvement of the basic models, while others have been devoted to the innovations in terms of the application. The development of the CRFs in the above two aspects has not only deepened the understanding of the CRF models but also accelerated their extension into various fields.

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The CRFs were first proposed by Lafferty et al. (2001) as probabilistic models to segment and label sequence data, with the aim of inheriting the advantages of the previous models, overcoming their defects, increasing their efficiency, and solving more practical problems. Since then, many scholars have conducted in-depth discussions on it, which has promoted the continuous improvement of the model in theory. Following the steps of predecessors, Wallach (2004) offered an explanation of the CRFs and deduced the forms and inference algorithms of the CRFs from the mathematical perspective. After that, Koller et al. (2007) discussed the differences between generative models and the CRFs, classified the CRF models and explained the models of each category, which enriched the connotations of the CRFs. Klinger and Tomanek (2007) started from some well-known probabilistic models and represented the CRFs by explaining graphical models that characterize the underlying probability distributions. Based on these studies, Sutton and McCallum (2012) systematically summarized the structures, modeling methods, implementations, and development directions of the CRFs, which perfected the framework of the CRF models, and promoted their further improvements and applications.

Since being proposed, the CRF models have drawn many attentions from scholars due to its excellent performance in labeling sequence data. Recently, they have been extensively applied to solving practical problems in various fields. In this paper, the current research on the CRFs is comprehensively reviewed, including presenting the improvements of the CRF models, reviewing the progress of their applications, and probing into their development prospect in the future.

The remaining of this paper is organized as follows. Section 2 reviews the background, modeling methods and some implementations of the CRFs. Section 3 presents different improved CRF models. This is followed by the application of the CRFs included in Sect. 4. Subsequently, Sect. 5 discusses and analyzes their advantages, flaws and future directions. Lastly, Sect. 6 gives the conclusions.

2 Conditional random fields: background, modeling and implementation

2.1 Research background

The CRF models were first proposed to solve the label bias problem existing in the MEMM (Lafferty et al. 2001). Before the CRFs were proposed, different models in the machine learning field had experienced abundant development. The emergence background of the CRF models is presented in Fig. 1.

As can be seen in Fig. 1, the emergence of the CRF models has undergone four stages. First, based on the Bayes' theorem and conditional independence assumptions, the Naive Bayesian model (NB) (Maron 1960) was put forward and then evolved into the Logistic Regression model (LR) (Verhulst 1838; Pearl and Reed 1920) when taking the input features into account. On this basis, the multi-feature conditional constraints were introduced to establish a Maximum Entropy Model (MEM) (Jaynes 1957a, b; Berger 1997). After that, time sequence was considered into the Naive Bayesian model to create the Hidden Markov Model (HMM) (Rabiner and Juang 1986; Rabiner 1989) according to the observational independence assumption and homogeneous Markov assumption. The advantages of the Hidden Markov Model and the Maximum Entropy Model were then combined to build

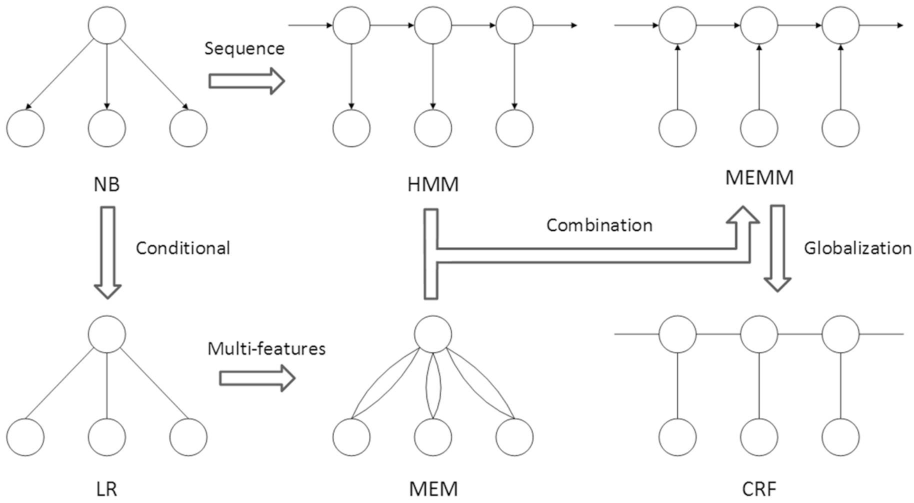

Fig. 1 The emergence background of the CRF models

the MEMM (Mccallum et al. 2000). Finally, a CRF model was put forward based on the consideration of the global normalization of input features (Lafferty et al. 2001).

It can be understood that the CRF is a sequential extension to the MEM, which models all that is known and assumes nothing about what is unknown (Tong et al. 2015). On the other hand, it avoids intricate computation of the prior distribution of observations and has a more flexible framework to comprehensively describe the temporal autocorrelations among the observations, while retaining the properties of HMMs that enable state transition descriptions (Koller et al. 2007). However, contrary to HMM, CRFs are not linearly-tied and can be structured arbitrarily (Yusuf et al. 2015).

2.2 Modeling process

The CRF was introduced as a kind of probabilistic graphical models, which is the combination of graph theory and probabilities, providing a framework for modeling global probability based on some observations of the local functions and representing a distribution over labels, as opposed to the generative nature of the Markov random field (MRF) (Li 2001). The CRF is a type of discriminative model which considers the dependencies between observation sequences with given labels, while the MRF is a type of generative model which tries to capture a probability distribution (Lin and Chuang 2017). The discriminative nature of CRF permits the arbitrary interactions among the observations without the independent assumptions (Li et al. 2015d).

A CRF can be defined as the Markov random field of the random variable Y under a given random variable X (Li 2012). The specific definition is as follows:

Definition 1 Assuming an undirected graph $G = (V, E)$ and random variable $Y = \{Y_v | v \in V\}$, if a random variable Y meets Markov property under a given random variable X (that is, $P(Y_v|X, Y_u, u \neq v) = P(Y_v|X, Y_u, u \sim v)$ holds for any node v), the conditional probability distribution $P(Y|X)$ will be referred to as a CRF.

In the above definition, X is an input variable and represents the observation sequence, Y is an output variable and represents the labeling sequence or state sequence, $u \neq v$ represents all the nodes other than node v in graph G, $u \sim v$ represents all the nodes having an edge connection with node v, Y_v and Y_u represent random variables corresponding to nodes v and u, respectively.

In a CRF, when the state sequence Y is linearly connected, the constituted CRF is a special model expressed by the linear chain, which is called the linear-chain CRF. The linear-chain CRF is the typical type of the CRF models. In order to make the contrast, the brief summarization of the features, advantages, and disadvantages of different models during the emergence of the linear-chain CRF is shown in Table 1.

The CRF can be represented in many forms (Li 2012), one of which is the parametric form provided in Table 1. In this form, t_k and s_j are the local eigenfunctions relying on the positions, where t_k is the transfer eigenfunction defined on the edge which represents the features in the transfer from one node to the next node and relies on the current and previous positions, and s_j is the state eigenfunction defined on a node which represents the features of a node and relies on the current position. Generally, the eigenfunctions are assigned with a value of 1 (when the feature conditions are met) or 0 (when the feature conditions are not met). Further, λ_k and μ_j represent the corresponding weights, and $Z(x)$ represents the normalization factor, where the summation is performed on all possible output sequences. The parametric form of the CRF intuitively shows the factors and parameters that influence the output of this model, which is completely determined by the eigenfunctions t_k and s_j as well as the corresponding weights λ_k and μ_j.

Similar to the HMM, the process of the CRF modeling also faces three basic problems: probability calculation, parameter estimation, and model inference. These three problems and their specific solutions are discussed in the following.

2.2.1 Probability calculation

As can be inferred in the definition, given a CRF model and input/output sequences, we need to calculate the conditional probabilities of the marginal distribution $P(Y_i = y_i|x)$ on a node and the marginal distribution $P(Y_{i-1} = y_{i-1}, Y_i = y_i|x)$ on an edge. Considering the time complexity caused by direct calculation, commonly, the forward–backward algorithm (Baum et al. 1970) (Algorithm 1) can be adopted for this purpose.

Table 1 Brief summary of different models during the emergence of the CRFs

Model	Model type	Model structure	Model representation	Model features	Advantages	Disadvantages
NB	Generative	Digraph	$P(y,x) = P(y)\prod_{i=1}^{N} P(x_i \mid y)$ $P(y_k \mid x) = \frac{P(y_k)\prod_{i=1}^{N} P(x_i \mid y_k)}{\sum_k P(y_k)\prod_{i=1}^{N} P(x_i \mid y_k)}, k = 1, 2, \ldots, K$	Joint probability distribution; Conditional independence assumption	Easy to realize Efficient	Unable to capture the relations between inputs
LR	Discriminative	Undigraph	$P(Y = k \mid x) = \frac{\exp(\omega_k \times x)}{1 + \sum_{k=1}^{K-1} \exp(\omega_k \times x)}$ $P(Y = K \mid x) = \frac{1}{1 + \sum_{k=1}^{K-1} \exp(\omega_k \times x)}$	Conditional probability distribution; Log-linear model	Considers input features	Independence assumption about features; Mainly solves binary classification problems
MEM	Discriminative	Undigraph	$P(y \mid x) = \frac{1}{Z(x)} \exp(\sum_{i=1}^{n} \omega_i f_i(x,y))$ $Z(x) = \sum_y \exp(\sum_{i=1}^{n} \omega_i f_i(x,y))$	Conditional probability distribution; Log-linear model	Flexible setting of constraint conditions; Solves the parameter smoothing problem	Unable to fully utilize the correlation between labels; Unable to grasp feature strength; Serious data sparsity problem
HMM	Generative	Digraph	$P(y,x) = \prod_{t=1}^{T} P(y_t \mid y_{t-1}) P(x_t \mid y_t)$ $P(y \mid t) = \frac{\prod_{t=1}^{T} \exp(\sum_{k=1}^{K} \omega_k f_k(y_t, y_{t-1}, x_t))}{\sum_{y'} \prod_{t=1}^{T} \exp(\sum_{k=1}^{K} \omega_k f_k(y'_t, y'_{t-1}, x_t))}$	Observational independence assumption; Homogeneous Markov assumption	Establishes the correlation between labels	Unable to solve long-distance correlations of observation sequences; Susceptible to local optimal solutions
MEMM	Discriminative	Digraph	$P(y \mid x) = \prod_{t=1}^{T} \frac{\exp(\sum_{k=1}^{K} \omega_k f_k(y_t, y_{t-1}, x_t))}{Z_t(y_{t-1}, x)}$ $Z_t(y_{t-1}, x) = \sum_{y'} \exp(\sum_{k=1}^{K} \omega_k f_k(y', y_{t-1}, x_t))$	Establish joint probability for state transition; Calculate conditional probability in statistics	Overcomes the observational independence assumption	Label bias problem; Susceptible to local optimal solutions
CRF	Discriminative	Undigraph	$P(y \mid x) = \frac{1}{Z(x)} \exp(\sum_{i,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,j} \mu_j s_j(y_i, x, i))$ $Z(x) = \sum_y \exp(\sum_{i,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,j} \mu_j s_j(y_i, x, i))$	Conditional probability distribution; Log-linear model	Overcomes the observational independence assumption; Solves the label bias problem	Low convergence speed; High susceptibility to feature sets

Algorithm 1 The forward-backward algorithm for the probability calculation of the CRF

Input: The model $P(Y|X)$, the input sequence x, the output sequence y, and the location i

Output: The conditional probabilities $P(Y_i = y_i|x)$, $P(Y_{i-1} = y_{i-1}, Y_i = y_i|x)$

1. Let $M_i(y_{i-1}, y_i|x) = \exp(\sum_{i,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,j} \mu_j s_j(y_i, x, i))$, $y_0 = start$, $y_{n+1} = stop$
2. Initialization, $\alpha_0(y_0|x) = 1$, $\beta_{n+1}(y_{n+1}|x) = 1$
3. Recursion, for $k = 1, 2, \ldots, i$
   $\alpha_k^T(y_k|x) = \alpha_{k-1}^T(y_{k-1}|x)M(y_{k-1}, y_k|x)$
4. Recursion, for $j = n, n-1, \ldots, i+1, i, i-1, \ldots, 1$
   $\beta_j(y_j|x) = M_{j+1}(y_j, y_{j+1}|x)\beta_{j+1}(y_{j+1}|x)$
5. Calculation, $Z(x) = 1^T \times \beta_1(x)$
6. Calculation, $P(Y_i = y_i|x) = \alpha_i^T(y_i|x)\beta_i(y_i|x)/Z(x)$
   $P(Y_{i-1} = y_{i-1}, Y_i = y_i|x) = \alpha_{i-1}^T(y_{i-1}|x)M_i(y_{i-1}, y_i|x)\beta_i(y_i|x)/Z(x)$

$\alpha_i(y_i|x)$ in this algorithm is the forward vector and represents the unnormalized probability of the forward label sequence which includes the position i and whose label at position i is y_i ; $\beta_i(y_i|x)$ is the backward vector and represents the unnormalized probability of the backward label sequence which includes the position i and whose label at position i is y_i ; $Z(x)$ represents the normalization factor, i.e., the sum of unnormalized probabilities that take "start" as an origin and "stop" as a destination and that pass through the state sequence $y_1 y_2 \ldots y_n$.

2.2.2 Parameter estimation

According to the parametric formulation of the CRF, there are two parameters λ_k and μ_j that need to be learned by using the training dataset to obtain the model $\hat{P}(Y|X)$. Basically, the maximum likelihood estimation or regularized maximum likelihood estimation are exploited for this purpose. The main optimized implementation algorithms include the Improved Iterative Scaling (IIS) (Berger 1997), Stochastic Gradient Descent (SGD) (Bottou 2010), Conjugate Gradient (CG) (Hestenes and Stiefel 1952; Fletcher and Reeves 1964), BFGS (Broyden 1969; Fletcher 1970; Goldfarb 1970; Shanno 1970) and L-BFGS (Nocedal 1980) (Algorithm 2) in Quasi-Newton Methods. The L-BFGS algorithm, through the approximation of the BFGS algorithm, simplifies the complexity of computing and alleviates memory burden.

In this flowchart, B_i represents $n \times n$ positive definite symmetric matrix, $f(\omega)$ represents the optimized objective function for model learning, and g_i represents its first-order gradient function. The basic idea of the L-BFGS algorithm is to simply use m recent record values of y_i and δ_i instead of storing the complete positive definite matrix B_i , and to use the approximate calculation as a substitute when matrix B_i is needed. Thus, the spatial complexity of the algorithm declines from the initial complexity $O(n^2)$ to $O(mn)$.

Algorithm 2 The L-BFGS algorithm for the parameter estimation of the CRF

Input: The eigenfunctions $f_1, f_2, \ldots, f_n$, and the empirical probability distribution $\tilde{P}(X,Y)$

Output: The optimal parameters λ_k and μ_j, the optimal model $\hat{P}(y|x)$

1. When $k = 1,2,\ldots,K_1$, let $\omega_k = \lambda_k$; when $k = K_1 + j$, and $j = 1,2,\ldots,K_2$, let $\omega_k = \mu_j$;
   $K = K_1 + K_2$; $\omega^{(i)} = (\omega_1^{(i)}, \omega_2^{(i)}, \ldots, \omega_K^{(i)})^T$
2. Initialization, let $i = 0$, choose $\omega^{(0)}$ and B_0
3. Calculation, $g_i = g(\omega^{(i)})$, if $g_i = 0$, stop the algorithm, otherwise, go to step 4
4. Calculation, $p_i = -B_i^{-1} g_i$
5. Calculation, find λ_i, so that $f(\omega^{(i)} + \lambda_i p_i) = \min_{\lambda \geq 0} f(\omega^{(i)} + \lambda_i p_i)$
6. Update, $\omega^{(i+1)} = \omega^{(i)} + \lambda_i p_i$
7. Calculation, $g_{i+1} = g(\omega^{(i+1)})$, if $g_{i+1} = 0$, stop the algorithm, otherwise, updateB_{i+1}
   $B_{i+1} = B_i + \frac{y_i y_i^T}{y_i^T \delta_i} - \frac{B_i \delta_i \delta_i^T B_i}{\delta_i^T B_i \delta_i}$, where $y_i = g_{i+1} - g_i$, $\delta_i = \omega^{(i+1)} - \omega^{(i)}$
8. Let $i = i+1$, go to step 4

2.2.3 Model inference

After training the parameters of the CRF based on the training dataset, we've got a fundamental model $\hat{P}(Y|X)$. Under this circumstance, we need to solve the output sequence $\hat{y}$ that maximizes the conditional probability $\hat{P}(y|x)$ under a given input sequence x,. Basically, the Viterbi algorithm (Viterbi 1967) (Algorithm 3) is adopted for this purpose, which is an algorithm employing the dynamic programming principle to find the optimal path.

Algorithm 3 The Viterbi algorithm for the prediction of the CRF

Input: The feature vector $F(y,x)$, the weight vector ω, and the observation sequence $x = (x_1, x_2, \ldots, x_n)$

Output: The optimal path $y^* = (y_1^*, y_2^*, \ldots, y_n^*)$

1. Initialization, $\delta_1(j) = \omega \times F_1(y_0 = start, y_1 = j, x)$, $j = 1,2,\ldots.m$
2. Recursion, for $i = 2,3,\ldots,n$
   $\delta_i(l) = \max_{1 \leq j \leq m} \{\delta_{i-1}(j) + \omega \times F_i(y_{i-1} = j, y_i = l, x)\}$. $l = 1,2,\ldots,m$
   $\psi_i(l) = \arg\max_{1 \leq j \leq m} \{\delta_{i-1}(j) + \omega \times F_i(y_{i-1} = j, y_i = l, x)\}$. $l = 1,2,\ldots,m$
3. Termination, $\max_y(\omega \times F(y,x)) = \max_{1 \leq j \leq m} \delta_n(j)$
   $y_n^* = \arg\max_{1 \leq j \leq m} \delta_n(j)$
4. Backtraking, $y_i^* = \psi_{i+1}(y_{i+1}^*)$, $i = n-1, n-2, \ldots, l$
   $y^* = (y_1^*, y_2^*, \ldots, y_n^*)$

The algorithm first uses the local feature vectors to infer backward the maximum possibility of each path. After that, it obtains m paths from the origin to the destination, each of which corresponds to a state sequence. Finally, it selects the optimal path through backtracking. Reducing the calculation complexity through recursion and making judgments based on the context of the entire sequence, it can satisfactorily analyze sequences containing "noises" as well.

2.3 Implementation tools

In the last 2 decades, the CRF theories have undergone continuous development, with many implementation tools emerged for further study. Nowadays, they have become one of the fundamental tools used by scholars in various fields of research. Table 2 lists some implementations of CRFs developed by different languages.

Wapiti written in C is a fast toolkit for segmenting and labeling sequences with discriminative models based on maxent models, maximum entropy Markov models and linear-chain CRF. CRF++ is a famous statistical CRF framework written in C++, offering effective training and optimization methods for prediction performance. Compared with CRF++, CRFsuite is another implementation of CRF providing arbitrary number of features for users, and outputing precision, recall, F1 scores of the model evaluated on test data. Python-CRFsuite is a python binding to CRFsuite, using Cython to wrap CRFsuite C++ API. It works in Python 2 and Python 3, and is faster than official SWIG wrapper without any external dependencies. NCRF++, a neural network version of CRF++, is a PyTorch based framework with flexiable choices of input features and output structures. Furthermore, there are Java, C#, Scala and Ruby versions of implementation appeared for in-depth research and use.

Note that the tools presented above are developed based on the basic linear-chain CRF model. As will be discussed below, the CRFs have various improvements, thus many implementations of improved models would have appeared, such as convolutional CRF(https://github.com/MarvinTeichmann/ConvCRF), dense CRF(https://github.com/lucasb-eyer/pydensecrf), hybrid semi-Markov CRF(https://github.com/ZhixiuYe/HSCRF-pytorch), BiLSTM-CRF(https://guillaumegenthial.github.io/sequence-tagging-with-tensorflow.html), CRF-RNN (https://github.com/torrvision/crfasrnn), etc.

Table 2 Some implementations of CRFs developed by different languages

Tool	URL	Language
Wapiti	https://wapiti.limsi.fr	C
CRF++	http://crfpp.sourceforge.net	C++
CRFsuite	http://www.chokkan.org/software/crfsuite	C++
Python-CRFsuite	https://pypi.org/project/python-crfsuite	Python
NCRF++	https://github.com/jiesutd/NCRFpp	Python with PyTorch
CRF	https://github.com/bojone/crf	Python with Keras
CRF	https://github.com/asher-stern/CRF	Java
CRFSharp	https://github.com/zhongkaifu/CRFSharp	C#
CRF	https://github.com/Intel-bigdata/imllib-spark	Scala
CRFPP	https://github.com/inukshuk/crfpp	Ruby

3 Various improvements of CRFs

As mentioned above, the original CRF model was first proposed to relax strong independence assumptions made in HMM, and avoid the label bias problem in MEMM. It was used for segmenting and labeling sequence data, with the form of a linear chain (Lafferty et al. 2001). Nowadays, with the increasing attention of the CRF, various improvements have been developed, which can be generally divided into three groups, as Fig. 2 presents.

3.1 Improved CRF models

A list of the improved CRF models is shown in Table 3. The details for each of these methods are as given below.

3.1.1 Marginalized CRF

The marginalized CRF framework was proposed to deal with the missing measurement problem that commonly occurred in industrial datasets, in which the conventional linear-chain CRF model is marginalized over the missing measurements, thus the two inference problems namely the marginal probability computation and the optimal mode estimation need to be solved, while performing offline training and online validation respectively (Fang et al. 2018). A new propagation algorithm was introduced to solve these problems by modifying the existing forward-backward algorithm. This CRF framework was validated to be effective in describing complex autocorrelations among the observations.

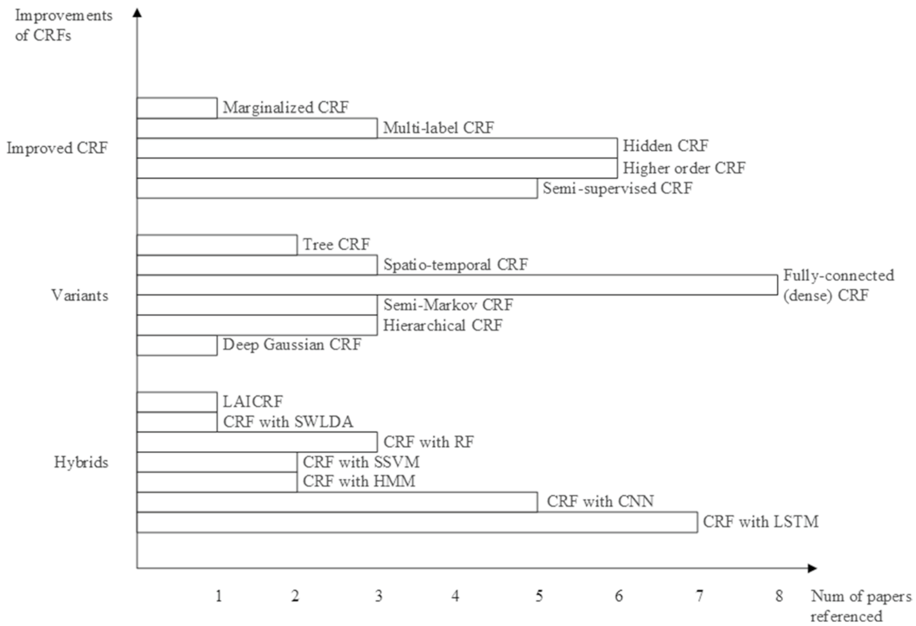

Fig. 2 Three groups divided by improvements of CRFs

Table 3 The improved CRF models

Name	Author (year)
Marginalized CRF	Fang et al. (2018)
Multi-label CRF	Yu et al. (2017)
	Wei et al. (2015)
	Zeggada et al. (2018)
Hidden (state) CRF (HCRF)	Tong et al. (2015)
	Xu et al. (2016)
Multi-modal hidden CRF (M-HCRF)	Jiang et al. (2015)
Coupled hidden CRF (CHCRF)	Liu et al. (2015a)
Joint CRF	Yang and Yang (2017)
Variable-state latent CRF(VSL-CRF)	Walecki et al. (2017)
Higher order CRF	Wang et al. (2015)
	Liu et al. (2015c)
	Li et al. (2015a)
Two-layer higher order CRF	Albert et al. (2017)
HOCRF-POE	Zhang et al. (2016)
Optimized higher order CRF	Jiang and Song (2016)
Semi-supervised CRF	Moharasan and Ho (2017)
Lexicon-based semi-supervised CRF	Xia et al. (2017)
Ontology-based semi-supervised CRF	Liu and El-Gohary (2017)
Posterior regularized mixture CRF (PRM-CRF)	Wen et al. (2017)
Online learned CRF	Chen and Bhanu (2016)

3.1.2 Multi-label CRF

The multi-label CRF has the ability to mark one symbol with more labels, it can view non-adjacent tokens as an entity and simultaneously detect objects of different classes in image segmentation tasks by incorporating context as long-range pairwise interactions between pixels (Wei et al. 2015). Yu et al. (2017) proposed the multi-label CRF for drug–drug interaction extraction and it was proved to have good performance in the entity detection task of medical texts. To exploit spatial contextual information and cross-correlation between labels, Zeggada et al. (2018) applied the multi-label CRF to iteratively improve the multi-label classification map, which demonstrated good classification results through experiments on different data sets.

3.1.3 Hidden CRF

The hidden CRF (HCRF) is an undirected graph model which introduces probability calculus and statistical inference, and expands CRF by incorporating hidden state variables which can capture internal sub-structures of a sequence by detecting causal dependencies from data. Tong et al. (2015) proposed the HCRF to recognize the abnormal activity in elderly persons' homes with the aim of computing activity consistence and finding abnormalities rather than finding activity labels. Xu et al. (2016) employed the HCRF for the spatial texture features of aurora sequences, this model is applied to automatically detect aurora events, which demonstrates good effectiveness through experimental results on labeled data.

Walecki et al. (2017) proposed the variable-state latent CRF (VSL-CRF) that can automatically select the optimal latent states for the target image sequence, and a novel graph-Laplacian regularization of the latent states was presented to reduce the model overfitting. Motivated by the assumption that different modalities in multi-modal data share latent structure, Jiang et al. (2015) presented a multi-modal Hidden CRF (M-HCRF) to learn the shared structure by exploiting the symbiosis of multiple-modality, and thus realized the classification of multi-modal data. Different from HCRF, M-HCRF tends to model the relationship between different observed data modalities as well as the unobserved random variables. Liu et al. (2015a) extended the HCRF to multiple chain-structure sequential observations, and put forward a coupled hidden CRF (CHCRF) that can learn temporal structure within individual sequence and transfer the common structuring information in-between for human action recognition. Moreover, Yang and Yang (2017) detected visual saliency of images by utilizing a joint CRF that uses latent variables to model the sparse representations of local observations with the dictionary and produces a saliency map of predicting the presence of target objects. The model was proved to achieve good performance and show significant improvements by updating dictionary modulated by the proposed CRF model.

3.1.4 Higher order CRF

The higher order CRF can decompose the high-order label dependencies into the low-order ones implied in the single and the pairwise cliques, and construct the non-parametric high-order potential to effectively capture high-order label dependencies (Zhang et al. 2016). Wang et al. (2015) used the higher order CRF to distinguish the natural scene text from non-text, computing data potentials, smooth potentials and higher order potentials to represent the probability of connected components strings being text. Liu et al. (2015c) utilized the higher order CRF to partition multi-view stereo reconstructed surfaces of large-scale urban environments into structural segments, since this model can not only incorporate 2D and 3D local cues, but also encode contextual geometric regularities to disambiguate the noisy local cues. Similarly, the higher order CRF was used to extract robust rooftop from visible band images due to its ability of incorporating both pixel-level information and segment-level information for the extraction task (Li et al. 2015a).

Albert et al. (2017) presented a two-layer higher order CRF for simultaneous classification of land cover and land use, in which higher order potentials are explicitly constructed to model the complex statistical dependencies between the land cover layer and land use layer, with the consideration of both spatial information and semantic context. Since the pairwise CRF (Dong et al. 2014) only considered the label dependencies of the pairwise cliques, Zhang et al. (2016) proposed the HOCRF-POE model and constructed the high-order potential to model the high-order label dependencies and thus provided better label consistency cost. Meanwhile, an optimized higher order CRF for automated video object segmentation was proposed by Jiang and Song (2016), who introduced a computerized optimization scheme to fine tune the CRF-associated parameters, and integrated the segmentation results from consideration of spatial information and consideration of temporal information. The results showed that the optimized algorithm had a better performance in computing cost reduction and simpler algorithm design.

3.1.5 Semi-supervised CRF

Since obtaining the annotated corpora is costly, time-consuming and requires much manual effort, and lack of domain knowledge may impact the quality of final model, the semi-supervised CRF is introduced. This model has the ability of exploiting partial annotated data and abundant unannotated data for effective detection and extraction. As an example, Moharasan and Ho (2017) used the semi-supervised CRF to recognize the temporal events from clinical text by exploiting unannotated text with gradual increasing of the number of annotated text in the corpus, and incorporating various feature sets for each word to extract temporal events. To improve the accuracy of Chinese clinical text word segmentation, Xia et al. (2017) proposed a lexicon-based semi-supervised CRF to adapt for partial labeled data that are obtained by the application of a bidirectional lexicon matching scheme. Experiments showed that the semi-supervised CRF received a high precision on different corpus. Furthermore, Liu and El-Gohary (2017) proposed a novel ontology-based semi-supervised CRF to extract information entities from bridge inspection reports. The proposed model was used to learn from a small set of labeled data and dynamically adapt itself to unseen instances by further learning from rich unlabeled data, which achieved the goal of reducing human effort and receiving high performance.

Wen et al. (2017) realized the activity recognition from partially observed behavior data by using posterior regularized mixture CRF (PRM-CRF), a modified version of CRF that can incorporate a posterior regularization term to help improve the activity inference, and can integrate the prior domain knowledge to reduce the negative influences caused by missing labels. Extensive experiments conducted on several datasets validated the performance of the proposed model. Additionally, in order to track multiple targets across cameras, Chen and Bhanu (2016) presented an online learned CRF that integrated high-level contextual information into the tracking system and minimized a global energy cost for reducing ambiguities in track association. The proposed approach did not require a large training set with known correspondence between samples, and performed well through experiments on different challenging real-world data sequences.

3.2 Variants of CRFs

Table 4 presents different variants of the CRF model. The details for each of these methods are presented herein.

3.2.1 Tree CRF

The tree CRF was presented to detect panels within comic images by Li et al. (2015d). It was used to label each visual pattern by modeling its contextual dependencies. The task was located on the construction of the tree structured observation of the comic page. Since an edge segment only had one parent whereas a connected component can have multiple descendants, the observation derived from the comic image could form a tree. An efficient tree-structured inference algorithm was developed for the tree CRF whose learning algorithm found a segmentation of higher quality by selecting different saliency thresholds at different locations of the image (Uzunbas et al. 2016). The framework was proved to modify the merging tree and thus improve the segmentation globally.

Table 4 Different variants of CRF

Name	Author (year)
Tree CRF	Li et al. (2015d)
	Uzunbas et al. (2016)
Spatio-temporal CRF (STCRF)	Bhole and Pal (2016)
	Rummelhard et al. (2017)
Temporal hierarchical adaptive texture CRF (THAT-CRF)	Karimaghaloo et al. (2015b)
Fully-connected (dense) CRF	Krähenbühl and Koltun (2011)
	Meier et al. (2016)
	Desmaison et al. (2016)
	Horne et al. (2015)
	Oh et al. (2017)
	Lin and Chuang (2017)
3D Dense CRF	Zanjani et al. (2018)
Convolutional CRF	Teichmann and Cipolla (2018)
Semi-Markov CRF (semi-CRF)	Zhang et al. (2017a)
	Seok and Kim (2015)
	Ye and Ling (2018)
Hierarchical semi-Markov CRF (HSCRF)	Tran et al. (2017)
Hierarchical span-based CRF	Adams et al. (2016)
Associative hierarchical CRF (AHCRF)	Yang et al. (2018c)
Deep Gaussian CRF (deep GCRF)	Vemulapalli et al. (2016)

3.2.2 Spatio-temporal CRF

Bhole and Pal (2016) proposed a spatio-temporal CRF (STCRF) for automatic person segmentation in unconstrained video, using a cross-validation technique for learning spatial and temporal smoothing parameters, and the inference was performed over the entire graph including the unknown nodes during parameter learning. (Rummelhard et al. 2017) used the STCRF for ground labeling in 3D point clouds, based on which spatial and temporal dependencies within the segmentation process were unified by a dynamic probabilistic framework. Besides, an interconnected expectation maximization (EM) algorithm variant was used to estimate ground elevation parameters. Through experimental results on real road data in various situations, the STCRF showed promising performance.

Karimaghaloo et al. (2015b) developed a temporal hierarchical adaptive texture CRF (THAT-CRF) for gad enhancing lesion segmentation in brain MRI, combining the spatio-temporal information at different scales within the CRF model. Concretely, the pseudo log-likelihood parameter learning was investigated to obtain optimal parameters, and the iterated conditional mode (ICM) was used for the inference of the THAT-CRF model. It was observed that the THAT-CRF showed effective segmentation results during experiments on multi-center clinical data sets.

3.2.3 Fully-connected (dense) CRF

The fully-connected CRF (dense CRF) is a type of discriminative model, in which pairwise potentials among all nodes in the graph can be defined, so that contextual relations between different class labels or long-range dependencies between voxels can be modeled to further refine the classification/detection results (Wolf et al. 2015; Meier et al. 2016). Krähenbühl and Koltun (2011) proposed a highly efficient approximate inference algorithm for fully connected CRF models in which the pairwise edge potentials are defined by a linear combination of Gaussian kernels, so that the dense connectivity at the pixel level could improve segmentation and labeling accuracy. Desmaison et al. (2016) used four efficient algorithms for the dense CRF energy minimization problem and performed continuous relaxations over the widely used mean-field algorithm on publicly available datasets. Horne et al. (2015) proposed to compute unary potentials at strategic locations in the image for efficient scene parsing.

Oh et al. (2017) used the fully-connected CRF to detect abnormal object by taking account of the relationships between objects and object-scene as the fully-connected relationships and performing inference on the fully-connected graph structures using mean field approximation. In order to extract the foreground from a given image, Lin and Chuang (2017) utilized the fully-connected CRF to correct the predicted matte at the pixel level, which provides promising results for commonly used test images. A 3D dense CRF was introduced by Zanjani et al. (2018) to detect coherent needle in ultrasound volumes by sampling 3D Gabor features over all voxels in the volume for measuring the similarity between the nodes in the graph. The experimental results showed that applying a 3D CRF model along with 3D Gabor features improves the robustness of needle detection. In addition, Teichmann and Cipolla (2018) proposed a convolutional CRF, which was designed to add the assumption of conditional independence to the framework of fully-connected CRFs and reformulate the inference in terms of convolutions. This improved model was proved to speed up training and inference processes of CRFs, and reduce the difficulty of learning the internal CRF parameters.

3.2.4 Semi-Markov CRF

The semi-Markov CRF (semi-CRF) is derived from the Chinese handwriting recognition system, which outputs a segmentation of the observation sequence X, together with the label sequence assigned to segments of X, rather than label individual elements of X. In semi-CRF, feature functions are utilized to capture attributes at different levels of granularity of the same observations (Zhang et al. 2017a). The cross-entropy (CE) method is used to optimize semi-CRF parameters to separate the target character from the others. Seok and Kim (2015) used the semi-CRF to realize the scene text recognition by firstly training a Hough forest to detect character candidates in the image and then verifying the candidates using a Viterbi-style algorithm in the semi-CRF. It is demonstrated that the semi-CRF can consider the gap uniformity and bi-gram language model together with the detection result. Ye and Ling (2018) improved the existing semi-CRF methods by employing word-level and segment-level information simultaneously, and described transitions between segments instead of words for the tasks of assigning labels to segments, which was approved to achieve good performance.

3.2.5 Hierarchical CRF

The hierarchical CRF is a generalization of linear-chain CRF, which offers hierarchical and multilevel semantic and is parameterized as an undirected log-linear model. A hierarchical semi-Markov CRF (HSCRF) was introduced by Tran et al. (2017) to model complex hierarchical and nested Markovian processes in a discriminative framework. It generalizes the semi-CRF to encode multilevel of semantics, obtaining efficient parameter learning via the Asymmetric Inside–Outside algorithm and decoding the semantics from an observational sequence by a generalized Viterbi algorithm. Adams et al. (2016) presented a hierarchical span-based CRF that included higher-order cardinality factors and inter-event duration factors to capture domain-specific structure in the label space. The inference algorithm of this model is closely related to inference in semi-CRF, and the maximum a posteriori (MAP) algorithm is leveraged to learn parameters of this model. Additionally, Yang et al. (2018c) attempted to improve the classification accuracy of high-resolution remote sensing images by using an associative hierarchical CRF (AHCRF) that was built on a graph hierarchy, including the pixel layer and multiple superpixel layers. The AHCRF model aims to improve superpixel segmentation quality and address the undersegmentation error, which is confirmed to have favorable results.

3.2.6 Deep Gaussian CRF

The deep Gaussian CRF (deep GCRF) network was proposed by Vemulapalli et al. (2016) for the purpose of discriminative denoising. It is capable of handling a range of noise level by modeling the input noise variance. In GCRF, the conditional probability density $P(Y|X)$ is modeled as a Gaussian distribution. In the deep GCRF network, a parameter generation network in which the pairwise potential function parameters are chosen based on the input image and an inference network in which an iterative optimization approach based on half quadratic splitting (HQS) is performed for the chosen parameters are considered. The proposed approach appears to be well capable of image denoising without training a separate network for each individual noise level.

3.3 Hybrid CRF models

Table 5 presents the hybrid CRF models. The details for each of these methods are presented in the following sections.

3.3.1 LAICRF

Ganapathy et al. (2016) developed an intelligent CRF based layered approach (LAICRF) model for network intrusion detection with the aim of reducing detection time and improving accuracy. The model is built to optimize the number of features by an intelligent CRF and perform classification with these reduced features using a layered approach based algorithm. Specifically, the LAICRF uses intelligent agents capable of analyzing the data set efficiently and performing actions based on the environmental conditions to select appropriate features from the underlying data set, then this intelligent CRF uses a layered approach to distinguish the normal records and different types of attacks. Through comparison of experimental results, it was observed that the

Table 5 The hybrid CRF models

Name	Author (year)
Layered approach based algorithm (LA)	Ganapathy et al. (2016)
Stepwise linear discriminant analysis (SWLDA)	Siddiqi et al. (2015)
Random forest (RF)	Wolf et al. (2015)
	Thøgersen et al. (2016)
	Pereira et al. (2016)
Structured support vector machine (SSVM)	Wang et al. (2017b)
	Ji et al. (2016)
Hidden Markov model (HMM)	Belgacem et al. (2017)
	Yusuf et al. (2015)
Convolutional neural network (CNN)	Luo et al. (2016)
Deep convolutional neural network (DCNN)	Kosov et al. (2017)
	Alam et al. (2016)
Fully convolutional neural network (FCNN)	Zhao et al. (2017)
	Liu and Pun (2018)
Long short-term memory (LSTM)	Cotterell and Duh (2017)
Bidirectional long short-term memory (BiLSTM)	Kadari et al. (2018)
	Lample et al. (2016)
	Dong et al. (2016)
	Le et al. (2018)
Attention-based bidirectional long short-term memory (Att-BiLSTM)	Luo et al. (2017)
Lattice-structured long short-term memory (lattice LSTM)	Zhang and Yang (2018)

LAICRF model performed better than the existing CRF based approach and the decision tree method.

3.3.2 CRF with SWLDA

Siddiqi et al. (2015) introduced a robust facial expression recognition system, employing the stepwise linear discriminant analysis (SWLDA) to select the localized features from the expression frames, as well as the hidden CRF to accurately classify the human facial expressions by approximating a complex distribution with a mixture of Gaussian density functions. SWLDA and hidden CRF are first utilized to recognize the expression category, then a separate set of SWLDA and hidden CRF are used to determine the label for the expression within the recognized category. Detailed experiments on several datasets carried out in this study validated the high accuracy of facial expression recognition.

3.3.3 CRF with RF

Wolf et al. (2015) combined a random forest (RF) classifier with a dense CRF for semantic segmentation of 3D point clouds. The RF classifier is employed to calculate conditional label probabilities, and the output of this classifier is then used to initialize the unary potentials of the dense CRF, for which the parameters for the pairwise potentials from training data can be learned. Thøgersen et al. (2016) unified the CRF and a stacked RF in a framework for indoor scene segmentation, using a multi-scale decomposition to spatially filter the predictions of the CRF, with the aim of adding heightened contextual awareness. Then the CRF was merged with the original feature set, and a stacked RF using random offset features was applied to give the final predictions. To perform reliable and robust automatic brain tissue segmentation, Pereira et al. (2016) proposed a framework based on the CRF, with a RF encoding the likelihood function. This framework is validated to have the ability of capturing strong contextual relations between different class labels, and performs well in normal and diseased subject segmentation.

3.3.4 CRF with SSVM

Wang et al. (2017b) proposed a spatio-temporal CRF for human interaction understanding in videos. The spatio-temporal CRF was considered to model human interactions in the spatio-temporal space and cover both the spatial configuration of human interactions and the temporal transition of actions by considering the interactions between different types of variables. And the parameters of the CRF was trained by Structured Support Vector Machine (SSVM) in order to obtain a preliminary recognition. It was demonstrated that the proposed model achieved competitive performance on both the action and activity recognition. Similarly, Ji et al. (2016) introduced an elastic CRF based on SSVM, which made edges elastically hidden/emergent during inference to conduct fast loopy belief propagation (LBP), while explicitly modeling the interdependency between depth and semantics. Besides, the SSVM was used to further accelerate the E-CRF inference.

3.3.5 CRF with HMM

Belgacem et al. (2017) combined the modeling ability of HMM and the discriminative ability of the CRF to propose an hybrid CRF/HMM system for the recognition of gestures in videos. The system was adapted to the one-shot learning context in order to suit to the real-world constraints of small labeled data sets. The experimental results show that this hybrid model is able to describe any dynamic scene using its motion, making it independent from the moving object type. Likewise, Yusuf et al. (2015) applied HMM and CRF classifiers to detect real-time audio event, in which HMM is used to parse time-based sequence information into the most closely identified state, and the CRF is constructed for describing potential state transition conditions or acoustic state transitions during a secure door entry situation. Simulation results compare the performance of the hybrid approach with many other optimization algorithms.

3.3.6 CRF with CNN

Luo et al. (2016) combined the prediction ability of Convolutional Neural Network (CNN) and the segmentation ability of CRF for retinal images segmentation. In this framework, the CNN was designed to extract features of vessels, and the CRF was concatenated at the end of CNN to widely take the spatial information into consideration.

Kosov et al. (2017) performed the environmental microorganism classification by using a Deep Convolutional Neural Network (DCNN) for pixel-level features extraction in microscopic images, as well as the CRF for pixel-level classification considering the spatial relations among pixel-level features and their relations to global features. Different from this, Alam et al. (2016) used both spectral and spatial information to segment remote sensing hyperspectral images by utilizing the DCNN for superpixel-level labelling. Zhao et al. (2017) integrated a Fully Convolutional Neural Networks (FCNN) and the CRF in a unified framework, with the aim of segmenting brain tumors in appearance and spatial consistency, which was indicated to achieve promising brain tumor segmentation performance. In order to locate splicing forgery without hand-crafted features, a FCN-CRF framework that consisted of three different Fully Convolutional Networks (FCNs) and a CRF was performed to yield pixel-to-pixel forgery prediction, which was concluded to achieve higher recall comparing to using single FCN alone (Liu and Pun 2018).

3.3.7 CRF with LSTM

Cotterell and Duh (2017) used the cross-lingual character-level neural CRF to solve the problem of low-resource named entity recognition (NER), and presented a transfer learning scheme for both high-resource languages and low-resource languages by extracting character-level features using recurrent neural network (RNN), as neural feature extractors are superior to hand-crafted approaches. Sentence's embeddings are defined as the concatenation of a Long Short-Term Memory (LSTM) run forward and backward, and the neural feature-extractor is considered to abstract the notion of a named entity across similar languages by conjoining the new language-specific atomic feature with the existing feature templates. This character-level neural CRF performed better than the linear-chain CRF in transferring entity-level abstractions cross-linguistically.

Kadari et al. (2018) combined the Bidirectional Long Short-Term Memory (BiLSTM) and the CRF for combinatory categorial grammar (CCG) supertagging. In this framework, the BiLSTM was used to memorize information for both previous and future words for long-range dependencies, and the CRF was exploited to jointly predict the final supertags by using sentence level tags. Comparing to machine learning models such as MEM and deep learning models such as RNN and BiLSTM based architectures, the combined BiLSTM-CRF model was efficient for CCG supertagging task and showed superior performances. Recently, the BiLSTM-CRF has been extensively used in NER tasks (Lample et al. 2016; Dong et al. 2016; Le et al. 2018; Luo et al. 2017). Furthermore, Zhang and Yang (2018) proposed a lattice-structured LSTM with CRF layer to integrate latent word information by representing lexicon words from sentences. The lattice LSTM structure was leveraged to automatically control information flow from the beginning of the sentence to the end, thus the model had the advantage of leveraging explicit word information over character sequence labeling without suffering from segmentation error.

4 Application fields of CRFs

As one of the most important types of the machine learning models, the CRFs are receiving more and more attention in various fields, and playing an increasingly important role, whether it's the basic linear chain CRF model or an improved one. As it is well known, currently, there are large amounts of data from various fields existing in the form of text, voice, image, and video, so the data processing for the CRF models are accordingly focused on these aspects. Different applications of the CRF model are mainly classified into four categories as Fig. 3 shows.

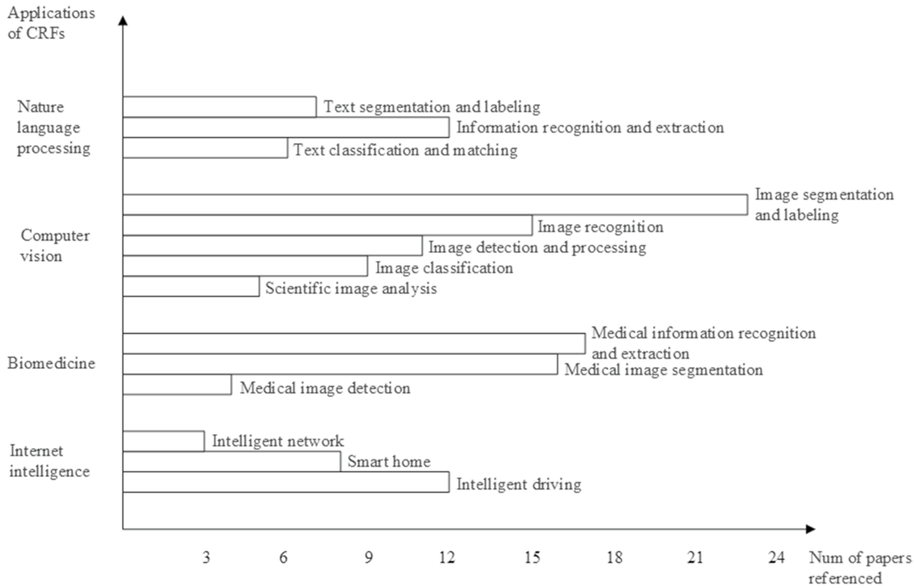

Fig. 3 Four categories classified by applications of CRFs

4.1 Nature language processing

Natural language processing is the first major application area of the CRFs, in which data in the form of text and voice are processed. Fei and Pereira (2003) applied the CRFs to the noun phrase segmentation in a large scale, the basic linear chain CRFs have been widely used in this field. Because the CRFs are primarily applied to solving the problems of sequence labeling, they have good performance in text segmentation and labeling, information recognition and extraction, text classification and matching. Table 6 presents a summary of the applications of CRF in this field.

4.1.1 Text segmentation and labeling

In terms of text segmentation and labeling, the CRFs are originally used to deal with basic problems such as Chinese word segmentation (Peng et al. 2004; Leng et al. 2016) and part of speech (POS) tagging (Huang et al. 2015; Zhang et al. 2017b), and they perform well. Presently, based on the increasing demand for massive document processing as well as the deeper understanding of the models, the CRFs are extensively applied to subtitle segmentation (Lvarez et al. 2017), word-labeling (Yao et al. 2014) and other problems. For Chinese word segmentation, Peng et al. (2004) demonstrated better robustness and accuracy of linear-chain CRF on different datasets, and integrated a probabilistic new word detection method in segmentation to further improve performance. Part of speech tagging is a typical direction of the CRFs application. As an example, Zhang et al. (2017b) used the POS tagging tasks in 8 different languages to evaluate their new proposed end-to-end neural CRF autoencoder (NCRF-AE) model, which indicates the fundamentality of the POS tagging task. In addition, it is represented that the proposed model can effectively utilize a small amount of labeled data as well as the hidden information from a large amount of unlabeled

Table 6 A summary of the CRF applications in nature language processing

Category	Application	Author (year)
Text segmentation and labeling	Automatic subtitle segmentation	Lvarez et al. (2017)
	Chinese word segmentation	Peng et al. (2004)
		Leng et al. (2016)
	Part of speech tagging	Huang et al. (2015)
		Zhang et al. (2017b)
	Word-labeling	Yao et al. (2014)
		Yang et al. (2018b)
Information recognition and extraction	Named entity recognition	Cotterell and Duh (2017)
		Mozharova and Loukachevitch (2016)
		Şeker and Eryiğit (2017)
		Dong et al. (2016)
		Dong et al. (2017)
		Ratinov and Roth (2009)
		Lample et al. (2016)
	Chinese dialogue act recognition	Zhou et al. (2015)
	Recognizing activities from partially observed streams	Wen et al. (2017)
	Automated information extraction from bridge inspection reports	Liu and El-Gohary (2017)
	Text summarization from legal documents	Kanapala et al. (2017)
	Summary sentences extraction oriented to live sports text	Zhu et al. (2016b)
Text classification and matching	Classification of multi-modal data	Jiang et al. (2015)
	Sentence type classification	Chen et al. (2017)
	Aspect extraction	Rana and Cheah (2016)
	MT phrasing	Tambouratzis (2015)
	Metallic materials ontology population	Zhang et al. (2018b)
	Chinese grammatical error diagnosis	Liao et al. (2017)

data, and is competitive in both supervised and semi-supervised scenarios. The automatic segmentation of subtitles is a novel field of research. In view of the demand for quality automatic subtitling, Lvarez et al. (2017) used a CRF method to deal with the automatic subtitling segmentation. Satisfactorily, through experiments on two corpora in Basque and Spanish, the new method presented has produced good results. In the word-labeling task, Yao et al. (2014) proposed a recurrent CRF, where RNNs are applied to assign labels to each word in the input sequence. The effectiveness of this model has been proved on the ATIS travel domain dataset and a variety of web-search language understanding datasets, which shows that the RNNs can be successfully merged with the CRF model to do language understanding, and the performance of an RNN tagger can be significantly improved by incorporating elements of the CRF model. Yang et al. (2018b) compared and analyzed different neural sequence labeling models including CRFs to reach practical conclusions on how to construct effective and efficient neural sequence labeling systems, thus misconceptions and inconsistent conclusions could be examined and clarified under statistical experiments.

4.1.2 Information recognition and extraction

The mainstream direction of the CRFs application in information recognition and extraction is NER (Cotterell and Duh 2017; Mozharova and Loukachevitch 2016; Şeker and Eryiğit 2017; Dong et al. 2016, 2017), as it is a fundamental research topic in NLP. Speaking of NER, design challenges and misconceptions as well as neural architectures are displayed by Ratinov and Roth (2009) and Lample et al. (2016) for more specific details, in which NER is typically viewed as a sequential prediction problem. In recent years, the latest applications of the CRFs have been extended to dialog act recognition (DAR), user activity recognition, legal text abstract extraction, etc. DAR is a fundamental step in computer understanding of natural language dialogues because it can reflect the speaker's intentions. However, due to heterogeneous features, statistical dependence between the dialog act tags, and complex relationship between features and the dialog act tags, it is difficult to adapt traditional machine learning models to DAR tasks. Therefore, Zhou et al. (2015) proposed a new model combining heterogeneous deep neural networks (HDNN) with the CRF to solve this problem. In this framework, the HDNN model is used to deal with heterogeneous features, and the statistical dependence between dialog act tags is captured by the CRF. Experiments have demonstrated that the proposed model has the ability to achieve high classification accuracy. Recognizing activities from behavioral data is also important to understand people's intents and interests, but in most cases, user behavior is partially observed or documented, which poses a big challenge to simulate user activities. Based on that, Wen et al. (2017) used the PRM-CRF to learn user activities from the behavior streams, combining contextual information with internal features of instances. The advantage of this model is that it uses a regularization term to integrate the prior domain knowledge, which reduces the negative impact of missing labels. At present, in the public domain, the amount of legal information is ever-increasing, making legal text processing an important area of research. Accessing relevant and useful legal information from a vast repository is important for different stakeholders such as scholars, professionals and ordinary citizens. Therefore, automatic text summaries can be an important tool to help different stakeholders. Based on this, Kanapala et al. (2017) introduced some of the most advanced text summarization techniques, in which CRF is one of the rhetorical role-based approaches, compared with other methodologies for legal text summarization. It has been concluded that the CRF is suitable for text segmentation of legal judgments, and can be applied to identifying term patterns and frequencies so as to extract important sentences.

4.1.3 Text classification and matching

Text classification and matching has always been a research hotspot of natural language processing. Machine translation (MT), knowledge question answering, content recommendation and situational dialogue are typical research directions. In addition, the application of the CRF model has been extended to phrase matching, sentiment analysis (SA), ontology filling and many other aspects. Phrase matching is an important branch of MT. Currently, because most state-of-the-art MT paradigms use phrases to translate sentences into parallel corpora at a sub-sentential level, Tambouratzis (2015) compares the template-matching technique with the CRF on a specific linguistic task such as phrasing of a sequence of words into phrases. This task represents that the text is parsed into linguistically-motivated phrases in a low sequence, and the two techniques are used for comparison to determine the most appropriate approach for extracting an accurate template. Sentiment analysis, also known as opinion mining (OM), is used to identify and extract user opinions or emotions. Aspect extraction is the extensively explored phase of SA, including extracting explicit aspects and identifying implicit aspects. Rana and Cheah (2016) classified the explicit extraction techniques into three classes i.e. unsupervised, semi-supervised and supervised. As one of the supervised approaches, the CRF is compared with other unsupervised and semi-supervised techniques. The results show that supervised approaches have produced better results as compared to semi-supervised approaches and are comparable with the unsupervised approaches. With respect to the comparatively insufficience of the metallic ontology instances, Link Open Data (LOD) provides huge open knowledge bases with a wealth of materials knowledge. Thus, Zhang et al. (2018b) converted the LOD into Chain Triples (CHT), using the CRF to achieve the filling positions of the CHT in the specified metallic materials ontology. This method has been proven to not only enrich the existing metallic materials ontology, but also greatly save the manual efforts in the process of ontology population.

The nature of the CRFs application in natural language processing is to extract and analyze the information existing in the form of text or voice. Currently, due to the rise of social platforms and Q&A communities, a large number of users on the Internet have access to mutual communication and knowledge acquisition, so there are many texts in natural language forms that need to be efficiently processed to assist decision-making and recommendation. The CRFs, through the effective processing of these texts, help to analyze users' emotions and behaviors intelligently.

4.2 Computer vision

Computer vision refers to the identification and analysis of digital images or videos using various computer knowledge and techniques including techniques for geometric modeling and cognitive processing in an attempt to obtain valuable information (Ballard 1982). In the era of big data, images and videos are forms of data that can be widely captured for efficient information acquisition, thus image-based processing becomes more and more demanding. Meanwhile, the CRF models are deepening and infiltrating in this field, where the specific directions include image segmentation and labeling, image recognition, image

Table 7 A summary of the CRF applications in computer vision

Category	Application	Author (year)
Image segmentation and labeling	SAR image segmentation	Zhang et al. (2016)
	Hyperspectral image segmentation	Alam et al. (2016)
	Segmentation of fallen trees in ALS point clouds	Polewski et al. (2017)
	Hippocampal segmentation	Platero and Carmen (2015)
	Semantic image segmentation	Liu et al. (2015b)
		Liu et al. (2017a)
		Arnab et al. (2015)
		Arnab et al. (2016)
		Arnab et al. (2018)
		Li et al. (2016)
		Zhang et al. (2018a)
		Chen et al. (2018)
		Shen et al. (2017)
		Wei et al. (2015)
		Jiang et al. (2017a)
	Semantic segmentation of 3D point clouds	Wolf et al. (2015)
	Automated labeling and segmentation of video objects	Jiang and Song (2016)
	Crowd flow segmentation in compressed domain	Kruthiventi and Babu (2015)
	Layered scene decomposition	Liu et al. (2016a)
	Depth estimation	Ji et al. (2016)
		Yan and Hu (2016)
	Semantic pixel labelling	Zheng et al. (2015)
		Paisitkriangkrai et al. (2015)

Table 7 (continued)

Category	Application	Author (year)
Image recognition	Facial expression recognition	Walecki et al. (2015)
		Walecki et al. (2017)
		Siddiqi et al. (2015)
	Gesture sequence recognition	Belgacem et al. (2017)
		Chang and Lee (2018)
		Chu et al. (2016)
	Human action recognition	Liu et al. (2015a)
		Liu et al. (2016b)
	Multiple human identification and cosegmentation	Zhu et al. (2016a)
	Automatic person segmentation in unconstrained video	Bhole and Pal (2016)
	Human interaction understanding	Wang et al. (2017b)
	Keyword spotting in handwritten chinese documents	Zhang et al. (2017a)
	Scene text recognition	Seok and Kim (2015)
		Wang et al. (2015)
		Wang et al. (2018)

Table 7 (continued)

Category	Application	Author (year)
Image detection and processing	Airport detection from remote sensing images	Yao et al. (2015)
	Linear street extraction	Corcoran et al. (2015)
	Panel detection in comic images	Li et al. (2015d)
	Visual saliency detection	Yang and Yang (2017)
		Qiu et al. (2017)
	Alpha matting	Lin and Chuang (2017)
	Single image haze removal	Kang and Kim (2018)
	Image denoising	Vemulapalli et al. (2016)
	Context-based abnormal object detection	Oh et al. (2017)
	Locating splicing forgery	Liu and Pun (2018)
	Multimodal obstacle detection	Kragh and Underwood (2017)
Image classification	High-resolution image classification	Zhao et al. (2016a)
		Cui et al. (2017)
		Yang et al. (2018c)
		Zhao et al. (2015)
		Albert et al. (2017)
		Tuia et al. (2018)
	Hyperspectral image classification	Zhong et al. (2017)
		Li et al. (2015b)
		Yang et al. (2018a)

Table 7 (continued)

Category	Application	Author (year)
Scientific image analysis	Multitemporal and multiscale classification of optical satellite imagery	Hoberg et al. (2015)
	Robust rooftop extraction from visible band images	Li et al. (2015a)
	Aurora sequences classification and aurora events detection	Xu et al. (2016)
	Satellite image radar altimetry	Roscher et al. (2017)
	UAV images classification	Zeggada et al. (2018)

detection and processing, and image classification. A summary of the applications of CRFs in this field is listed in Table 7.

4.2.1 Image segmentation and labeling

Semantic image segmentation is the process of labeling each pixel in an image using predefined object categories. It has many applications in image scene understanding. Wei et al. (2015) performed the context-based global multi-class semantic image segmentation through wireless multimedia sensor networks, using context to aid object detection. A framework that uses encoding schemes in multi-label CRFs is proposed to develop the multi-class image segmentation tasks as energy minimization problems and find global optimal solutions using a single graphics cut under certain conditions. The experimental evaluation results show that this new proposed model is suitable for multi-class segmentation problems. More recent progress in semantic image segmentation are presented by Liu et al. (2017a). Besides, semantic image segmentation in video is also a hot topic of recent research. In order to improve the accuracy of crowd flow segmentation in video surveillance, Kruthiventi and Babu (2015) modeled the motion vector field as a CRF, and proposed an algorithm for segmenting flows in compressed video in a completely unsupervised manner. The superior performance of the proposed algorithm in accuracy and computational time was demonstrated by evaluation on a standard crowd flow dataset, which proved the efficiency of the improved CRF model. In terms of image labeling, Ji et al. (2016) studied the interdependency between depth and semantics of a single image, and proposed an elastic conditional random field (E-CRF) deployed upon super-pixel segmentations to refine each other in an iterative manner. Besides, the SSVM was introduced so as to speed up the processing of inference. Through outdoor scenes training and indoor scenes testing, the E-CRF model has been demonstrated to have significant improvement in accuracy and inference speed.

4.2.2 Image recognition

Image recognition is the process of recognizing objects in images or videos for further analysis. The application of the CRFs to image recognition mainly falls in human identification (Siddiqi et al. 2015; Walecki et al. 2015, 2017; Belgacem et al. 2017; Chang and Lee 2018; Chu et al. 2016; Liu et al. 2015a, 2016b; Zhu et al. 2016a; Bhole and Pal 2016; Wang et al. 2017b) as well as scene text recognition (Zhang et al. 2017a; Seok and Kim 2015; Wang et al. 2015, 2018). Currently, the detection of facial action units from videos and the automatic recognition of the dynamic facial expression depend on the modeling of their dynamics, and the general Latent Conditional Random Fields (L-CRF) framework gives a restrictive assumption that the latent states for encoding dynamics are either unordered or completely ordered. Therefore, Walecki et al. (2017) proposed the VSL-CRF that can automatically select the optimal latent states for the target image sequence. Compared with traditional L-CRF and other related models, the proposed model has achieved better generalization performance. In view of the human interactions in videos, Wang et al. (2017b) simultaneously considered the interactions between people, the actions of each individual and the overall activities of all people, and proposed the STCRF to cover both action and activity variables. Based on local image information and the local recognition results, the recognition task is divided into two stages, and the parameters of the CRF are learned by SSVM. As a result, this ST CRF model has demonstrated good performance in semantic level understanding of human interactions in videos. In order to achieve text detection in natural scene images, Wang et al. (2018) proposed a CRF framework that combines the CNN and contextual information. The framework takes into account four different features including color, shape, stroke and spatial features and a special layout of texts in natural scene images. Experimental results on four common benchmark datasets show that the proposed method can achieve comparable performance.

4.2.3 Image detection and processing

Image detection and processing is the process of detecting and extracting the targets based on input images. Visual saliency detection is an important module of visual attention, based on which, Yang and Yang (2017) adopted a layered structure from top to bottom, used the structured output of the CRF layer to learn a dictionary in a supervised manner, and employed the sparse coding as features to train CRF parameters. The experimental results indicate that the model has a good effect on target object localization, and the dictionary update significantly improves the performance of the model as well. Corcoran et al. (2015) proposed a novel method for extracting linear streets from street networks. The given street network is modeled as CRF, and the task of extracting linear streets is equivalent to learning and inference with respect to this model. It is evaluated by experiments that the proposed approach is superior to the traditional solutions that employ heuristic search procedures. Image denoising is also one of the directions of image processing. Vemulapalli et al. (2016) proposed a novel end-to-end trainable deep network architecture based on a Gaussian conditional random field (GCRF) model, which is able to handle a range of noise levels through a parameter generation network and an inference network. According to the validation experiments conducted on several datasets, the proposed method has achieved competitive effectiveness.

4.2.4 Image classification

The process of image classification is to identify and classify the input images for information integration and decision support, and the application of the CRFs in this direction mainly includes high-resolution image classification and hyperspectral image classification. In order to improve the classification accuracy of high-resolution remote sensing images, Yang et al. (2018c) proposed an AHCRF model, which considered the segmentation quality of super-pixels and avoided the time-consuming selection of optimal scale parameters. Furthermore, different experiments have confirmed that, the overall classification accuracy of the model is improved, and the selection of suitable segmentation parameters is reduced as well. Albert et al. (2017) proposed a two-layer high-order CRF to classify land cover and land use layers simultaneously considering spatial and semantic context. In the land-cover layer, the nodes represent super-pixels, and in the land-use layer, the nodes correspond to objects from the geospatial database. The Intra-layer edges of the CRF model spatial correlation between adjacent image sites, and the two-layer space simulates the semantic relation between all land cover and land use sites in the clique. This method is designed for input data based on aerial images, and the classification results of this method are effectively improved, through experiments on two test points. In the hyperspectral image classification task, Zhong et al. (2017) proposed a new DBN-CRF model, showing how to improve hyperspectral image classification by using deep representation and contextual information. The model uses the strength of the DBN to learn the ability of the CRFs to observe and label contextual information. At the same time, joint training of parameters makes full use of the advantages of DBN and CRF. Satisfactorily, the proposed method has demonstrated good performance through several experiments.

In addition, with the continuous development of the CRF models, the directions of the CRFs application in recent years have also expanded to scientific image analysis, such as satellite image radar altimetry (Roscher et al. 2017), UAV images classification (Zeggada et al. 2018), aurora events detection (Xu et al. 2016), satellite imagery classification (Hoberg et al. 2015), etc.

4.3 Biomedicine

Biomedicine is an application field separated from natural language processing and computer vision, which has become a hot research topic with people's increasing demands for health. In view of the good performance of the CRF models, their application directions in biomedicine mainly include medical information recognition and extraction, medical image segmentation and medical image detection. Table 8 presents a summary of the applications of CRFs in this field.

4.3.1 Medical information recognition and extraction

The biomedical knowledge deposited in a large amount of unstructured texts is of high value, yet the employment of LSTM networks does not utilize all useful linguistic information. Therefore, in order to transform biomedical knowledge into a well-structured format and improve the performance of biomedical NER, Le et al. (2018) proposed a D3NER model using the CRFs and BiLSTM network improved with fine-tuned embeddings of various linguistic information. Compared with the seven state-of-the-art NER models, the results demonstrate the out-performance and stability of the new proposed method. In medical practices, doctors need to detail patients' care plan through discharge summaries in unstructured free texts. In this case, Tao et al. (2017) presented a machine learning method to extract and organize medication names and prescription information in patients' care plan. Specifically, the CRFs and word embedding are applied to perform extraction tasks, which are proved to achieve great improvement in the extraction of medication names. A large number of clinical texts in electronic medical records (EMR) can also facilitate text processing and information extraction for healthcare and medical research. Mostly, existing methods extract temporal information by using annotated corpora that are costly and time consuming to obtain. Therefore, Moharasan and Ho (2017) proposed a two-stage semi-supervised CRFs framework, which exploits abundant unannotated clinical text to automatically detect temporal events, and is proved to have improvements in the stability and accuracy of temporal event extraction.

4.3.2 Medical image segmentation

Medical image segmentation is a mainstream direction in biomedicine, in which the CRFs are mainly used for brain tumor segmentation, retinal vessel segmentation and lesion detection. Accurate and reliable brain tumor segmentation is a key component of cancer diagnosis, treatment planning, and evaluation of treatment outcomes. In order to improve the accuracy of segmentation, Zhao et al. (2016b) developed a new brain tumor segmentation method, combining the FCNN and the CRFs in a unified framework. This proposed

Table 8 A summary of the CRF applications in biomedicine

Category	Application	Author (year)
Medical information recognition and extraction	Biomedical named entity recognition	Yu et al. (2016)
		Li et al. (2015c)
		Le et al. (2018)
		Xu et al. (2015)
		Tang et al. (2015)
		Liu et al. (2017b)
	The chemical compound and drug name recognition	Lu et al. (2015b)
	Continuous and discontinuous adverse drug reaction recognition	Tang et al. (2018)
	De-identification of medical records	Liu et al. (2017d)
		Jiang et al. (2017b)
		Liu et al. (2015d)
	Biomedical event trigger detection	Wang et al. (2017a)
	Drug–drug interaction(DDI) detection	Yu et al. (2017)
	Extraction of temporal events from clinical text	Moharasan and Ho (2017)
	Event extraction from biomedical text	Majumder and Ekbal (2015)
	Prescription extraction	Tao et al. (2017)
	Clinical concept extraction	Chalapathy et al. (2016)

Table 8 (continued)

Category	Application	Author (year)
Medical image segmentation	Brain tumor segmentation	Shen and Zhang (2017)
		Zhao et al. (2016b)
		Zhao et al. (2017)
		Meier et al. (2016)
	Automatic brain tissue segmentation	Pereira et al. (2016)
	Brain lesion segmentation	Kamnitsas et al. (2016)
	Low-grade glioma segmentation	Chen et al. (2017)
	Multi-target osteosarcoma MRI recognition	Huang et al. (2016)
	Multiple sclerosis lesions detection	Karimaghaloo et al. (2015b)
	Automatic liver and lesion segmentation	Christ et al. (2016)
	Automatic and interactive neuron segmentation	Uzunbas et al. (2016)
	Retinal vessel segmentation	Fu et al. (2016)
		Luo et al. (2016)
		Zhou et al. (2017)
	Detection and segmentation of small enhanced pathology	Karimaghaloo et al. (2015a)
	Left atrial appendage segmentation	Jin et al. (2018)
Medical image detection	Detection of CRISPR arrays	Wang and Liang (2017)
	Coherent needle detection in ultrasound volumes	Zanjani et al. (2018)
	Epileptogenic cortical malformations detection	Ahmed et al. (2014)
	Transmembrane topology prediction	Lu et al. (2015a)

method is able to obtain the segmentation results with appearance and spatial consistency, and proved to possess competitive performance through experimental evaluation. As stated by Zhou et al. (2017), the retinal blood vessels in color fundus images are elongated structures that can be expressed as linear models, but the hand-crafted unary features applied in the energy function of a dense CRF are suboptimal for a linear model. To address this, they used the image preprocessing technology, trained CNN to generate discriminative features, applied a combo of filters, and then adopted the dense CRF model to achieve the retinal vessel segmentation. It is demonstrated that the improvement of the dense CRF model has presented good performance in the retinal vessel segmentation task. Currently, the activities of many chronic inflammatory diseases of the central nervous system such as multiple sclerosis (MS) are widely diagnosed and monitored by magnetic resonance imaging (MRI), and the frequency of gad lesion is routinely used in clinical trials to provide biological evidence of drug efficacy. However, these lesions are often completely manually segmented by several raters, based on which, Karimaghaloo et al. (2015a) developed a THAT-CRF for segmentation of small enhanced pathologies. The framework is used to utilize multiple higher order textures to distinguish true lesion enhancements from the pool of other enhancements, and combine the temporal texture analysis to study textures of enhanced candidates over time. Furthermore, the new proposed model is proved to achieve positive effectiveness through evaluation in a real clinical trial.

4.3.3 Medical image detection

Medical image detection is a process of target detection and analysis on medical images to judge and predict the states of targets. Automated needle detection is helpful to improve the quality of image-guided medical interventions, however, the currently applied needle detection method classifies each voxel separately, without considering the global relations between voxels. To this end, Zanjani et al. (2018) introduced the needle labeling by using dense CRFs and 3D space-frequency features, including long-distance dependencies in voxel pairs. As a result, the performance of this method is significantly improved compared to the baseline using only linear SVM for voxel classification. In order to detect and isolate abnormal cortical tissue regions in MRI of patients, Ahmed et al. (2014) proposed an image segmentation framework, where firstly the surface image is divided into segments of different sizes, then each segment is compared with the same region aross controls, and finally the probability of outliers of each segment is determined by using a tree-structured hierarchical conditional random field. Experiments show that the proposed method can correctly detect abnormal regions in 90% of patients. In the field of cell transport biology, transmembrane proteins play an important role, thus understanding the count and location of helixes in transmembrane proteins is critical for structural and functional analysis. In this case, Lu et al. (2015a) proposed an improved conditional random field, CRF-TM, to predict the helix count and locations, using long-range correlations in the full-length sequence as joint probabilities. The results of this study show that the CRF-TM method can achieve better evaluations than other widely used transmembrane predictors.

The effective extraction of biomedical texts and the precise segmentation of medical images are important directions of research in biomedicine, and the application of the CRFs in this field is helpful to improve the clinical medical level and promote the medical development.

4.4 Internet intelligence

Internet intelligence is an important field in the era of intelligence, and it is also an application branch of natural language processing and computer vision from the perspective of the data form being processed. The advent of "intelligence" has promoted more and more in-depth research on this field, besides, the intelligent network, smart home, intelligent driving and other directions are becoming increasingly popular in recent years, in which the CRFs play an important role. A summary of the applications of CRFs in this field is presented in Table 9.

4.4.1 Intelligent network

With the rapid growth of Internet applications, the intrusions of network systems are also increasing. Thus it is necessary to provide security to the networks through effective intrusion detection and prevention methods. However, the existing network intrusion detections have limitations in terms of detection time and accuracy. On this basis, Ganapathy et al. (2016) proposed an intelligent CRF based feature selection algorithm in the intrusion detection system to optimize the number of features. Compared to the existing approaches,

Table 9 A summary of the CRF applications in Internet intelligence

Category	Application	Author (year)
Intelligent network	Process operating mode diagnosis	Fang et al. (2018)
	Intrusion detection	Ganapathy et al. (2016)
	Detection of new intentions from users	Xie and Chang (2015)
Smart home	Audio event recognition	Yusuf et al. (2015)
	Real-time building occupancy estimation	Zikos et al. (2016)
	Events labeling and segmentation in wearable sensor data streams	Adams et al. (2016)
	Abnormal activity recognition in smart homes	Tong et al. (2015)
	Human activities of daily living (ADLs) recognition	Tran et al. (2017)
	RGB-D indoor scenes segmentation	Thøgersen et al. (2016)
	Lightweight map matching for indoor localisation	Xiao et al. (2014)
	First-person activity recognition on elders and disabled patients	Zhan et al. (2014)
Intelligent driving	Multi-target tracking	Yang and Nevatia (2014)
		Zhou et al. (2018)
		Chen and Bhanu (2016)
	Curb Detection based on stereo matching	Wang et al. (2016)
		Knobelreiter et al. (2017)
		Sodhi et al. (2016)
	Ground estimation and point cloud segmentation	Rummelhard et al. (2017)
	Road detection	Xiao et al. (2015)
		Xiao et al. (2018)
	Driving safety and vehicle crash prediction	Halim et al. (2016b)
	Map-matching	Liu et al. (2017c)
	Haptic mapping of robots	Shenoi et al. (2016)

this intrusion detection system has achieved high efficiency of attack detection. Process operating mode diagnosis is important for process monitoring, and the widely used HMM has some drawbacks due to the relaxation from its inherent assumptions. In these circumstances, Fang et al. (2018) proposed a marginalized CRF framework to improve the operating mode diagnosis performance, in which a new propagation algorithm is developed by summing the operating modes and missing measurements. Through validation studies, the proposed CRF-based algorithms have achieved favorable performances. The new requirements of users for a system are key factors driving the development of software services. When users are dissatisfied with an existing system, there will be new requirements, which are usually reflected in their different behaviors. Based on this, Xie and Chang (2015) utilized the CRFs to infer users' desires, explore their new intentions, and imply their new requirements. By experimenting on a research system, the process of new intention detections using the CRFs can be duly observed, which is conducive to drive the evolution of systems.

4.4.2 Smart home

Indoor tracking and navigation is a fundamental requirement for context-aware smartphone applications. Despite the increasing availability of indoor maps, there is currently no practical and reliable indoor map-matching solution. To this end, Xiao et al. (2014) expressed the tracking problem as a CRF that can capture arbitrary constraints to express how well the observations support state transitions. The proposed approach is energy-efficient and believed to enable a new era of location-aware applications. The Mobile Health (mHealth) has provided new insights into human daily activities by analyzing continuously recorded data on wearable devices. Zhan et al. (2014) proposed a system designed in a form of reading glasses to classify human activities of daily living. The reading glasses, named "smart glasses", integrate a three-axis accelerometer and a first-person perspective camera. Connections are established through the multi-scale CRFs, using contextual information from the entire global network to compute the local activities. At the same time, the daily activities of disabled or elderly people are classified according to visual acuity and head movement data to remind people with cognitive impairments of hazardous situations. Similarly, Tong et al. (2015) introduced the HCRF method to provide elderly people with better care by detecting and assessing their normal and abnormal activities. Besides, the HCRF model-based algorithm is used to compare the effectiveness on abnormal activities recognition with the feature vector distance-based algorithm, and is proved to achieve better performance.

4.4.3 Intelligent driving

Recently, researches on the intelligent driving are of great population, and the artificial intelligence network (ANN) is widely used to profile drivers (Halim et al. 2016a), profile players (Halim et al. 2017) and construct metadata-based model (Muhammad and Halim 2016). Meanwhile, the multi-target tracking, stereo matching, driving safety and other related aspects have gradually attracted the attention of scholars. Online multi-target tracking is a challenging problem and has wide applications in intelligence surveillance, robot navigation and autonomous driving (Zhou et al. 2018). Different from most approaches that focus on generating discriminative motion and appearance models for all targets, Yang and Nevatia (2014) considered discriminative features for distinguishing difficult pairs of targets, and transformed the tracking problem into an energy minimization problem. The tracking problem is developed using an online learned CRF, which is more powerful in distinguishing spatially close targets with similar appearances. Compared to several state-of-the-art methods, the effectiveness of the online CRF approach has been significantly improved. As a long-standing problem in computer vision, stereo matching has been widely used in 3D reconstruction, panoramic stereo imaging (Dubois 2014), depth of field rendering (Wang et al. 2014), etc. Local methods and global methods are two kinds of techniques generally used in the stereo matching task. On this basis, Wang et al. (2016) proposed a deep conditional random field (DCRF) model, extending the traditional CRF framework by incorporating CNN into the energy function and formulating the inference of CRF as RNN. Furthermore, the algorithm has been shown to outperform the method based on MRF or general CRF. In the case that driving safety and vehicle crash prediction are becoming critical aspects of road safety, Halim et al. (2016b) presented a study on AI techniques for accident prediction and unsafe driving pattern analysis, where the CRF model as well as the ANN is proposed as supervised learning models, reflecting a wide range of the CRFs application in accident prediction.

In addition to the four major fields mentioned above, the application of the CRFs is also extended to clothes analysis (Simo-Serra et al. 2014), slope designs (Li et al. 2016), tunnel soil performance analysis (Gong et al. 2018), scramjet computations (Huan et al. 2019) and other aspects. With the advent of the Internet and artificial intelligence era, a large amount of data in the form of text, voice, image, and video will be efficiently processed and analyzed, then transformed into information that is conducive to human understanding and decision-making so as to facilitate people's production and life.

5 Discussions and analysis

Based on the analysis of the CRF modeling process and application fields, we have learned some characteristics of this model. In this section, we will theoretically discuss the advantages and flaws of the CRFs, and address the future directions of the CRF models subsequently.

5.1 Advantages and flaws of the CRFs

5.1.1 Advantages and strengths

The conditional random fields are probabilistic graphical models that have the ability to represent the long-distance dependence and overlapping features. They define the posterior distribution as a Gibbs field and allow one to capture the dependencies of the observed data (Zhang et al. 2016). Moreover, the training of CRFs involves only the convex objective functions, which helps to obtain global optimal parameter estimation (Sutton and McCallum 2012). Since all features can be globally normalized to obtain the optimal solution, the CRFs are able to solve the label bias problem existed in MEMM satisfactorily. Through continuous and in-depth discussion conducted by scholars in recent years, the theoretical framework of the CRFs has been constantly improved. Besides, they have effectively solved the three basic problems and exhibited good performance in sequence labeling problems. The modeling process of the basic linear-chain CRF and its variants may be quite complicated. However, on the one hand, the basic CRF model is able to solve most of the existing problems. On the other hand, improvements and optimizations of the basic model can improve the CRF performance meeting different application demands.

5.1.2 Flaws and challenges

Despite the advantages and strengths discussed above, the CRFs still need to be optimized and improved based on the specific algorithm requirements and various application demands. Objectively, the CRFs are not superior to all the other machine learning models in the aforementioned fields, as Yang et al. (2017), Kim (2014), Lam et al. (2015) presented. Since the CRF is a supervised learning model, the quality and scale of training data will affect the outcome of the model, and the efficient and accurate parameter training algorithm also has an important impact on the process of modeling. However, the CRF has presently met a problem of slow convergence at the time of training. Improving the performance of the model requires a large amount of training data, but the massive data will simultaneously bring computational efficiency and time complexity problems during training. Besides, the CRF and its extended model are easily affected by the feature set. The type, quantity and complexity of the feature are able to bring great influence on the final results of the models. The application of the CRFs to the sequence labeling problem has become a trend, but there is still a lack of systematic standardization evaluation methods for model validity.

5.2 Future directions of the CRFs

On the basis of the advantages and flaws of the CRFs aforementioned, we give the future research directions of the CRF models, which can be predicted from the following three aspects.

5.2.1 Optimization of the CRF models

The CRF models have overcome the observational independence assumption of HMM, combined the advantages of HMM and MEM, and solved the label bias problem of MEMM. However, most of the basic linear chain models are still used. As can be seen in Table 1, the basic CRF model has the disadvantages of slow convergence speed and high susceptibility to feature sets. Therefore, the effective improvement of this model can be taken into account in the future, including the broadening of model assumptions, the extension of model structure (Vaisman 2017) and the optimization of model inference algorithms (Zaremba and Blaschko 2016). In recent years, the development of the CRFs has mainly concentrated on the model space and structure, by elevating the CRF order or expanding the feature connections. On this basis, according to the characteristics of this model, the input and output assumptions can be further broadened, making it available for a wider range of problems than sequence labeling. At the same time, the structure of the CRF models can be extended to construct a model which is more consistent with the semantic context by considering the interaction between the contexts, or the induction, deduction and progressive structures in the text paragraphs. In addition, as one of supervised learning methods, the CRFs need more optimized algorithms to solve the rapid inference of the model as well as the precise selection of features, so that the three basic problems needed to be solved can be more conveniently processed.

5.2.2 Integration with different models

With the continuous development and maturation of machine learning, combining the CRFs with various machine learning models has become a hot topic of discussion. Through the combination with the BiLSTM model, the CRFs have shown good results. In the future development, the CRFs can be integrated with more such models to give play to their respective advantages. Specifically, the input of the CRF models can be replaced by the output of other machine learning models in order to achieve better performance, and the output of the CRFs can be considered as an intermediate processing of other models for integration purpose. Meanwhile, we can explore the possibilities of combining the advantages of conditional training and directed models (Sutton and Mccallum 2010). Besides, the specific application demands can also be taken into account while integrating the improved CRFs with other models. On the one hand, as an important type of the supervised learning methods, the CRFs are expected to be supported by massive data sets and advanced computing tools. On the other hand, the models can be further integrated with reinforcement learning (Sutton 1998) and meta-learning (Vilalta and Drissi 2002) to make good use of their respective advantages, optimize the model effectiveness, and achieve more extensive and more profound applications.

5.2.3 Extension of the application field

Currently, the nature language processing, computer vision, biomedicine, and Internet intelligence are popular research fields of the CRFs application. The development of the artificial intelligence requires different kinds of machining learning models, including the CRFs, to be constantly improved so as to adapt to the application demands in various fields. In the future, with the continuous advancement of scientific theories, the application of the CRFs will be extended to many areas (such as industrial engineering, natural sciences, and intelligent life) as well as various practical occasions (such as building matching, objective constituent analysis, and intelligent equipment identification). In addition, the improvement of computer performance and the development of cloud platform technology will also contribute to the extension of the CRFs application field (Ai et al. 2017). Thus, the improved CRFs are expected to have better performance in more universal and practical situations.

The CRFs represent one of the most important types of the machine learning models and are considered as useful artificial intelligence tools that can effectively solve the sequence labeling problems. Besides, they are believed to have broad application prospect, according to the predictions of the future development of the models mentioned above. Therefore, it can be expected that in the future, the CRFs will be applied to more extensive research fields for better solutions to problems as well as higher levels of lifestyles via continuous improvement and perfection.

6 Conclusion

The CRFs are attractive in the field of machine learning. They have drawn great attention of scholars in various research area since being proposed. This study reviewed the recent research about the CRF models in the literature. Firstly, this paper elaborates on the CRF background and summarizes different models during the emergence of the CRF models.

Secondly, it reviews the improvements of the CRF models in the past 5 years after the analysis of the three basic problems to be solved for the CRFs. Thirdly, we investigate the application of the CRFs in four major fields, i.e., the natural language processing, computer vision, biomedicine, and Internet intelligence. Finally, the future directions of the CRF models are discussed. The development of artificial intelligence has promoted the advancement of the CRFs, which in turn accelerates the arrival of the artificial intelligence era. In the future, the CRF models are expected to receive further improvement and optimization and have integration with different machine learning models to solve various practical problems.

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