A Survey on Deep Learning for Named Entity Recognition

Jing Li et al.
Presentation by Maxim Tikhonov        May 14, 2024
Outline

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2. Evaluation metrics
3. Traditional approaches
4. Deep learning approach
5. Context encoder architectures
6. Tag decoder architectures
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Task definition

\[< w_1, w_3, \text{Person} > \quad \text{Michael Jeffrey Jordan} \]
\[< w_7, w_7, \text{Location} > \quad \text{Brooklyn} \]
\[< w_9, w_{10}, \text{Location} > \quad \text{New York} \]

\[\uparrow \quad < I_s, I_e, t > \]

**Named Entity Recognition**

\[\uparrow \quad s = < w_1, w_2, ..., w_N > \]

Michael Jeffrey Jordan was born in Brooklyn, New York.
Evaluation metrics

- **Exact-match evaluation**
  consider a prediction correct if it has both boundaries and type matching ground truth.

- **Relaxed-match evaluation**
  credit a predicted type if it matches the ground truth and overlaps with ground truth boundaries; credit predicted boundaries if they match the ground truth boundaries regardless of a predicted type.
F-score

\[
F\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},
\]

where \( \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \), \( \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \).

**Macro-averaged F-score** treats all entity types equally (average is taken of scores for each entity type).

**Micro-averaged F-score** treats all entities equally (average is taken of scores for all entities).
Relaxed-match evaluation

Evaluation doesn’t require the prediction to match both the boundary and entity type:

- Correct type is credited when the predicted type matches the ground truth and there is an overlap with ground truth boundaries.
- Correct boundaries are credited only when they match perfectly with ground truth.

Improvement (?): ACE proposed a metric that takes into account subtypes of named entities.
Rule-based approaches

- Reliance on hand-crafted/inferred rules.
- Regexp.
- Works well when we know enough language-specific information and resources (dictionaries, lexicons, linguists).
- Rules can’t easily represent some dependencies.
Unsupervised learning approaches

• Clustering – gathering of named entities from clustered groups based on the similarity of context.

• Usage of hyperonyms/hyponyms (location>country, creature>animal>bear).

• Querying the web/database for patterns (Google queries like "such as X").

• Mining named entities from several newspapers at time X.

• Reliance on lexical resources (e.g. word net), lexical patterns.
Feature-based approaches

• Feature engineering.

• Features – descriptors or characteristic attributes of words designed for algorithmic consumption (abstraction layer over the text/words).
Word-level features

Case : capitalization, uppercase, mixed case.

Punctuation : word has a period (ends with it, letters are separated by it)/apostrophe/hyphen/ampersand.

Digit : digit patterns (dates, time, IDs, serial numbers, ...), Roman numerals, abbreviations with digits.

Morphology : utilization of morphemes: {pre-,suf-}fixes, root words.

Part-of-speech : proper name, verb, noun, foreign word.
List lookup features

General list : stop words, capitalized nouns (months/days of the week), abbreviations.

List of entities : organizations, names, geographical entities

List of entity cues : name prefixes, titles, typical words in organization names.
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Deep Learning techniques

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1. Distributed representations for input
   - Pre-trained word embedding, Character-level embedding, POS tag, Gazetteer,

2. Context encoder
   - CNN, RNN, Language model, Transformer,

3. Tag decoder
   - Softmax, CRF, RNN, Point network,
Input representation

Word-level

• One-hot, Word2vec (CBOW/Skip-gram), Glove, fastText, Bert, ...

• Use pre-trained word embeddings.

• One of the mentioned works utilizes a model that is trained for two sub-tasks: it first segments the text, and then predicts labels.
Input representation

Character-level

CNN-based char-level representation

RNN-based char-level representation

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Methodologies

• Use representations from both levels – first, extract char-level word representations using CNN and concatenate them with word embedding (can also add a gate to make the model decide which representation to utilize more), then feed it into a (bidirectional) RNN context encoder.

• Consider a sentence as a sequence of characters and apply utilize RNN (LSTM) to extract char-level representation. Output a tag distribution for each character.
Input representation

- Contextual string embeddings: use string char-level LM to generate contextualized embeddings for a string in a sentence context.

Forward (red) LM extract the hidden state after the last character in the word, backward (blue) LM extracts the hidden state before the first one.
Input representation

Hybrid – a combination of feature-based and neural approaches

• Yields even better results than neural approaches.

• Systems employ rich features such as POS tags, morphological features, capitalization, etc.

• Resulting representations are often concatenations of embeddings vector and vector of features.
Each word is embedded to a multidimensional vector, then a convolution layer is applied to produce features around each word, then a global feature vector is built by combining these features. Both local and global features are then fed to a linear NN for decoding.
BRNN allows the model to contain information from the whole input sequence.
Recursive Neural Nets allow us to parse the sentence node by node using a constituency structure. The bottom-up direction calculates the semantic composition of the subtree of each node, and the top-down counterpart propagates to that node the linguistic structures which contain the subtree.
LM-LSTM-CRF model. The language model and sequence tagging model share the same character-level layer in a multi-task learning manner.
Just as in previous architectures, transformer embeddings are contextualized.
MLP + softmax decoder reformulates the NER problem to a multi-class classification problem. Tag for each word is independently predicted based on context-dependent representations.
Conditional Random Fields

![Diagram of Conditional Random Fields]

- B-PER
- I-PER
- E-PER

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RNNs
Pointer networks

Pointer networks first identify a segment and then label it.
Multi-task Learning

Let the model discover internal representations that are useful for many tasks.

Approaches:

- Train a model to jointly perform additional tasks like POS tagging, segmentation, SRL (Semantic Role Labeling).

- Modelling NER as two related subtasks: entity segmentation and category prediction.
Deep Learning Transfer

Approaches:

• Bootstrapping
Deep Reinforcement Learning

"Maximizing some heuristic helps to train a better performing model: the agent learns from the environment by interacting with it and receiving rewards."

Key components of the environment

- State transition function.
- Output function.
- Reward function

Key components of the agent:

- State transition function.
- Policy function.
Deep Adversarial Learning

"Learn to generate from a training distribution through a 2-player game: one network generates candidates, and the other evaluates them"

Adversarial examples can be produced in 2 ways

1. Consider instances in a source domain as adversarial examples for a target domain, and vice versa.

2. Prepare an adversarial sample by adding an original sample with a perturbation. Useful when dealing with a low-resource setting. The classifier is trained on both original and adversarial examples.
Neural attention

Application:

• When combining word-level and char-level input representations, use the attention mechanism to make the model decide what representations are more important.

• Obtaining relevant information from the entire document.