Abstract—Keyphrases are a very short summary of an input text and provide the main subjects discussed in the text. Keyphrase extraction is a useful upstream task and can be used in various natural language processing problems, for example, text summarization and information retrieval, to name a few. However, not all the keyphrases are explicitly mentioned in the body of the text. In real-world examples there are always some topics that are discussed implicitly. Extracting such keyphrases requires a generative approach, which is adopted here. In this paper, we try to tackle the problem of keyphrase generation and extraction from news articles using deep sequence-to-sequence models. These models significantly outperform the conventional methods such as Topic Rank, KPMiner, and KEA in the task of keyphrase extraction.

Index Terms—Keyphrase Generation, Sequence-to-sequence Learning, Recurrent Neural Networks

I. INTRODUCTION

Keyphrases are single words or sequences of words that express the main topics discussed in a piece of text. Knowing the main topics discussed in a text can play an important role in a variety of downstream tasks such as text categorization [1], opinion mining [2], information retrieval [3] and text summarization [4]. Keyphrases themselves can be regarded as very dense summarization of the input text which can come of help in many problems.

Keyphrase extraction is quite a well-known task in Natural Language Processing, the purpose of which is to extract words pertaining to the main topics discussed in the input piece of text. The purpose of keyphrase extraction task is to extract explicit keyphrases from a given text. Keyphrase generation on the other hand, is a task of extracting explicit and implicit keyphrases. In real-world examples, there are always keyphrases that are not present in the article, but rather hinted at implicitly. Since we are dealing with implicit keyphrases in this paper, such a task cannot be treated as a sequence labeling, phrase/word classification or scoring problem. In this paper we take an approach of deep sequence-to-sequence learning, similar to neural machine translation.

In the next section we discuss the different approaches to keyphrase extraction and generation in English and Persian.
As for deep approaches to keyphrase extraction, Zhang et al. [14] use joint-layer recurrent neural networks to extract keyphrases from tweets, treating the problem as a sequence labelling task. Another work that takes the same approach is [15] that aims to extract keyphrases from microblog posts with the help of encoding the context.

However, in this work we also focus on the problem of keyphrase generation, as well as extraction. The first work to address this problem using deep neural networks is that of Meng et al. [17] which tries to tackle the problem using an encoder-decoder, attention, and copying mechanism. Their bidirectional RNN with gated recurrent units cannot outperform non-deep approaches in extracting present keyphrases from most of the datasets, but Copynet [18] does significantly. Some other works taking the same approach are [19] and [20], the latter of which uses a convolutional sequence-to-sequence model.

As for the other works, Zhang et al. [15] try to tackle the problem of keyphrase extraction from microblogs. They make use of the context, which is other blog posts, to inform the model of the previous events. Chen et al. [21] address the problem of keyphrase duplication and try to solve it by taking previous phrases into account.

### B. Work on Persian

Literature of keyphrase/keyword extraction from Persian texts is quite minimal. Mohammadi and Analou [22], after removing stop words and stemming, extracts keywords using TF (Term Frequency), TTF (Total Term Frequency), and DF (Document Frequency) matrices and fuzzification.

Khozani and Bayat [23], after stemming and removing stop words, uses TFIDF (Term Frequency times Inverse Document Frequency) to calculate the weights of the words in the documents. After calculating the weights of the tokens, the weights of the bi-token keyphrases are calculated using a co-occurrence matrix.

Kian and Zahedi [24] uses attention attractive strings to improve keyword extraction from 800 documents from Hamshahri news collection [25]. Three to seven keyphrases were assigned to each document, the length of each keyphrase ranging from two to four words. The best result, an F1 of 40.23, is achieved using attention attractive strings and training on 400 documents.

### III. Methodology

In this paper, we use an encoder-decoder model [26], [27] with Bahdanau’s attention mechanism [28]. In the training phase, the data is converted from \((x_j, y_{j1}, y_{j1+1}, ..., y_{jT})\) format to \((x_j, y_{j1}), (x_j, y_{j1+1}), ..., (x_j, y_{jT})\), \(x\) being the concatenation of the news article’s title and body, and \(y\) it’s keyphrases. It means that a training sample is repeated to the number of its keyphrases which increases training samples from the number of the news articles to the number of their keyphrases.

#### A. Encoder-Decoder Model

An encoder-decoder model consists of two RNNs, the last hidden layer or the concatenation of all hidden layers of the first one considered an encoded representation of the input document the second one is going to decode. Here, the input for the encoder is the concatenation of the title and the body of the news and the output of the decoder, the words in the keyphrase. The hidden layer of the encoder, as explained in [26], is calculated as:

\[
h_j = f(x_j, h_{j1})
\]

in which, \(f\) is a nonlinear function (as we use GRU, \(f\) is a Gated Recurrent Unit here) which takes the input \(x\) at timestep \(j\) and the hidden state of the last timestep, \(h_{j-1}\). By obtaining \(h_j\), the hidden state of the encoder at timestep \(j\), we can easily calculate \(p(y_{i1}|y_{i1}, \ldots, y_{i1}, X)\), the probability of producing the output \(y\) at timestep \(i\), given the previous \(y\)’s and the input \(X\), by the equation below:

\[
s_i = q(s_{i-1}, y_{i-1}, c)
\]

\(s_{i-1}\) being the representation of all previous \(y\)’s, except the most previous one and \(c\), the context vector, being the representation of \(X\), which is either the output of the last timestep, \(h_T\), or the context vector computed by the attention mechanism.

#### B. Attention Mechanism

Attention mechanism [28] gives different weights to different timesteps from the encoder, presuming that different words in an input sentence have different levels of importance to a timestep of the output. So, a hidden state in the decoder is calculated as \(s_i = q(s_{i1}, y_{i1}, c_i)\). The context vector \(c_i\) can be obtained using the formula below:

\[
c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j
\]

\(\alpha_{ij}\) being the weight of the state \(h_j\) of the encoder to the state \(s_i\) of the decoder which is calculated as:

\[
\alpha_{ij} = \frac{\exp(a(s_{i1}, h_j))}{\sum_{k=1}^{T_x} \exp(a(s_{i1}, h_k))}
\]

where \(a\) is a feed forward neural network, a soft alignment (not a latent variable as in traditional machine translation), a model which scores how well the inputs around position \(j\) and the output at position \(i\) match. You can see the schema of the model in figure 1.

### IV. Experiments

#### A. Training and Testing Datasets

Here, we use a subset of the PerKey dataset introduced in [29] with at least 3 keyphrases for each news article. As concluded in PerKey paper, news articles with at least 3 keyphrases are more reliable in terms of recall.
The dataset is stored in JSON format, each news article containing the following information:

{title, body, summary, keyphrases, category, url}

The data used in this paper comprises 395,645 news articles crawled from 6 news websites and agencies which provided high-quality keyphrases. After cleaning the data, an assessment was conducted by 5 human evaluators to ensure the quality of the keyphrases. The result was an F1-score of 4.264 which guarantees the quality of the keyphrases. As shown in Table I, most of the articles contain less than 300 tokens and only 25% of them contain more than that.

| # of tokens | # of articles | % of total |
|-------------|---------------|------------|
| 40-100      | 72,467        | 18.31%     |
| 100-200     | 129,996       | 32.85%     |
| 200-300     | 92,691        | 23.42%     |
| 300-400     | 59,989        | 15.16%     |
| 400-500     | 40,502        | 10.23%     |
| total       | 395,645       | 100%       |

It appears that half of the articles have 3 keyphrases and 20% of them have 4. More information on the number of the keyphrases in news articles can be found in Table II.

| # of keyphrases | # of articles | % of total |
|-----------------|---------------|------------|
| 3               | 202,748       | 51.24%     |
| 4               | 81,500        | 20.59%     |
| 5               | 56,278        | 14.22%     |
| 6 & more        | 55,119        | 13.8%      |
| total           | 395,645       | 100%       |

Table V shows that most of the keyphrases contain either 1 or 2 tokens. News articles containing keyphrases with more than 7 tokens in them were removed.

| # of tokens | # of keyphrases | % of total |
|-------------|-----------------|------------|
| 1           | 874,685         | 50.65%     |
| 2           | 586,481         | 33.96%     |
| 3           | 170,288         | 9.86%      |
| 4           | 65,727          | 3.80%      |
| 5           | 18,616          | 1.07%      |
| 6 & more    | 10,897          | 0.63%      |
| total       | 1,726,694       | 100%       |

TABLE IV
NUMBER OF ABSENT AND PRESENT KEYPHRASES

| # of keyphrases | % of total |
|-----------------|------------|
| present         | 1,183,689  | 68.55%     |
| absent          | 543,005    | 31.44%     |
| total           | 1,726,694  | 100%       |

before, in real-world instances, there are topics that are not explicitly mentioned in the text and spoken of implicitly.

After shuffling, we divided the dataset into three subsets, 345,645 samples for training, 25,000 for validation, and 25,000
for test. The dataset can be found in this project’s Github repository.

B. Implementation Details

We used dynamic word embeddings for the 100,000 most frequent words in the training set with embedding size of 150. Number of the units in the GRU cell for both the encoder and the decoder is 256. As for the beam search decoding hyperparameters, we set the beam width to 50 and beam depth to 5. Finally, we used batch size of 32, Adam Optimizer with learning rate of $1e-3$ and gradient clipping by 0.1. We also used dropout of 0.5 as regularization on the input embeddings and the output of the encoder.

C. Baseline Models

Our baseline models constitute of unsupervised and supervised methods. As for the unsupervised models, we used graph-based models SingleRank [30], TopicRank [31], and MultipartiteRank [31]. Unsupervised statistical methods include phrase-level TFIDF [32], KPMiner [33], and YAKE [34], [35]. We used KEA [36] as our supervised base-line method. For more information on the hyperparameters, settings and implementation of the base-line models see [29].

D. Evaluation Metrics

Following the convention, we use precision, recall, and their harmonic average, $F_1$-score, to evaluate the models. As these metrics may be too strict, we also measure the performance of the keyphrases using ROUGE-1 and ROUGE-2 [37]. Using ROUGE metrics may help with the instances where there is only one (usually optional) word difference between gold keyphrase and the predicted one.

V. EXPERIMENTAL RESULTS

We evaluated the performance of each method with their $k$ best outputs, $k$ being 5 and 10, using precision, recall and $F_1$-score. As expected, RNN with GRU cell outperformed all the other supervised and unsupervised (statistical and graph-based) methods by a great margin. Table V contains the results for performance of all the methods on whole dataset, i.e. absent and present keyphrases. After RNN, the best performance belongs to statistical methods, supervised and unsupervised, and lastly graph-based methods. TFIDF, as the simplest method, shows a good performance, especially in predicting present keyphrases. One may argue that despite the high performance of such algorithms, they require huge amount of training data. In this paper, we showed that we can overcome the barrier, having access to the largest database of all times, internet. However, not all the supervised

| Method | P@5 | R@5 | F@5 | P@10 | R@10 | F@10 |
|--------|-----|-----|-----|------|------|------|
| TFIDF  | .1724 | .2060 | .1877 | .1216 | .2877 | .1710 |
| KPMiner | .1900 | .1948 | .1924 | .1632 | .2513 | .1979 |
| YAKE   | .0726 | .0820 | .0770 | .0658 | .1481 | .0911 |
| S.Rank | .0532 | .0671 | .0994 | .0623 | .1533 | .0886 |
| T.Rank | .0986 | .1208 | .1086 | .0665 | .1583 | .0937 |
| M.Rank | .1093 | .1319 | .1196 | .0771 | .1835 | .1086 |
| KEA    | .1837 | .2226 | .2013 | .1300 | .3115 | .1835 |
| RNN    | .3126 | .3888 | .3466 | .1947 | .4732 | .2759 |

In table VIII you can see the results of the ROUGE-1 and ROUGE-2 metrics on the predictions. We measured the performance of the model using these metrics as suggested in [5]. The metrics may appear to be less strict as they show 8 percent more $F_1$-score, but the precision drops when $k$ is 10, as the reference keyphrases decrease, and so does the $F_1$-score, consequently. This shows that ROUGE metric may not be a better choice to measure the performance of the keyphrase extraction and generation models.

VI. DISCUSSION

We saw that the recurrent neural network with gated recurrent units could outperform other methods by a huge margin, especially in predicting present keyphrases. One may argue that despite the high performance of such algorithms, they require huge amount of training data. In this paper, we showed that we can overcome the barrier, having access to the largest database of all times, internet. However, not all the supervised

TABLE VI

| Method | P@5 | R@5 | F@5 | P@10 | R@10 | F@10 |
|--------|-----|-----|-----|------|------|------|
| TFIDF  | .1726 | .2173 | .2110 | .1218 | .3392 | .1843 |
| KPMiner | .1902 | .2523 | .2169 | .1634 | .3240 | .2173 |
| YAKE   | .0733 | .1089 | .0876 | .0664 | .1974 | .0994 |
| S.Rank | .0533 | .0996 | .0694 | .0624 | .2180 | .0970 |
| T.Rank | .0987 | .1634 | .1230 | .0665 | .2136 | .1015 |
| M.Rank | .1093 | .1761 | .1549 | .0771 | .2468 | .1176 |
| KEA    | .1839 | .2237 | .2062 | .1301 | .3124 | .1979 |
| RNN    | .3249 | .4794 | .5012 | .4621 | .5588 | .5089 |

TABLE VII

| Method | P@5 | R@5 | F@5 | P@10 | R@10 | F@10 |
|--------|-----|-----|-----|------|------|------|
| TFIDF  | .1786 | .2053 | .2226 | .1524 | .2053 | .2319 |
| KPMiner | .0505 | .0920 | .0905 | .0219 | .0515 | .0421 |
| YAKE   | .0505 | .0920 | .0905 | .0219 | .0515 | .0421 |

TABLE VIII

P@5 | R@5 | F@5 | P@10 | R@10 | F@10 | P@20 | R@20 | F@20 | P@50 | R@50 | F@50 |
methods can produce such results. KEA, having access to the same training data as RNN, could not beat KPMiner, as it uses only two features, hence not powerful enough to do so.

Another problem we addressed in this paper was measuring the performance of the models. As discussed in other papers on keyphrase extraction and generation, the current performance measure is not perfectly suitable for the task, as it is too strict, meaning that it does not tolerate even a single word difference with the reference keyphrases, let alone understanding the different ways of expressing the same concept. The reference keyphrases themselves are another matter. Choosing them is quite subjective, in a way that different annotators most probably come up with different keyphrases, not even agreeing on the number of them. As an example to illustrate this, in table IX, you see the predicted keyphrases of a random news article and its reference keyphrases annotated by the author of it. For these predictions, the precision will be 0.2 and recall 0.5, you can see that they are of more quality however.

Most of these keyphrases are related to the main topics of the news article, expect for the last two. They are generated most probably because of some mentions of Iraq’s ‘territorial integrity’ and ‘security’. One interesting predicted keyphrase in this example is ‘Rajab Tayyeb Ardoğan’, which is not mentioned in the article, except for an implicit mention of the title, ‘Turkey’s president’.

We also measured the performance of the models using another suggested performance measure, ROUGE, which was not a better measurement, as discussed in section V.

VII. CONCLUSION AND FUTURE WORK

In this work, we compared the results of a couple of unsupervised and supervised methods on the tasks of keyphrase extraction and generation in Persian language, concluding that RNN with GRU cells can significantly outperform other methods in both tasks. We also measured the performance using ROUGE-1 and ROUGE-2 metrics, as they are less strict and may be more accurate and discuss their shortcomings. As of the future work, we are going to address the task of multi-document keyphrase extraction and generation from Persian news articles.

REFERENCES

[1] A. Hulth and B. B. Megyes, “A study on automatically extracted keywords in text categorization,” in Proceedings of the 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 2006, pp. 537–544.

[2] G. Berend, “Opinion expression mining by exploiting keyphrase extraction,” in Proceedings of 5th International Joint Conference on Natural Language Processing, 2011, pp. 1162–1170.

[3] E. Frank, G. W. Paynter, I. H. Witten, C. Gutwin, and C. G. Nevill-Manning, “Domain-specific keyphrase extraction,” in 16th International joint conference on artificial intelligence (IJCAI 99), vol. 2. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1999, pp. 668–673.

[4] Y. Zhang, N. Zincir-Heywood, and E. Milios, “World wide web site summarization,” Web Intelligence and Agent Systems, vol. 2, no. 1, pp. 39–53, 2004.

[5] K. S. Hasan and V. Ng, “Automatic keyphrase extraction: A survey of the state of the art,” in Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), vol. 1, 2014, pp. 1262–1273.

[6] P. D. Turney, “Learning to extract keyphrases from text,” National Research Council Canada, Institute for Information Technology, Technical Report ERT-1057, 1999.

[7] I. H. Witten, G. W. Paynter, E. Frank, C. Gutwin, and C. G. Nevill-Manning, “Kea: Practical automated keyphrase extraction,” in Proceedings of the 4th ACM Conference on Digital Libraries, 1999, pp. 254–255.

[8] W. Yih, J. Goodman, and V. R. Carvalho, “Finding advertising keywords on web pages,” in Proceedings of the 15th international conference on World Wide Web. ACM, 2006, pp. 213–222.

[9] P. Lopez and L. Romary, “Hum: Automatic key term extraction from scientific articles in grid,” in Proceedings of the 5th International Workshop on Semantic Evaluation, 2010, pp. 248–251.

[10] X. Jiang, Y. Hu, and H. Li, “A ranking approach to keyphrase extraction,” in Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval. ACM, 2009, pp. 756–757.

[11] S. Brin and L. Page, “The anatomy of a large-scale hypertextual web search engine,” Computer networks and ISDN systems, vol. 30, no. 1-7, pp. 107–117, 1998.

[12] Z. Liu, P. Li, Y. Zheng, and M. Sun, “Clustering to find exemplar terms for keyphrase extraction,” in Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing; Volume 1-Volume 1. Association for Computational Linguistics, 2009, pp. 257–266.
[13] Z. Liu, W. Huang, Y. Zheng, and M. Sun, “Automatic keyphrase extraction via topic decomposition,” in *Proceedings of the 2010 conference on empirical methods in natural language processing*. Association for Computational Linguistics, 2010, pp. 366–376.

[14] Q. Zhang, Y. Wang, Y. Gong, and X. Huang, “Keyphrase extraction using deep recurrent neural networks on twitter,” in *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2016, pp. 836–845.

[15] Y. Zhang, J. Li, Y. Song, and C. Zhang, “Encoding conversation context for neural keyphrase extraction from microblog posts,” in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, vol. 1, 2018, pp. 1676–1686.

[16] E. Doostmohammadi, M. H. Bokaei, and H. Sameti, “Persian keyphrase generation using sequence-to-sequence models,” in *2019 27th Iranian Conference on Electrical Engineering (ICEE)*, April 2019, pp. 2010–2015. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8786505

[17] R. Meng, S. Zhao, S. Han, D. He, P. Brusilovsky, and Y. Chi, “Deep keyphrase generation,” in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, vol. 1, 2017, pp. 582–592.

[18] J. Gu, Z. Lu, H. Li, and V. Li, “Incorporating copying mechanism in sequence-to-sequence learning,” in *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2016. Association for Computational Linguistics., 2016.

[19] Y. Zhang and W. Xiao, “Keyphrase generation based on deep seq2seq model,” *IEEE Access*, vol. 6, pp. 46047–46057, 2018.

[20] Y. Zhang, Y. Fang, and X. Weidong, “Deep keyphrase generation with a convolutional sequence to sequence model,” in *Systems and Informatics (ICSIAI), 2017 4th International Conference on*. IEEE, 2017, pp. 1477–1485.

[21] J. Chen, X. Zhang, Y. Wu, Z. Yan, and Z. Li, “Keyphrase generation with correlation constraints,” in *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 2018, pp. 4057–4066.

[22] M. Mohammadi and M. Analoui, “Extracting keywords from persian documents,” in *13th Annual Conference of Computer Society of Iran*. Computer Society, 2008.

[23] S. M. H. Khozani and H. Bayat, “Specialization of keyword extraction approach to persian texts,” in *Soft Computing and Pattern Recognition (SoCPaR)*, 2011 International Conference of. IEEE, 2011, pp. 112–116.

[24] H. Kian and M. Zahedi, “Improving precision in automatic keyword extraction using attention attractive strings,” *Arabian Journal for Science and Engineering*, vol. 38, no. 8, pp. 2063–2068, 2013.

[25] A. AlEahmad, H. Amir, E. Darrudi, M. Rahgozar, and F. Oroumchian, “Hamshahri: A standard persian text collection,” *Knowledge-Based Systems*, vol. 22, no. 5, pp. 382–387, 2009.

[26] K. Cho, B. van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, “Learning phrase representations using rnn encoder-decoder for statistical machine translation,” in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014, pp. 1724–1734.

[27] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in *Advances in neural information processing systems*, 2014, pp. 3104–3112.

[28] D. Bahdanau, K. Cho, and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” *arXiv preprint arXiv:1409.0473*, 2014.

[29] E. Doostmohammadi, M. H. Bokaei, and H. Sameti, “Perkey: A persian news corpus for keyphrase extraction and generation,” in *2018 9th International Symposium onTelecommunications (IST)*, 2018, pp. 460–465.

[30] X. Wan and J. Xiao, “Single document keyphrase extraction using neighborhood knowledge,” in *Proceedings of the 23rd national conference on Artificial intelligence-Volume 2*. AAAI Press, 2008, pp. 855–860.

[31] A. Bougoun, F. Boudin, and B. Daille, “Topocrank: Graph-based topic ranking for keyphrase extraction,” in *Proceedings of the Sixth International Joint Conference on Natural Language Processing*, 2013, pp. 543–551.

[32] S. N. Kim, O. Medelyan, M.-Y. Kan, and T. Baldwin, “Automatic keyphrase extraction from scientific articles,” *Language resources and evaluation*, vol. 47, no. 3, pp. 723–742, 2013.