Bilingual Language Modeling, A transfer learning technique for Roman Urdu

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Abstract
Pretrained language models are now of widespread use in Natural Language Processing. Despite their success, applying them to Low Resource languages is still a huge challenge. Although Multilingual models hold great promise, applying them to specific low-resource languages e.g. Roman Urdu can be excessive. In this paper, we show how the code-switching property of languages may be used to perform cross-lingual transfer learning from a corresponding high resource language. We also show how this transfer learning technique termed Bilingual Language Modeling can be used to produce better performing models for Roman Urdu. To enable training and experimentation, we also present a collection of novel corpora for Roman Urdu extracted from various sources and social networking sites, e.g. Twitter. We train Monolingual, Multilingual, and Bilingual models of Roman Urdu - the proposed bilingual model achieves 23% accuracy compared to the 2% and 11% of the monolingual and multilingual models respectively in the Masked Language Modeling (MLM) task.

1 Introduction
Most ground breaking research nowadays focuses on Multilingual language modelling (Conneau and Lample, 2019; Conneau et al., 2020; Pires et al., 2019; Khawaja et al., 2018; Beg, 2008; Beg and Dahlin; Farooq et al., 2019b). This is also desirable from an industrial perspective where most app makers would like to easily scale to a global audiences. However a lot of research is also being done on pretraining large monolingual language models for each language (Virtanen et al., 2019; de Vries et al., 2019; Baly et al., 2020; Yu and Arkhipov, 2019; Polignano et al., 2019; Canete et al., 2020; Martin et al., 2020; Le et al., 2020; Rani et al., 2015; Beg, 2009, 2007; Koleilat et al., 2006). This can be desirable for achieving better and faster performance as compared to cross and multilingual language modeling. It has also been shown by recent works that monolingual models tend to outperform their multilingual counterparts of the same size in similar settings (de Vries et al., 2019; Martin et al., 2020; Virtanen et al., 2019; Pyysalo et al., 2020; Farooq et al., 2019a; Zafar et al., 2019a, 2018; Thaver and Beg, 2016). Multilingual is also not always desirable, like when interested only in improving performance for a specific language. This is because Multilingual models suffer from the capacity dilution problem (Arivazhagan et al., 2019) also termed as the curse of multilinguality (Conneau et al., 2020). This is can be handled by increasing model capacity but at the cost of memory and inference time. As the number of languages increase this leaves lesser space for each language.

Roman Urdu is a code-switched language (Beg et al., 2006) formed by a mixture of Urdu and English. It shares the vocabulary and uses the same Latin script as English and other words are transliterated from Urdu (Alvi et al., 2017; Zafar et al., 2020). It is widely used on many social media platforms and chat apps mainly in South Asian countries like India and Pakistan. However it is a resource starved language as there is not a single corpus, tools or techniques to create Large Pretrained Language models and enable out-of-the-box Natural Language Processing (NLP) tasks (Beg and Dahlin). In this research we take a bilingual language modeling approach instead of a multilingual one for Roman Urdu and show that its code-switching property with English can be intelligently
used to obtain a better performance as compared to Mono and Multi lingual models. The main contributions of this work are as follows:

1. We show how performance of a specific low-resource language can be improved by taking advantage of its code-switching property and a typo-logically similar high-resource language.

2. We introduce a new method for producing Bilingual models from Monolingual models using additional pretraining.

3. We apply the proposed Bilingual Language modeling techniques to Roman Urdu and show that significant performance gains can be achieved as compared to Monolingual modeling.

4. We also show how languages can be added to the linguistic space of Mono and Multilingual models by using vocabulary augmentation and additional pretraining.

5. We apply the proposed Bilingual Language modeling techniques to Roman Urdu and show that significant performance gains can be achieved as compared to Monolingual modeling.

6. We propose a novel collection of Roman Urdu corpora gathered from various sources and also transliterated from Urdu.

7. We make the corpora and pretrained Mono, Bi and Multi lingual BERT and RoBERTa models publicly available.

The paper is organized as follows. In section 2 we explain in detail the pretraining methodology and dataset used. Section 3 discusses the evaluation methodology. Finally the Related work is discussed in section 4.

2 Bilingual Language Modeling

2.1 Vocabulary Augmentation

The main contribution of this paper which enables the cross-lingual transfer learning (Baig et al.) involves vocabulary augmentation. This involves changing the existing vocabulary of a pretrained model using a specific criteria. After the vocabulary augmentation additional cycles of pretraining are carried out to produce the final model.

The vocabulary augmentation technique (Seth and Beg, 2006) can in theory be applied to any low resource language which shares vocabulary with a high resource language (Awan and Beg, 2021). In this research we apply this technique to Roman Urdu, a language which shares a significant amount of vocabulary (Javed et al., 2019) with English and show that we achieve significantly improved performance. Roman Urdu uses the same Latin script as English and many other Languages in addition to this Roman Urdu also consists of many English words such that these are often used interchangeably (Beg and Beek, 2013) in a code switched mode (Bangash et al., 2017). This opens up exciting opportunities when building a Roman Urdu Language model. An abstract representation of this idea is also shown in Figure 2. Consider the sentence Abbas school main parhata hai (Abbas teaches in a school). In this sentence the English model knows the context of school. Thus is able to learn better word representations for the surrounding words as compared to training the model from scratch (Naem et al., 2020).

The advantage of this cross-lingual transfer (Sahar et al., 2019) is that it will enable a significantly improved performance for Roman Urdu without the need of extensive data and training cycles. An example of augmenting a small set of Roman Urdu vocabulary with English (Qamar et al.) is shown in Fig. 1. The words driver and show are common in both languages thus their positions from the

Table 1: Statistics of the collected Urdu and Roman Urdu corpora. The Urdu corpora have all been cleaned and transliterated to Roman Urdu. In addition to this a novel corpus for Roman Urdu has also been proposed.

| Corpus                  | Reference                   | Sentence Count | Word Count  |
|-------------------------|------------------------------|----------------|-------------|
| Urdu NER                | (Khana et al., 2016)        | 1,738          | 49,021      |
| COUNTER                 | (Sharjeel et al., 2017)     | 3,587          | 105,124     |
| Urdu Fake News          | (Amjad et al., 2020)        | 5,722          | 312,427     |
| Urdu IMDB Reviews       | (Azam et al., 2020)         | 608,693        | 14,474,912  |
| Roman Urdu sentences    | (Sharf and Rahman, 2018)    | 20,040         | 267,779     |
| Roman Urdu Twitter      | Proposed                    | 3,040,153      | 54,622,490  |
original language (English) are retained.

The vocabulary augmentation method (Uzair et al., 2019) can be extended to any language which satisfy certain conditions. The augmentation method and its are described in detail as follows. Consider two languages \( x \) and \( y \) where \( x \) is a low resource language and \( y \) is high resource. Vocabulary augmentation can be applied for \( x \) if equations 1 and 2 hold true. \( L(x) \) is the super set of all the words of language \( x \) and produces the vocabulary vector \( V(x) = [x_1, x_2, x_3, ..., x_n] \). Consider the vocabulary vector \( V(y) = [y_1, y_2, y_3, ..., y_n] \) given \( L(x) \cap L(y) = \{y_1, y_3\} \), the augmented vocabulary vector \( V(z) \) will be produced as follows \( V(z) = [y_1, x_2, y_3, x_4, ..., x_n] \). The positions of the common elements between \( V(x) \) and \( V(y) \) will not be changed while the other elements from \( V(x) \) will be added without changing their position to \( V(z) \).

\[
L(x) \cap L(y) \neq \emptyset \quad (1)
\]
\[
L(y) \subset L(x) \quad (2)
\]

2.2 Training and Architecture

This section explains the steps to transform data (Zafar et al., 2019b) for pretraining and the changes made to the pretraining cycles to enable cross-lingual transfer from English to Urdu. We also discuss the architectures used to perform pretraining for Mono, Bi and Multilingual models.

Architecture. The architectures used in this research are mainly based on BERT and RoBERTa. All types of pretraining cycles use the BASE architecture (Beg and Van Beek, 2010) which consists of 12 layers, 768 hidden nodes, 12 attention heads and 110M parameters. The pretraining tasks of MLM (Masked Language Modeling) (Dilawar et al., 2018), NSP (Next Sentence Prediction) (Javed et al., 2020b) and SOP (Sentence Order Prediction) use uncased vocabulary. These Uncased models typically have better performance overall. However cased versions are useful (Asad et al., 2020) for tasks such as Part-of-Speech tagging or named entity recognition where the case of a letter encodes useful information.

Pretraining. Multilingual models (Karsten et al., 2007) such as XLM and XLM-R have been trained on hundreds of languages of which Roman Urdu is not a part of. One way to solve this is using cross-lingual transfer which involves fine-tuning a Multilingual model on a specific Roman Urdu task or zero-shot cross-lingual transfer (Beg et al., 2019) where model is fine-tuned on an English task and tested on Roman Urdu tasks. However this type of cross-lingual transfer is bound to yield a higher perplexity as the model has seen very less examples of Roman Urdu and the representation space is shared with many other languages.

To overcome both these issues we perform cross-lingual transfer (Javed et al., 2020a) during pretraining phase using vocabulary augmentation and cut down the languages to a minimal. So the model’s representation space only contains the high resource language the transfer is being made from and the low resource language to which the transfer is being made. To enable the cross-lingual transfer during training phase we run additional pretraining cycles. This involves running some steps of the pretraining phase for the new language after
augmenting Roman Urdu vocabulary with English.

This notion of cross-lingual transfer (Beg, 2006) can also be applied to Multilingual models however the learning space is shared with many other languages and the curse of multilinguality comes into play. These hypothesis are confirmed by the three types of pretraining Experiments we perform. The first type involves training from scratch. The second type involves additional pretraining of a Monolingual English model and the third type involves additional pretraining of a multilingual model. The results of these experiments are discussed in detail in Section 3.

2.3 Pretraining Dataset

This section explains the data gathering process and the preprocessing steps applied to transform the data in a suitable form as expected by the Byte Pair Encoder (BPE).

**Collection.** Roman Urdu as mentioned earlier is a resource starved language, little (Zahid et al., 2020; Majeed et al., 2020; Khawaja et al., 2018) or no work has been done for Roman Urdu and almost no large publicly available dataset exists. Therefore to enable pretraining of Large Transformer based language models we propose a novel collection of corpora cleaned and transliterated to Roman Urdu (Tariq et al., 2019). In addition to this we also propose a novel Roman Urdu dataset consisting of 3 million Roman Urdu sentences and 54 million tokens. This dataset has been scraped from twitter where tweets contain at-least a small amount of Roman Urdu. The statistics of the Twitter scraped dataset and all other datasets is shown in Table 1. All the above mentioned datasets have also been made publicly available.

**Transliteration.** Most of the collected datasets are taken from prominent research works on Urdu while a few were taken from research works on Roman Urdu (Sharf and Rahman, 2018; Arshad et al., 2019). The collected Urdu datasets Khana et al. (2016); Sharjeel et al. (2017); Amjad et al. (2020); Azam et al. (2020); Nacem et al. (2020) have then been transliterated to Roman Urdu. The transliteration process involves changing the Urdu Devanagri script to the Latin script used by Roman Urdu. All of the transliteration is performed using ijunoon’s Urdu to Roman Urdu transliteration API

3 Experiments

In this section we describe the methods used for evaluation and discuss the results obtained for the three different types of pretraining.

3.1 Evaluation

Large Pretrained language models are usually evaluated on a range of NLP tasks by fine tuning the

1https://www.ijunoon.com/transliteration/urdu-to-roman/
model on each of the specific task. Previously BERT and BERT like models have been evaluated on the General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018) which consists of a range of Natural Language Understanding (NLU) tasks. The tasks range from simple semantic analysis, textual entailment to complex reading comprehension such as in the SQuAD (Rajpurkar et al., 2016, 2018) and QNLI (Wang et al., 2018) tasks. Other stricter evaluation tasks have also been proposed over time which consist of the SQuAD v2.0 (Rajpurkar et al., 2018) and the SWAG (Zellers et al., 2018) datasets.

As research progressed, larger and better models like GPT (Radford et al., 2018, 2019), XLNET (Yang et al., 2019) achieved close to human level performance on the GLUE benchmark. This lead to the introduction of SuperGLUE (Wang et al., 2019) a set of more challenging tasks for producing better language models. However these evaluation tasks were only for English models and Multilingual or Monolingual models in other languages could not be evaluated. As the trend towards multilingual and universal language modeling increased this lead to the creation of Multi-task and Multilingual benchmarks like Xtreme (Hu et al., 2020) and XGLUE (Liang et al., 2020). Despite of the abundance of Multilingual and Multitask evaluation sets covering hundreds of languages no dataset provides support for Roman Urdu. Thus for evaluation of the performance of our pretrained models we use the validation metrics calculated during the pretraining phase of each model. The validation dataset is based on data that is put aside during the creation of pretraining data.

The Evaluation metrics include two tasks for BERT based models namely Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) while the RoBERTa models are evaluated in terms of MLM loss and MLM perplexity. The Masked Language modeling task involves predicting a randomly masked word. A word is masked randomly about 15% of the time for each given sentence. The Next Sentence prediction task involves predicting whether two given sentences are consecutive in the correct order i.e. sentence 2 comes after sentence 1. The MLM perplexity is calculated using eqn. 3. This represents how sure the model is when predicting the masked word.

$$PP(W) = \frac{1}{P(w_1, w_2, ..., w_N)^\pi} \quad (3)$$

### 3.2 Results

The evaluation of all BERT based models as mentioned before is performed using Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) while the evaluation of RoBERTa models is done using Loss and Perplexity for the MLM task. Table 2 shows the accuracies of MLM and NSP tasks for the Monolingual, Bilingual and Multilingual BERT based models that we have trained.

| Model          | MLM   | NSP   |
|----------------|-------|-------|
| BERT Monolingual | 0.02  | 0.53  |
| BERT Multilingual | 0.11  | 0.91  |
| BERT Bilingual  | 0.23  | 0.95  |

Table 2: A comparison of MLM and NSP accuracies for three types of BERT models. As proposed the Bilingual model achieves the highest performance.
| Model           | Train loss | Valid loss | Train perplexity | Valid perplexity |
|-----------------|------------|------------|------------------|------------------|
| RoBERTaMonolingual | 2.01       | 2.46       | 4.08             | 5.49             |
| RoBERTaBilingual | 1.72       | 2.19       | 3.24             | 4.56             |

Table 3: Loss and perplexity for the MLM pretraining task. The proposed Bilingual modeling technique is able to outperform in both training and validation.

shown in Table 3. It can be seen that the Bilingual modeling approach is also able to outperform here.

From the above experiments we see that Bilingual models of Roman Urdu significantly outperform their Monolingual and Multilingual counterparts in similar settings. This performance is significant in the MLM task as compared to the NSP task which also reiterates the idea in Liu et al. (2019) that NSP is an easier task compared to MLM. The experiments conclude that the proposed vocabulary augmentation technique can be effectively used to significantly improve performance for Low Resource languages given that they share vocabulary with a high resource language.

4 Related Work

Neural Language modeling was first proposed by (Bengio et al., 2003; Collobert and Weston, 2008) who showed that the model implicitly learnt useful representations. The technique popularly came to be known as word embeddings. These embeddings were a leap forward in the field of NLP notably after the introduction of techniques like word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), fastText (Joulin et al., 2017). These early techniques were mostly context-free and a major shortcoming was that they couldn’t handle Polysemy. This started the search for contextual embeddings. ELMo (Peters et al., 2018) and ULMFiT (Howard and Ruder, 2018) were the first to achieve substantial improvements using LSTM based language models. Following the line of work of contextual models, GPT (Radford et al., 2018) was proposed to tackle tasks in the GLUE benchmark (Wang et al., 2018). The new approach to contextual language modelling was to replace LSTMs entirely with then recently released Transformers (Vaswani et al., 2017). GPT used a 12-layer decoder-only transformer which was trained for 100 epochs on the BookCorpus (Zhu et al., 2015) and achieved considerable improvements as compared to ELMo on the same NLP tasks. The hugely popular BERT was based on a similar strategy as GPT containing 12 levels but only used the encoder part of the Transformer and looked at sentences bidirectionally.

Many studies have been performed in the area of bilingual and multilingual language modeling. Several works focus on mapping word representations in multiple languages to a unified embedding space so words in different languages can be compared. One line of work focuses on using bilingually aligned corpora at sentence level (Zou et al., 2013; Hermann and Blunsom, 2014; Luong et al., 2015) and another tries to achieves the same on document level (Vulić and Moens, 2016; Levy et al., 2016). Another line of work focuses on utilising the isomorphic structure of languages, dictionary mappings and shared vocabulary for ad-hoc mappings between languages (Artetxe et al., 2018; Faruqui and Dyer, 2014).

5 Conclusion

In this research we propose a large Roman Urdu corpus with 3M sentences in addition to a novel collection of corpora cleaned and transliterated from Urdu. The corpora cover a variety of domains from news, IMDB reviews to tweets. In addition to this we introduce a novel vocabulary augmentation method that enables adding new languages to pretrained models. We also show how this new method can be used for cross-lingual transfer and improving performance for Low Resource languages. We have also shown that the proposed Bilingual language modeling is able to outperform multilingual modeling given a code-switched language like Roman Urdu. In the future we would like to better evaluate these Roman Urdu Language models on downstream NLP tasks which can be done by producing a GLUE like benchmark for Roman Urdu. We hope that the corpora and methods proposed in this paper will enable the NLP community to produce better language models especially for Low resource and resource starved Languages like Roman Urdu.
References

Hamza M Alvi, Hareem Sahar, Abdul A Bangash, and Mirza O Beg. 2017. Ensights: A tool for energy aware software development. In 2017 13th International Conference on Emerging Technologies (ICET), pages 1–6. IEEE.

Maaż Amjad, Grigori Sidorov, Alisa Zhila, Helena Gómez-Adorno, Ilia Voronkov, and Alexander Gelbukh. 2020. “bend the truth”: Benchmark dataset for fake news detection in urdu language and its evaluation. Journal of Intelligent & Fuzzy Systems, 51(Preprint):1–13.

Naveen Arivazhagan, Ankur Bapna, Orhan Firat, Dmitriy Lepikhin, Melvin Johnson, Maxim Krikun, Mia Xu Chen, Yuan Cao, George Foster, Colin Cherry, et al. 2019. Massively multilingual neural machine translation in the wild: Findings and challenges. arXiv preprint arXiv:1907.05019.

Muhammad Umair Arshad, Muhammad Farrukh Bashir, Adil Majeed, Waseem Shahzad, and Mirza Omer Beg. 2019. Corpus for emotion detection on roman urdu. In 2019 22nd International Multitopic Conference (INMIC), pages 1–6. IEEE.

Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings. arXiv preprint arXiv:1805.06297.

Muhammad Asad, Muhammad Asim, Talha Javed, Mirza O Beg, Hasan Mujtaba, and Sohail Abbas. 2020. Deepdetect: detection of distributed denial of service attacks using deep learning. The Computer Journal, 63(7):983–994.

Mubashar Nazar Awan and Mirza Omer Beg. 2021. Top-ranking: a topical position rank for extraction and classification of keyphrases in text. Computer Speech & Language, 65:101116.

Nazish Azam, Bilal Tahir, and Muhammad Amir Mehmood. 2020. Sentiment and emotion analysis of text: A survey on approaches and resources. LANGUAGE & TECHNOLOGY, page 87.

Zubair Baig, Mirza Omer Beg, Baber Majid Bhatti, Farzana Ahamed Bhuian, Tegawendé F Bissyandé, Shizhan Chen, Mohan Baruwal Chhetri, Marco Couto, João de Macedo, Randy de Vries, et al. Ahmed, sanam 124 aleti, aldeida 105 alo’sio, joão Gómez-Adorno, Ilia Voronkov, and Alexander Gelbukh. 2020. “bend the truth”: Benchmark dataset for fake news detection in urdu language and its evaluation. Journal of Intelligent & Fuzzy Systems, 51(Preprint):1–13.

Fady Baly, Hazem Hajj, et al. 2020. Arabet: Transformer-based model for arabic language understanding. In Proceedings of the 4th Workshop on Open-Source Arabic Corpora and Processing Tools, with a Shared Task on Offensive Language Detection, pages 9–15.

Abdul Ali Bangash, Hareem Sahar, and Mirza Omer Beg. 2017. A methodology for relating software structure with energy consumption. In 2017 IEEE 17th International Working Conference on Source Code Analysis and Manipulation (SCAM), pages 111–120. IEEE.

M Beg. 2008. Critical path heuristic for automatic parallelization.

Mirza Beg. 2009. Flecs: A framework for rapidly implementing forwarding protocols. In International Conference on Complex Sciences, pages 1761–1773. Springer.

Mirza Beg and Peter van Beek. 2013. A constraint programming approach for integrated spatial and temporal scheduling for clustered architectures. ACM Transactions on Embedded Computing Systems (TECS), 13(1):1–23.

Mirza Beg, Laurent Charlin, and Joel So. 2006. Maxsm: A multi-heuristic approach to xml schema matching.

Mirza Beg and Mike Dahlin. A memory accounting interface for the java programming language.

Mirza Omer Beg. 2006. Performance analysis of packet forwarding on ixp2400 network processor.

Mirza Omer Beg. 2007. Flecs: A data-driven framework for rapid protocol prototyping. Master’s thesis, University of Waterloo.

Joshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. Journal of machine learning research, 3(Feb):1137–1155.

José Canete, Gabriel Chaperon, Rodrigo Fuentes, and Jorge Pérez. 2020. Spanish pre-trained bert model and evaluation data. PML4DC at ICLR, 2020.

Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In Proceedings of the 25th international conference on Machine learning, pages 160–167.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. ACL 2020, Online, July 5-10, 2020, pages 8440–8451. Association for Computational Linguistics.
Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems, pages 7059–7069.

Noman Dilawar, Hammad Majeed, Mirza Omer Beg, Naveed Ejaz, Khan Muhammad, Irfan Mehmood, and Yunyoung Nam. 2018. Understanding citizen issues through reviews: A step towards data informed planning in smart cities. Applied Sciences, 8(9):1589.

Muhammad Umer Farooq, Mirza Omer Beg, et al. 2019a. Bigdata analysis of stack overflow for energy consumption of android framework. In 2019 International Conference on Innovative Computing (ICIC), pages 1–9. IEEE.

Muhammad Umer Farooq, Saif Ur Rehman Khan, and Mirza Omer Beg. 2019b. Melta: A method level energy estimation technique for android development. In 2019 International Conference on Innovative Computing (ICIC), pages 1–10. IEEE.

Manaal Faruqui and Chris Dyer. 2014. Improving vector space word representations using multilingual correlation. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 462–471.

Karl Moritz Hermann and Phil Blunsom. 2014. Multilingual models for compositional distributed semantics. arXiv preprint arXiv:1404.4641.

Jeremy Howard and Sebastian Ruder. 2018. Universal language model fine-tuning for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 328–339.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. arXiv preprint arXiv:2003.11080.

Abdul Rehman Javed, Mirza Omer Beg, Muhammad Asim, Thar Baker, and Ali Hilal Al-Bayatti. 2020a. Alphalogger: Detecting motion-based side-channel attack using smartphone keystrokes. Journal of Ambient Intelligence and Humanized Computing, pages 1–14.

Abdul Rehman Javed, Muhammad Usman Sarwar, Mirza Omer Beg, Muhammad Asim, Thar Baker, and Hissam Tawfik. 2020b. A collaborative healthcare framework for shared healthcare plan with ambient intelligence. Human-centric Computing and Information Sciences, 10(1):1–21.

Hafiz Tayyeb Javed, Mirza Omer Beg, Hasan Mujtaba, Hammad Majeed, and Muhammad Asim. 2019. Fairness in real-time energy pricing for smart grid using unsupervised learning. The Computer Journal, 62(3):414–429.

Armand Joulin, Édouard Grave, Piotr Bojanowski, and Tomáš Mikolov. 2017. Bag of tricks for efficient text classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 427–431.

Martin Karsten, Srinivasan Keshav, Sanjiva Prasad, and Mirza Beg. 2007. An axiomatic basis for communication. ACM SIGCOMM Computer Communication Review, 37(4):217–228.

Wahab Khana, Ali Daoudb, Jamal A Nasira, and Tehmina Amjada. 2016. Named entity dataset for urdu named entity recognition task. LANGUAGE & TECHNOLOGY, page 51.

Hussain S Khawaja, Mirza O Beg, and Saira Qamar. 2018. Domain specific emotion lexicon expansion. In 2018 14th International Conference on Emerging Technologies (ICET), pages 1–5. IEEE.

Wald Koleilat, Joel So, and Mirza Beg. 2006. Wata-gent: A fresh look at tac-scm agent design.

Hang Le, Loïc Vial, Jibriel Frej, Vincent Segonne, Max- imin Coavoux, Benjamin Lecouteux, Alexandre Allauzen, Benoît Crabbé, Laurent Besacier, and Didier Schwab. 2020. Flaubert: Unsupervised language model pre-training for french. In Proceedings of The 12th Language Resources and Evaluation Conference, pages 2479–2490.

Omer Levy, Anders Søgaard, and Yoav Goldberg. 2016. A strong baseline for learning cross-lingual word embeddings from sentence alignments. arXiv preprint arXiv:1608.05426.

Yaobo Liang, Nan Duan, Yeyun Gong, Ning Wu, Fen-fei Guo, Weizhen Qi, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, et al. 2020. Xglue: A new benchmark dataset for cross-lingual pre-training, understanding and generation. arXiv preprint arXiv:2004.01401.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Minh-Thang Luong, Hieu Pham, and Christopher D Manning. 2015. Bilingual word representations with monolingual quality in mind. In Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing, pages 151–159.

Adil Majeed, Hasan Mujtaba, and Mirza Omer Beg. 2020. Emotion detection in roman urdu text using machine learning. In Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering Workshops, pages 125–130.

Louis Martin, Benjamin Müller, Pedro Javier Ortiz Suárez, Yoann Dupont, Laurent Romary, Éric de la Clergerie, Djamé Seddah, and Benoît Sagot. 2020.
Camembert: a tasty french language model. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 7203–7219. Association for Computational Linguistics.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems (NIPS), pages 3111–3119.

Saad Nacem, Majid Iqbal, Muhammad Saqib, Muhammad Saad, Muhammad Soban Raza, Zaid Ali, Naveed Akhtar, Mirza Omer Beg, Waseem Shahzad, and Muhammad Umair Arshad. 2020. Subspace gaussian mixture model for continuous urdu speech recognition using kaldi. In 2020 14th International Conference on Open Source Systems and Technologies (ICOSST), pages 1–7. IEEE.

Bilal Naeem, Aymen Khan, Mirza Omer Beg, and Hasan Mujtaba. 2020. A deep learning framework for clickbait detection on social area network using natural language cues. Journal of Computational Social Science, pages 1–13.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.

Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of NAACL-HLT, pages 2227–2237.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.

Marco Polignano, Pierpaolo Basile, Marco de Geminis, Giovanni Semeraro, and Valerio Basile. 2019. Alberto: Italian BERT language understanding model for NLP challenging tasks based on tweets. In Proceedings of the Sixth Italian Conference on Computational Linguistics, Bari, Italy, November 13-15, 2019, volume 2481 of CEUR Workshop Proceedings. CEUR-WS.org.

Sampo Pyysalo, Jenna Kanerva, Antti Virtanen, and Filip Ginter. 2020. Wikibert models: deep transfer learning for many languages. CoRR, abs/2006.01538.

Saira Qamar, Hasan Mujtaba, Hammad Majeed, and Mirza Omer Beg. Relationship identification between conversational agents using emotion analysis. Cognitive Computation, pages 1–15.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know what you don’t know: Unanswerable questions for squad. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 784–789.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392.

Uzma Rani, Aamer Imdad, and Mirza Beg. 2015. Case 2: Recurrent anemia in a 10-year-old girl. Pediatrics in review, 36(12):548–550.

Hareem Sahar, Abdul A Bangash, and Mirza O Beg. 2019. Towards energy aware object-oriented development of android applications. Sustainable Computing: Informatics and Systems, 21:28–46.

Aaditeshwar Seth and Mirza Beg. 2006. Achieving privacy and security in radio frequency identification. In Proceedings of the 2006 International Conference on Privacy, Security and Trust: Bridge the Gap Between PST Technologies and Business Services, pages 1–1.

Zareen Sharf and Saif Ur Rahman. 2018. Performing natural language processing on roman urdu datasets. International Journal Of Computer Science And Network Security, 18(1):141–148.

Muhammad Sharjeel, Rao Muhammad Adeel Nawab, and Paul Rayson. 2017. Counter: corpus of urdu news text reuse. Language resources and evaluation, 51(3):777–803.

Muhammad Tariq, Hammad Majeed, Mirza Omer Beg, Farrukh Aslam Khan, and Abdelouahid Derhab. 2019. Accurate detection of sitting posture activities in a secure iot based assisted living environment. Future Generation Computer Systems, 92:745–757.

Danyal Thaver and Mirza Beg. 2016. Pulmonary crohn’s disease in down syndrome: A link or linkage problem. Case reports in gastroenterology, 10(2):206–211.

Ahmed Uzair, Mirza O Beg, Hasan Mujtaba, and Hammad Majeed. 2019. Weec: Web energy efficient computing: A machine learning approach. Sustainable Computing: Informatics and Systems, 22:230–243.
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Antti Virtanen, Jenna Kanerva, Rami Ilo, Jouni Luoma, Juhan Liutolahti, Tapio Salakoski, Filip Ginter, and Sampo Pyysalo. 2019. Multilingual is not enough: Bert for Finnish. arXiv, pages arXiv–1912.

Wietse de Vries, Andreas van Cranenburgh, Arianna Bisazza, Tommaso Caselli, Gertjan van Noord, and Malvina Nissim. 2019. Bertje: A Dutch bert model. arXiv preprint arXiv:1912.09582.

Ivan Vulić and Marie-Francine Moens. 2016. Bilingual distributed word representations from document-aligned comparable data. Journal of Artificial Intelligence Research, 55:953–994.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. SuperGLUE: A stickier benchmark for general-purpose language understanding systems. In Advances in neural information processing systems, pages 3266–3280.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. XLNet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems, pages 5753–5763.

Kuratov Yu and M Arkhipov. 2019. Adaptation of deep bidirectional multilingual transformers for Russian language. Computational Linguistics and Intellectual Technologies, pages 333–339.

Adeel Zafar, Hasan Mujtaba, Sohrab Ashiq, and Mirza Omer Beg. 2019a. A constructive approach for general video game level generation. In 2019 11th Computer Science and Electronic Engineering (CEEC), pages 102–107. IEEE.

Adeel Zafar, Hasan Mujtaba, Mirza Tauseef Baig, and Mirza Omer Beg. 2019b. Using patterns as objectives for general video game level generation. ICGA Journal, 41(2):66–77.

Adeel Zafar, Hasan Mujtaba, and Mirza Omer Beg. 2020. Search-based procedural content generation for gvg-ig. Applied Soft Computing, 86:105909.

Adeel Zafar, Hasan Mujtaba, Mirza Omer Beg, and Sajid Ali. 2018. Deceptive level generator.

Rabail Zahid, Muhammad Owais Idrees, Hasan Mujtaba, and Mirza Omer Beg. 2020. Roman urdu reviews dataset for aspect based opinion mining. In 2020 35th IEEE/ACM International Conference on Automated Software Engineering Workshops (ASEW), pages 138–143. IEEE.

Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. Swag: A large-scale adversarial dataset for grounded commonsense inference. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 93–104.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In Proceedings of the IEEE international conference on computer vision, pages 19–27.

Will Y Zou, Richard Socher, Daniel Cer, and Christopher D Manning. 2013. Bilingual word embeddings for phrase-based machine translation. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1393–1398.