E-fashion Product Discovery via Deep Text Parsing

Uma Sawant
IIT Bombay
uma.sawant@gmail.com

Vijay Gabale
Huew
vijay@huew.co

Anand Prabhu Subramanian
Huew
anand@huew.co

Background and Problem Statement

While product listings are getting complex, e-commerce search engines are still stuck with simple text-based parsing.

- ~35% of fashion listings contain text for multiple products
- Product text information is spread over unstructured title, description and structured key value pairs.
- ~30% words have semantic ambiguity to assign appropriate labels for keyword indexing.

Deep text parsing of product listings for relevant product and attribute indexing is vital for e-commerce search engines.

How do we discover potentially **multiple** products present in an e-commerce listing, along with their respective **relevant attributes** by processing the **entire title and description** text description?

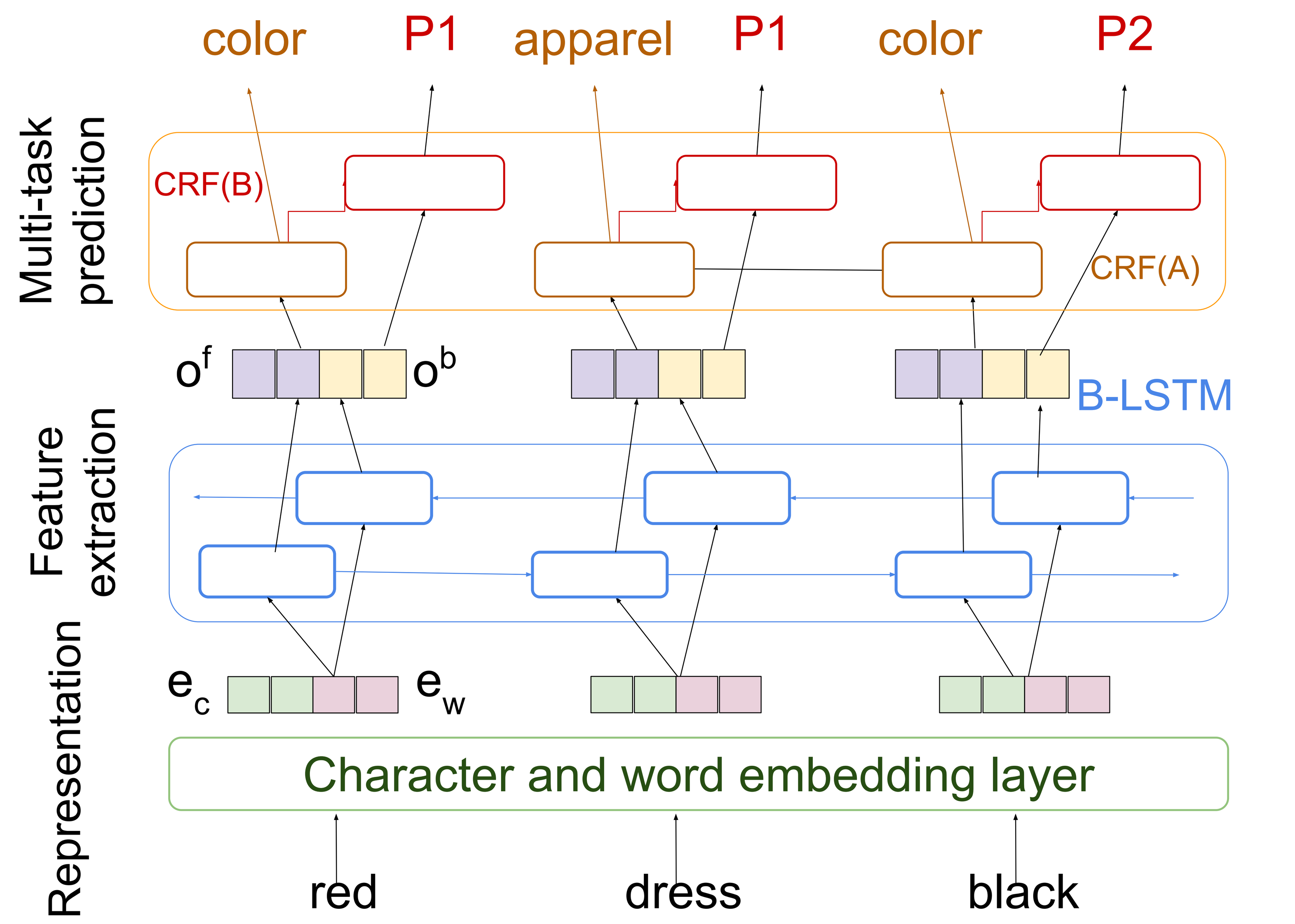
Unstructured Input To Structured Output

Title: Perfectly designed printed tops
Description: This mandarin top from Indigo fashion will make you go gaga this season, dress up for that perfect cocktail party. This georgette top is soft against your skin, team it with a black jegging to accentuate blue color, waist length, 3/4 sleeves.

Challenges:
Partially known schema
Keyword ambiguity
Product-attribute attachment ambiguity

product 1: {apparel = top, pattern = printed, neck = mandarin, fabric = georgette, color = blue, sleeve = three-fourth, length = waist-height, occasion = cocktail-party, brand = Indigo fashion}
product 2: {apparel = jegging, color = black}

End-To-End Deep Parsing of A Listing



Solution: Deep Networks + Cascaded CRFs

- Deep neural network based multi-task learning and sequence labeling with two types of labels - keyword (items, attributes) and affiliation (product)
- Representation :
  - Pre-trained word embedding lookup
  - Character embeddings input to CNN to form character-level word embeddings
- Feature Extraction : A bi-directional LSTM to extract features and long-term sequence dependencies
- Multi-task prediction using Cascaded CRFs:
  - Capture conditional dependency between affiliation labels and keyword labels
  - Two CRFs for sequence label prediction for two types of labels

Experimental Setup

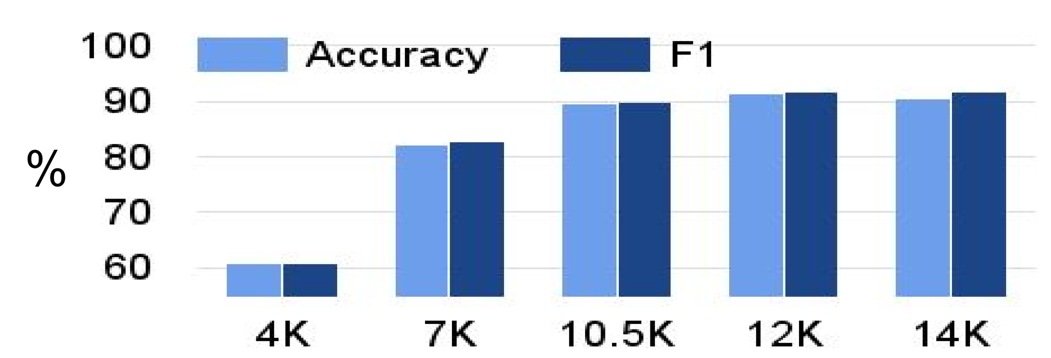
Dataset and setup :
- 23 labels, 5311 unique label-values, 110K tagged values
- Training data : 12.7 K listings (all labels)
- Validation data : 4.9 K listings
- Test data : 7.2 K listings (20% unseen label-values)
- Theano (Lasagne) with AWS G2 instances

Prior works :
- Prior A [5] : RNNs for multi-task learning with two separate CRFs for two different tasks
- Prior B [1] : word2vec with CRF to discover attributes only from title text of e-commerce listings

Application :
- On 2 Million listings discovered 2.6 Million fashion items and 9.5 Million attribute values

Comparison and Results

Criteria	approach	(accuracy, F1)	(prec, recall)
product discovery	prior-A	(81%, 80.8%)	(81.4%,80.3%)
	prior-B	(75.4%, 74.8%)	(73.4%,74.2%)
	Our work	(92.1%, 92.2%)	(92.7%,91.8%)
OOV prediction	prior-A	(75.9%, 76.6%)	(75.9%,77.3%)
	Our work	(92.2%,92.3%)	(92.5%,92.1%)
brand-label disambig	prior-A	(71.2%, 70.6%)	(70.9%,70.3%)
	Our work	(85.2%,85.3%)	(85.5%,85.1%)



No. of training samples vs. accuracy

References

1. M. Joshi, E. Hart, M. Vogel, and J.-D. Ruvini. Distributed word representations improve ner for e-commerce. In Proceedings of NAACL-HLT, 2015.
2. X. Ma and E. Hovy. End-to-end sequence labeling via bi-directional lstm-cnns-crf. In Proceedings of 54th ACL, 2016, Germany.
3. K. Mauge, K. Rohanimanesh, and J.-D. Ruvini. Structuring e-commerce inventory. In Proceedings of the 50th ACL, 2012.
4. K. Pallika, W. Michael, and P. Adam. Attribute extraction from noisy text using character-based sequence tagging models. In Machine Learning for eCommerce workshop, NIPS, 2015.
5. N. Peng and M. Dredze. Multi-task multi-domain representation learning for sequence tagging. CoRR, abs/1608.02689, 2016.