

# Classification of Persian Product Reviews Using Neural Networks

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Karim Akhavan Azari  
Dr. Mohammad Bahrani

Languages and Linguistics Center, Sharif University of Technology, Tehran, Iran. karim.akhavan@sharif.edu  
Department of Computer Science, Allameh Tabataba'i University, Tehran, Iran. bahrani@atu.ac.ir

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## Different Sentiments in Reviews



کالا در این رنج قیمت  
محصولات نوا عالی  
هستند حتما بخرید

**Recommended**



پلاستیکی هستش ولی  
با توجه به قیمتش  
شاید بیارزه

**Neutral**



نداشتن درپوش  
پلاستیکی

**Not  
Recommended**

## One Type of Challenge in Sentiment Analysis



رنگش قرمز بود!

Neutral



سایزش مثل عکس  
نبود

Neutral



اصن اینقدر خوب بود  
که همون تو جعبه  
میموند بهتر بود :

Neutral

# Types of Sentiment Analysis

- Document level
  - متأسفانه علیرغم جنس خوب ، سایز رویه بیرونی ۹ سانتی که با مشخصات فنی موجود مطابقت ندارد. خوب  
تو سینک فیت نمیشه و عملاً بلا استفاده ست. بدرد سینکهای قدیمی میخوره. ارزش برگشت زدن هم نداره  
و باز هم آدم به این نتیجه میرسه که محصولی که فروشنده غیر خود دیجیکالا باشه خرید نشه
- Sentence level
  - خیلی خوشگله حتما همه بخرید
- Entity & Aspect level
  - صدای قابل قبولی دارد

# Motivation Behind the Work

- Helps businesses to monitor product sentiment in customer feedback, and understand customer needs
  - More than 58 million internet users in Iran and around 46% of them (more than 26 million) make online transactions with many of them being online shopping<sup>1</sup>
- Helps customers in deciding on the best product to buy
  - Product ratings and comments impact the buyers' opinion on the shopping item<sup>2</sup>
- Analyzing Data at Scale
- Real-Time Analysis
  - Can be applied to conversations with customers, brand/product mentions (e.g. twitter), comments (e.g. Instagram, YouTube), etc.

1. DataReportal (2020), "DIGITAL 2020: IRAN", retrieved from <https://datareportal.com/reports/digital-2020-iran>
2. von Helversen, Bettina, et al. "Influence of Consumer Reviews on Online Purchasing Decisions in Older and Younger Adults." Decision Support Systems, vol. 113, Sept. 2018, pp. 1–10. ScienceDirect, <https://doi.org/10.1016/j.dss.2018.05.006>.

# Literature Review

- Machine learning algorithms such as Naive Bayes, Logistic Regression, Tree Classifiers, SVM
- Turney et al. (2003)
  - Classify words based on their polarity with an accuracy of 82.84% using LDA
- Catal et al. (2017)
  - Ensemble learning method with the combination of two SVM variants and a Naive Bayes algorithm. Classifies by majority voting, which on the average achieved an accuracy of 83.25% on three different datasets
- Abdi et al. (2019)
  - Deep learning combined feature vectors in terms of statistical, linguistic and sentiment knowledge, sentiment shifter rules, and word-embedding. Saw an improvement over other deep-learning-based sentiment classification researches
- (Wei, Y., Lao, While clustering algorithms (Rehioui, H., & Idrissi, A., 2020; Mostafa, M.M., 2019)
  - Combination of clustering techniques which resulted in better clustering
- Roshanfekr et al. (2017)
  - Compares NBSVM with two a Bidirectional-LSTM and a Convolutional Neural Network. Although the NBSVM outperforms the other two (70% compared to 54.2 and 59.1 for BiLSTM and CNN in order), both of the deep learning methods had an overall much better performance considering their recall and F-score
- Zobeidi et al. (2019)
  - Classifies by feature extraction using a CNN and using a BiLSTM network on the Digikala Persian dataset on mobile and digital cameras resulting in an accuracy of 95% for two classes and 92% for multi-class classification

# Dataset<sup>1</sup>

**Size of dataset:** 100000 documents

**Labels:** “recommended”, “Not\_recommended”, or “no\_idea”

**Size of dataset after preprocessing:** 62131 documents

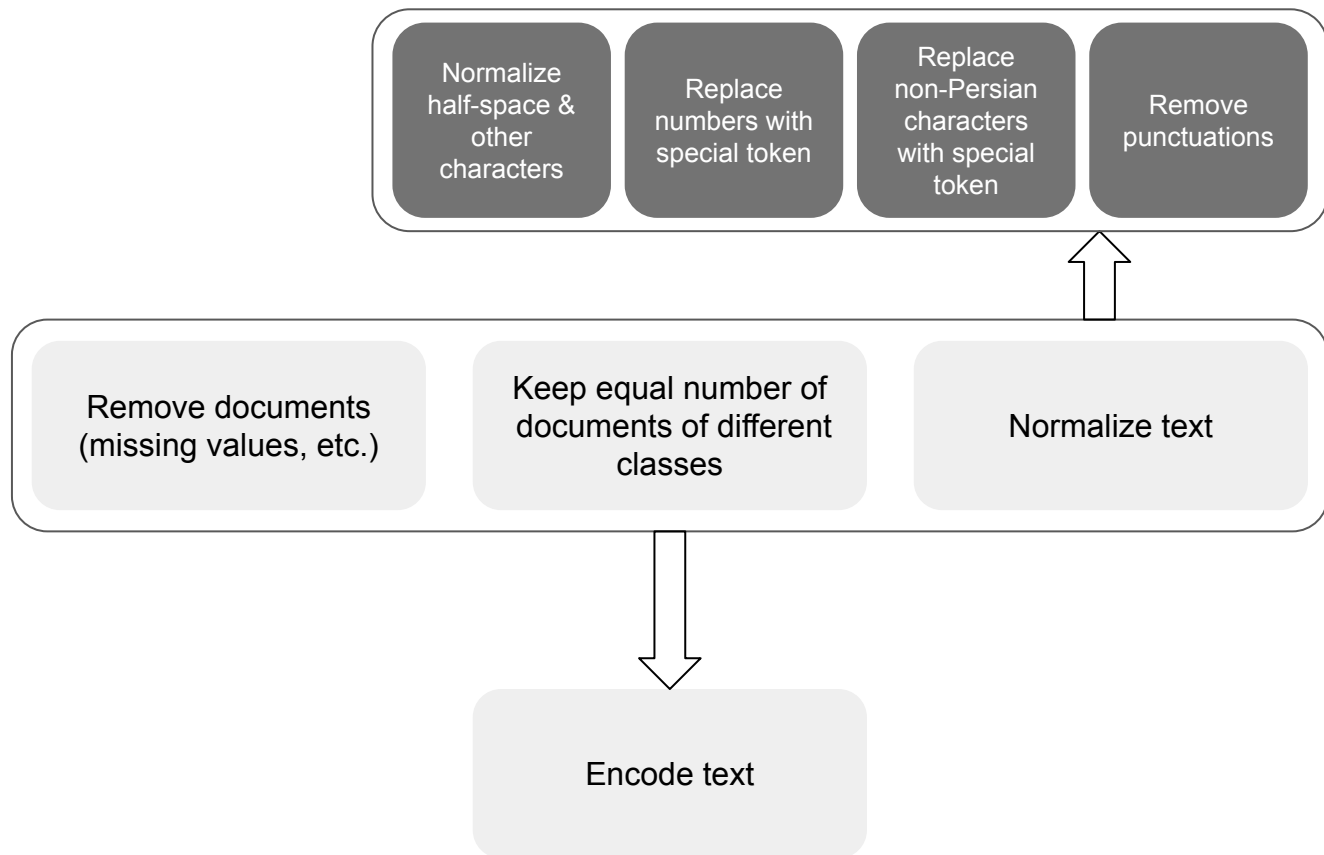
**Train/evaluation ratio:** 90% / 10%

product_id	product_title	recommend	comment
1	SD1001 ساعت دیواری آرام مدل هنرکار	recommended	خیلی ساعت فشنگیه تنها ایرادی که داره اینه که رو دیوار ...مسطح وای نمی ایسته
2	MC-2017 اتو مو مک استایلر مدل	not_recommended	دختر عمه ی من ارایشگره و این اتو رو خریده من بیار ...استفاده کردم عالی بود
3	ساعت مچی عقربه ای مردانه کاسیو جی-شاک GA-100-1A1DR	recommended	خیلی کاربردی و خوبه
4	25 Focus xدوربین دوچشمی سلسترون مدل 12 View	recommended	اگر در پیشنهاد ویژه خریداری شود به نسبت قیمت، دوربین ...مناسبست

1. <https://www.digikala.com/opendata/>



## Pipeline: Preprocessing



# **Pipeline: Network Architecture**

Three different models:

- RNN (baseline)
- LSTM
- BiLSTM

# Pipeline: Network Architecture

The embedding layer:

- Feed 1000 selected features as the input to this layer
- Project the input features into a 300 dimension layer

The hidden layer:

Each has a layer with 128 neurons

- RNN
- LSTM
  - Has another second layer, similar to the first one
  - The first layer returns a dense representation of input for each time step
- BiLSTM

Dense layer:

- Three neurons (3 classes)
- Softmax

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# **Pipeline: Network Architecture**

Config:

- Batch size: 64
- LR: 0.002
- Dropout: 0.4
- Optimizer: Adam
- Loss function: Categorical cross-entropy

# Evaluation

Performance of each model:

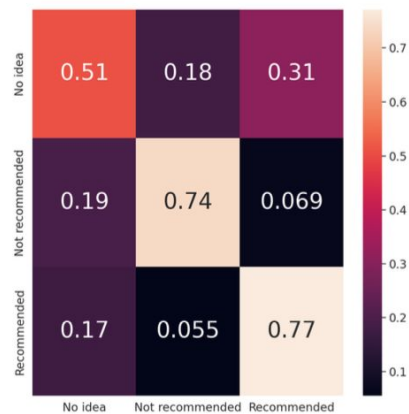
Model	Accuracy[%]	Precision[%]	Recall[%]	F1 Score[%]
RNN*	66.02	76.66	72.4	74.03
LSTM*	68.86	78.97	73.7	75.53
BiLSTM*	67.1	78.67	76.1	77.15
NBSVM-bi <sup>1</sup>	-	70.7	31.9	44.0
BiLSTM <sup>1</sup>	-	54.2	52.2	53.2
CNN <sup>1</sup>	-	59.1	52.2	55.4

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i} \quad \text{Recall}_i = \frac{TP_i}{TP_i + FN_i}$$

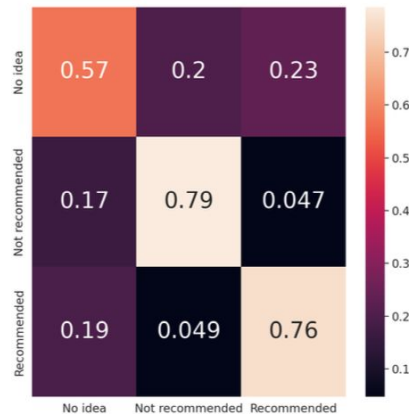
1. Roshanfekar, B., Khadivi, S., & Rahmati, M. (2017). Sentiment analysis using deep learning on Persian texts. 2017 Iranian Conference on Electrical Engineering (ICEE), 1503-1508.

# Evaluation

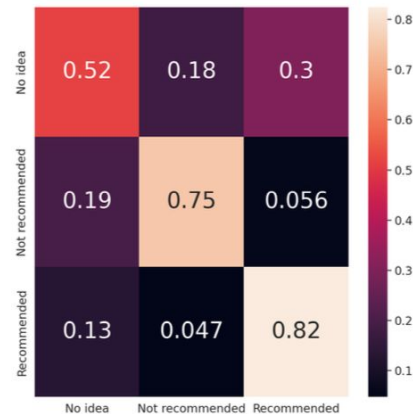
Confusion matrix of each model:



RNN Model



LSTM Model



BiLSTM Model



## Conclusion & Summary

- Sentiment analysis are of great help to both businesses and users alike
- Seq2Seq networks like BiLSTM are both effective & fast to train
  - Increasing the data could help even more
- Lack of data in Persian
- Use of transformer networks such as Bert
  - Might be more costly to train
  - Might need more data

## Further Research

- Working with other types of sentiment analysis
  - Graded Sentiment Analysis
  - Emotion detection
  - Aspect-based Sentiment Analysis
- Collecting larger datasets
  - Translating Yelp dataset or Amazon Reviews Corpus

## References

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# Thanks for Your Attention!



erfan226@sharif.edu



erfan226



erfan226.github.io