UNICORN on RAINBOW:
A Universal Commonsense Reasoning Model on a New Multitask Benchmark

Nicholas Lourie♣ Ronan Le Bras♣ Chandra Bhagavatula♣ Yejin Choi♣
♣ Allen Institute for AI, WA, USA
♣ Paul G. Allen School of Computer Science & Engineering, WA, USA

Abstract
Commonsense AI has long been seen as a near impossible goal—until recently. Now, research interest has sharply increased with an influx of new benchmarks and models. We propose two new ways to evaluate commonsense models, emphasizing their generality on new tasks and building on diverse, recently introduced benchmarks. First, we propose a new multitask benchmark, RAINBOW, to promote research on commonsense models that generalize well over multiple tasks and datasets. Second, we propose a novel evaluation, the cost equivalent curve, that sheds new insight on how the choice of source datasets, pretrained language models, and transfer learning methods impacts performance and data efficiency. We perform extensive experiments—over 200 experiments encompassing 4800 models—and report multiple valuable and sometimes surprising findings, e.g., that transfer almost always leads to better or equivalent performance if following a particular recipe, that QA-based commonsense datasets transfer well with each other, while commonsense knowledge graphs do not, and that perhaps counter-intuitively, larger models benefit more from transfer than smaller ones. Last but not least, we introduce a new universal commonsense reasoning model, UNICORN, that establishes new state-of-the-art performance across 8 popular commonsense benchmarks, αNLI (→87.3%), COSMOSQA (→91.8%), HELLSWAG (→93.9%), PIQA (→90.1%), SOCIALIQA (→83.2%), WINGRANDE (→86.6%), CYCIC (→94.0%) and COMMONSENSEQA (→79.3%).

1 Introduction
In AI’s early years, researchers sought to build machines with common sense (McCarthy 1959); however, in the following decades, common sense came to be viewed as a near impossible goal. It is only recently that we see a sudden increase in research interest toward commonsense AI, with an influx of new benchmarks and models (Mostafazadeh et al. 2016; Talmor et al. 2019; Sakaguchi et al. 2020).

This renewed interest in common sense is ironically encouraged by both the great empirical strengths and limitations of large-scale pretrained neural language models. On one hand, pretrained models have led to remarkable progress across the board, often surpassing human performance on leaderboards (Radford et al. 2018; Devlin et al. 2019; Liu et al. 2019b; Raffel et al. 2019). On the other hand, pretrained language models continue to make surprisingly silly and nonsensical mistakes, even the recently introduced GPT-3.1 This motivates new, relatively under-explored research avenues in commonsense knowledge and reasoning.

In pursuing commonsense AI, we can learn a great deal from mainstream NLP research. In particular, the introduction of multitask benchmarks such as GLUE (Wang et al. 2019b) and SUPERGLUE (Wang et al. 2019a) has encouraged fundamental advances in the NLP community, accelerating research into models that robustly solve many tasks and datasets instead of overfitting to one in particular. In contrast, commonsense benchmarks and models are relatively nascent, thus there has been no organized effort, to

1https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/
date, at administering a collection of diverse commonsense benchmarks and investigating transfer learning across them.

We address exactly this need, proposing two new ways to evaluate commonsense models with a distinct emphasis on their generality across tasks and domains. First, we propose a new multi-task benchmark, RAINBOW, to facilitate research into commonsense models that generalize well over multiple different tasks and datasets. Second, we propose a novel evaluation, the cost equivalent curve, that sheds new insight on how different choices of source datasets, pre-trained language models, and transfer learning methods affect performance and data efficiency in the target dataset.

The primary motivation for cost equivalent curves is data efficiency. The necessary condition for state-of-the-art neural models to maintain top performance on any dataset is a sufficiently large amount of training data for fine-tuning. Importantly, building a dataset for a new task or a domain is an expensive feat, easily costing tens of thousands of dollars (Zellers et al. 2018). Therefore, we want the models to generalize systematically across multiple datasets, instead of relying solely on the target dataset.

Shown in Figure 1, the cost equivalent curve aims to answer the following intuitive question: how much data does a transfer learning approach save over the baseline that doesn’t benefit from transfer learning? We provide a more detailed walk-through of this chart in §2. As will be seen, cost equivalent curves have distinct advantages over simple evaluations at the full dataset size or classical learning curves drawn for each method and dataset separately, as they provide more accurate comparative insights into data efficiency in the context of multitasking and transfer learning.

We leverage these new tools to reevaluate common approaches for intermediate-task transfer (Pruksachatkun et al. 2020). Through extensive experiments, we identify multiple valuable and sometimes surprising findings, e.g., that intermediate-task transfer can always lead to better or equivalent performance if following a particular recipe, that QA-based commonsense datasets transfer well to each other, while commonsense knowledge graphs do not, and that perhaps counter-intuitively, larger models benefit much more from transfer learning compared to smaller ones.

In addition to the empirical insights, we also introduce a new universal commonsense reasoning model: UNICORN, establishing new state-of-the-art performances across 8 benchmarks: αNLI (87.3%) (Bhagavatula et al. 2020), COSMOSQA (91.8%) (Huang et al. 2019), HELLASWAG (93.9%) (Zellers et al. 2019), PIQA (90.1%) (Bisk et al. 2020), SOCIALIQA (83.2%) (Sap et al. 2019b), WinoGRANDE (86.6%) (Sakaguchi et al. 2020), CYCIC (94.0%).\(^2\) as well as the popular COMMONSENSEQA dataset (79.3%) (Talmor et al. 2019). Beyond setting records with the full training sets, our ablations show UNICORN also improves data efficiency for all training dataset sizes.

For reproducibility, we publicly release the UNICORN model and code, all the experimental results, and the RAINBOW leaderboard at https://github.com/allenai/rainbow.

\(^2\)The CYCIC dataset and leaderboard are available at https://leaderboard.allenai.org/cycic.

2 Cost Equivalent Curves

Cost equivalent curves show equivalent costs between the single-task baseline and a new transfer-based approach. In this work, we define cost as the number of training examples in the target dataset. Intuitively, we want to measure how many examples the new approach needs to match the single-task baseline’s performance as the amount of data varies.

Figure 1 illustrates cost equivalent curves with COMMONSENSEQA as the target dataset. The x-axis shows the number of examples used by the single-task baseline, while the y-axis shows the examples from the target dataset used by the new multitask method. The curve is where they achieve the same performance. The numbers on top of the figure show the performance corresponding to the number of base-line examples from the x-axis. For example, with 4.9k examples, the baseline achieves 70% accuracy. For any number of examples the baseline might use, we can see how many examples the new approach would require to match it. In Figure 1, to match the baseline’s performance on ~10k examples, multitasking with RAINBOW requires about 5k, while multitasking with GLUE requires more than 10k. Thus, lower is better, with curves below the diagonal (y = x) indicating that the new method improves over the baseline.

The construction of cost equivalent curves makes one technical assumption: the relationship between performance and cost is continuous and strictly monotonic (i.e., increasing or decreasing). This assumption holds empirically for parameters, compute, and data (Kaplan et al. 2020). Thus, we can safely estimate each learning curve with isotonic regression (Barlow et al. 1972), then construct the cost equivalent curve by mapping each dataset size to the baseline performance, finding the matching performance on the new method’s curve, and seeing how many examples are required.

Cost equivalent curves visualize how a new approach impacts the cost-benefit trade-off, i.e. examples required for a given performance. This reframes the goal from pushing up performance on a fixed-size benchmark to most efficiently solving the problem. While we focus on data efficiency in this work, the idea of cost equivalent curves can be applied to other definitions of cost as well (e.g., GPU compute).

3 RAINBOW

We define RAINBOW, a suite of commonsense benchmarks, with the following datasets. To keep evaluation clean-cut, we only chose multiple-choice question-answering datasets.

αNLI (Bhagavatula et al. 2020) tests abductive reasoning in narratives. It asks models to identify the best explanation among several connecting a beginning and ending.

COSMOSQA (Huang et al. 2019) asks commonsense reading comprehension questions about everyday narratives.

HELLASWAG (Zellers et al. 2019) requires models to choose the most plausible ending to a short context.

PIQA (Bisk et al. 2020) is a multiple-choice answering benchmark for physical commonsense reasoning.

SOCIALIQA (Sap et al. 2019b) evaluates commonsense reasoning about social situations and interactions.
Table 1: A comparison of transfer methods’ dev accuracy (%) on the RAINBOW tasks, using the T5-LARGE model.

| TRANSFER    | αNLI | COSMOSQA | HELLASWAG | PIQA | SOCIALIQ | WINOGRANDE |
|------------|------|----------|-----------|------|----------|------------|
| multitask  | 78.4 | 81.1     | 81.3      | 80.7 | 74.8     | 72.1       |
| fine-tune  | 79.2 | 82.6     | 83.1      | 82.2 | 75.2     | 78.2       |
| sequential | **79.5** | **83.2** | **83.0** | **82.2** | **75.5** | **78.7**   |
| none       | 77.8 | 81.9     | 82.8      | 80.2 | 73.8     | 77.0       |

WINOGRANDE (Sakaguchi et al. 2020) is a large-scale collection of Winograd schema-inspired problems requiring reasoning about both social and physical interactions.

4 Empirical Insights

We present results from our large-scale empirical study, using pretrained T5-LARGE to transfer between datasets. We’ve grouped our findings and their relevant figures around the four following thematic questions.

4.1 What’s the Best Approach for Transfer?

We compare three recipes for intermediate-task transfer:

1. **multitask training** (Caruana 1995): training on multiple datasets (including the target dataset) all at once,

2. **sequential training** (Pratt, Mostow, and Kamm 1991): first training on multiple datasets (excluding the target dataset) through multitask training, and then continuing to train on the target dataset alone,

3. **multitask fine-tuning** (Liu et al. 2019a): first training on all datasets (including the target dataset) through multitask training, and then continuing to fine-tune on the target dataset alone.

Figure 2 compares these three methods on each of the six RAINBOW tasks, using the other five datasets for transfer.

Finding 1: Sequential training almost always matches or beats other approaches. Generally, sequential and multitask fine-tune training use fewer examples to achieve the same performance as multitask training or the single task baseline. For some tasks (αNLI and SOCIALIQ), all three methods achieve the same performance for the same number of examples.
methods perform similarly; however, on the rest, sequential and multitask fine-tune training greatly improve data efficiency. While sequential and multitask fine-tune training are often comparable, sequential training appears to be slightly more data efficient, both from comparing cost equivalent curves in Figure 2 and full dataset performance in Table 1.

**Finding 2: Sequential training rarely hurts performance.**
While multitask training doesn’t always beat the single task baseline, sequential and multitask fine-tune training uniformly outperform it—for all RAINBOW tasks and dataset sizes (including full datasets). This pattern mostly holds with other source and target tasks, especially for sequential training which rarely significantly harms performance.

**Finding 3: Multitask training helps most often in the low-data regime.** One mystery researchers currently face is the inconsistent effect of multitask learning: sometimes it helps, sometimes it hurts, sometimes it has no effect. Cost equivalent curves reveal one potential explanation: multitask learning tends to help when data is scarce, but may hurt performance if data is plentiful. In Figure 2, all cost equivalent curves initially require fewer examples than the single-task baseline (the $y = x$ line), while on some tasks (HELLASWAG and WINOGRANDE) multitasking eventually needs more data than the baseline. Table 1 reinforces this story, where multitask learning hurts performance on three of the six tasks (COSMOSQA, HELLASWAG, and WINOGRANDE), with WINOGRANDE dropping from 77.0% to 72.1% accuracy. The fact that such trends depend on things like data size shows the importance of examining a range of scenarios: changing the context can even reverse one’s conclusions.
4.2 What Transfers Best for Common Sense?

Understanding when datasets transfer well is still an open and active area of research (Vu et al. 2020; Pruksachatkun et al. 2020). At present, modelers usually pick datasets that seem similar to the target, whether due to format, domain, or something else. To investigate common sense transfer, we compare how the RAINBOW tasks transfer to each other against two other popular dataset collections: GLUE and SUPERGLUE. Following the insights from Section 4.1, we use the strongest transfer method, sequential training, for the comparison. Figure 3 presents cost equivalent curves and Table 2 provides full dataset numbers.

Finding 4: RAINBOW transfers best for common sense.
Across all six RAINBOW tasks and all training set sizes, the RAINBOW tasks transfer better to each other than GLUE and SUPERGLUE do to them. The same result also holds for the popular benchmark COMMONSENSEQA. Following the insights from Section 4.1, we use the strongest transfer method, sequential training, for the comparison. Figure 3 presents cost equivalent curves and Table 2 provides full dataset numbers.

Finding 5: Only RAINBOW uniformly beats the baseline.
With sequential training and T5-LARGE or larger, RAINBOW improves data efficiency and performance for every task considered. Importantly, this pattern breaks down when multitask training, for which no multiset uniformly improved performance. Thus, sequential training can unlock useful transfer even in contexts where multitask training cannot. Likewise, smaller models demonstrated less transfer, as discussed further in Section 4.3. Consequently, T5-SMALL (the smallest model) did not always benefit. In contrast to RAINBOW, GLUE and SUPERGLUE often had little effect or slightly decreased data efficiency.

4 For these additional experiments, see the extended experimental results at https://github.com/allenai/rainbow.

Caveats about GLUE, SUPERGLUE, and T5. There’s an important caveat to note about T5, the model used in our experiments, and its relationship to GLUE and SUPERGLUE. The off-the-shelf T5’s weights come from multitask pretraining, where many tasks are mixed with a language modeling objective to learn a powerful initialization for the weights. In fact, both GLUE and SUPERGLUE were mixed into the pretraining (Raffel et al. 2019). So, while RAINBOW clearly improves data efficiency and performance, our experiments do not determine whether some of the benefit comes from the novelty of RAINBOW’s knowledge to T5, as opposed to containing more general information than GLUE and SUPERGLUE.

4.3 Does Model Size Affect Transfer?

Most of our exhaustive experiments use T5-LARGE (770M parameters), but in practice, we might prefer to use smaller models due to computational limitations. Thus, we investigate the impact of model size on intermediate-task transfer using the T5-BASE (220M parameters) and T5-SMALL (60M parameters) models. Figure 4 presents the results for transferring with different model sizes from RAINBOW to COMMONSENSEQA.

Finding 6: Larger models benefit more from transfer.
Since larger pretrained models achieve substantially higher performance, it’s difficult to compare transfer’s effect across model size. The baselines start from very different places. Cost equivalent curves place everything in comparable units, equivalent baseline cost (e.g., number of training examples). Capitalizing on this fact, Figure 4 compares transfer from RAINBOW to COMMONSENSEQA across model size. The cost equivalent curves reveal a trend: larger models seem to benefit more from transfer, saving more examples over the relevant baselines. Since smaller models require more gradient updates to converge (Kaplan et al. 2020), it’s important to note that we held the number of gradient updates fixed for comparison. Exploring whether this trend holds in different contexts, as well as theoretical explanations, are promising directions for future work.
Finding 7: Sequential training wins across model sizes.
Figure 4 expands Finding 1, that sequential training generally matches or beats the other transfer approaches, by supporting it across model sizes. In all three plots, sequential training appears in line with or better than the other transfer methods.

4.4 Can Models Transfer from Knowledge Graphs to QA Datasets?
Due to reporting bias (Gordon and Van Durme 2013), common sense rarely appears explicitly in text, though it does appear implicitly. While language models learn much of the common sense implicit in natural language (Trinh and Le 2018), crowdsourced and expert curated knowledge might provide complementary information. To investigate, we used two popular common sense knowledge graphs, ConceptNet (Speer, Chin, and Havasi 2017) and ATOMIC (Sap et al. 2019a), to create additional knowledge graph generation tasks (Bosselut et al. 2019). In the forward direction, the model predicts the object given the subject and relation concatenated in XML tags. In the backward direction, the model predicts the subject given the object and relation. The results are summarized in Figure 5 and Table 3.

Finding 8: Knowledge graph multitasking shows little impact. The results are generally negative. Only SocialIQA benefits, which might come from the use of ATOMIC during its construction. We offer two possible explanations: the serialized language from the knowledge graphs is not in a QA format, and the knowledge graph completion task is generative while all other tasks are discriminative. These discrepancies may present too large an obstacle for effective transfer. Our findings encourage future research to better close the gap between knowledge graphs and datasets. Given sequential training’s strength, as exemplified in Findings 1, 2, and 7, it may lead to different results than the multitask transfer we explore here.
5 Unicorn

Finally, we present our universal commonsense reasoning model, UNICORN. Motivated by Finding 1, our primary goal with UNICORN is to provide a pretrained commonsense reasoning model ready to be fine-tuned on other downstream commonsense tasks. This is analogous to how off-the-shelf reasoning models are fine-tuned on other downstream tasks. In order to see the limit of the best performance achievable, we start by multitasking T5-11B on RAINBOW. We then trained UNICORN on each task individually, except for WINOGRANDE which required separate handling since it evaluates models via a learning curve. For WINOGRANDE, we multitasked the other five RAINBOW datasets and then trained on WINOGRANDE. In each case, we used the same hyper-parameters as UNICORN did during its initial multi-task training, extending each of the 8 combinations tried at that stage. The best checkpoints were chosen using accuracy on dev.

SOTA on RAINBOW. We establish new SOTA on all RAINBOW datasets: αNLI (87.3%), COSMOSQA (91.8%), HELLSWAG (93.9%), PIQA (90.1%), SOCIALIQA (83.2%), and WINOGRANDE (86.6%).

SOTA on datasets beyond RAINBOW. While SOTA results on RAINBOW are encouraging, we still need to check if UNICORN’s strong performance is confined to RAINBOW or generalizes beyond it. Thus, we evaluated on two additional commonsense benchmarks: CYCIC (94.0%) and COMMONSESEQA (79.3%). Again, UNICORN achieved SOTA on both.

6 Related Work

Scaling Laws In contemporary machine learning, simple methods that scale often outperform complex ones (Sutton 2019). Accordingly, recent years have seen a sharp rise in compute used by state-of-the-art methods (Amodei and Hernandez 2018). Performance gains from increasing data, parameters, and training are not only reliable, but empirically predictable (Hestness et al. 2017; Sun et al. 2017; Rosenfeld et al. 2020; Kaplan et al. 2020). For example, Sun et al. (2017) found that models need exponential data for improvements in accuracy. These observations, that scaling is reliable, predictable, and critical to the current successes, motivate our focus on evaluation based on cost-benefit trade-offs, i.e. the cost equivalent curve.

Commonsense Benchmarks Rapid progress in modeling has led to a major challenge for NLP: the creation of suitable benchmarks. Neural models often cue off statistical biases and annotation artifacts to solve datasets without understanding tasks (Gururangan et al. 2018). To address this issue, recent commonsense benchmarks often use adversarial filtering (Zellers et al. 2018; Le Bras et al. 2020): a family of techniques that remove easily predicted examples from datasets. Besides COSMOSQA, all RAINBOW tasks use this technique. Many more common sense benchmarks exist beyond what we could explore here (Roemmele, Bejan, and Gordon 2011; Levesque, Davis, and Morgenstern 2011; Mostafazadeh et al. 2016).

Transfer Learning Semi-supervised and transfer learning have grown into cornerstones of NLP. Early work learned unsupervised representations of words (Brown et al. 1992; Mikolov et al. 2013), while more recent work employs contextualized representations from neural language models (Peters et al. 2018). Radford et al. (2018) demonstrated that language models could be fine-tuned directly to solve a wide-variety of tasks by providing the inputs encoded as text, while Devlin et al. (2019) and others improved upon the technique (Yang et al. 2019; Liu et al. 2019b; Lan et al. 2019). Most relevant to this work, Raffel et al. (2019) introduced T5 which built off previous work to reframe any NLP task as text-to-text, dispensing with the need for task-specific model adaptations.

Data Efficiency & Evaluation Other researchers have noted the importance of cost-benefit trade-offs in evaluation (Schwartz et al. 2019). Dodge et al. (2019) advocate reporting the compute-performance trade-off caused by hyperparameter tuning for new models, and provide an estimator for expected validation performance as a function of hyperparameter evaluations. In an older work, Clark and Matwin (1993) evaluated the use of qualitative knowledge in terms of saved training examples, similarly to our cost equivalent curves. In contrast to our work, they fitted a linear trend to the learning curve and counted examples saved rather than plotting the numbers of examples that achieve equivalent performance.

7 Conclusion

Motivated by the fact that increased scale reliably improves performance for neural networks, we reevaluated existing techniques based on their data efficiency. To enable such comparisons, we introduced a new evaluation, the cost equivalent curve, which improves over traditional learning curves by facilitating comparisons across otherwise hard-to-compare contexts. Our large-scale empirical study analyzed state-of-the-art techniques for transfer on pretrained language models, focusing on learning general, commonsense knowledge and evaluating on common sense tasks. In particular, we introduced a new collection of common sense datasets, RAINBOW, and using the lessons from our empirical study trained a new model, UNICORN, improving state-of-the-art results across 8 benchmarks. We hope others find our empirical study, new evaluation, RAINBOW, and UNICORN useful in their future work.
Acknowledgements

We would like to thank the anonymous reviewers for their valuable feedback. This research was supported in part by NSF (IIS-1524371), the National Science Foundation Graduate Research Fellowship under Grant No. DGE 1256082, DARPA CwC through ARO (W911NF15-1-0543), DARPA MCS program through NIWC Pacific (N66001-19-2-4031), and the Allen Institute for AI. Computations on beaker.org were supported in part by credits from Google Cloud. TPU machines for conducting experiments were generously provided by Google through the TensorFlow Research Cloud (TFRC) program.

References

Abadi, M.; Barham, P.; Chen, J.; Chen, Z.; Davis, A.; Dean, J.; Devin, M.; Ghemawat, S.; Irving, G.; Isard, M.; Kudlur, M.; Levenberg, J.; Monga, R.; Moore, S.; Murray, D. G.; Steiner, B.; Tucker, P.; Vasudevan, V.; Warden, P.; Wicke, M.; Yu, Y.; and Zheng, X. 2016. TensorFlow: A system for large-scale machine learning. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16). 265–283. URL https://www.usenix.org/system/files/conference/osdi16/osdi16-abadi.pdf.

Agirre, E.; M‘arquez, L.; and Wicentowski, R., eds. 2007. Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007). Prague, Czech Republic: Association for Computational Linguistics.

Amodei, D.; and Hernandez, D. 2018. AI and Compute. URL https://openai.com/blog/ai-and-compute/.

Bar Haim, R.; Dagan, I.; Dolan, B.; Ferro, L.; Giampiccolo, D.; Magnini, B.; and Szpektor, I. 2006. The second PASCAL recognising textual entailment challenge.

Barlow, R.; Bartholomew, D.; Bremner, J.; and Brunk, H. 1972. Statistical Inference Under Order Restrictions: The Theory and Application of Isotonic Regression. J. Wiley. ISBN 9780471049708.

Bentivogli, L.; Dagan, I.; Dang, H. T.; Giampiccolo, D.; and Magnini, B. 2009. The Fifth PASCAL Recognizing Textual Entailment Challenge.

Bhagavatula, C.; Le Bras, R.; Malaviya, C.; Sakaguchi, K.; Holtzman, A.; Rashkin, H.; Downey, D.; Yih, S.-W.-t.; and Choi, Y. 2020. Abductive commonsense reasoning. ICLR.

Bisk, Y.; Zellers, R.; Le Bras, R.; Gao, J.; and Choi, Y. 2020. PIQA: Reasoning about Physical Commonsense in Natural Language. In Thirty-Fourth AAAI Conference on Artificial Intelligence.

Bosselut, A.; Rashkin, H.; Sap, M.; Malaviya, C.; Çelikyilmaz, A.; and Choi, Y. 2019. COMET: Commonsense Transformers for Automatic Knowledge Graph Construction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL).

Brown, P. F.; Della Pietra, V. J.; deSouza, P. V.; Lai, J. C.; and Mercer, R. L. 1992. Class-Based n-gram Models of Natural Language. Computational Linguistics 18(4): 467–480. URL https://www.aclweb.org/anthology/J92-4003.

Caruana, R. 1995. Learning Many Related Tasks at the Same Time with Backpropagation. In Tesauro, G.; Touretzky, D. S.; and Leen, T. K., eds., Advances in Neural Information Processing Systems 7, 657–664. MIT Press. URL http://papers.nips.cc/paper/959-learning-many-related-tasks-at-the-same-time-with-backpropagation.pdf.

Clark, C.; Lee, K.; Chang, M.-W.; Kwiatkowski, T.; Collins, M.; and Toutanova, K. 2019. BoolQ: Exploring the Surprising Difficulty of Natural Yes/No Questions. In Proceedings of NAACL-HLT 2019.

Clark, P.; and Matwin, S. 1993. Using qualitative models to guide inductive learning. In Proceedings of the 1993 international conference on machine learning.

Dagan, I.; Glickman, O.; and Magnini, B. 2006. The PASCAL recognising textual entailment challenge. In Machine learning challenges. evaluating predictive uncertainty, visual object classification, and recognising textual entailment, 177–190. Springer.

De Marneffe, M.-C.; Simons, M.; and Tonhauser, J. 2019. The CommitmentBank: Investigating projection in naturally occurring discourse. To appear in proceedings of Sinn und Bedeutung 23. Data can be found at https://github.com/mcdm/CommitmentBank/.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1423. URL https://www.aclweb.org/anthology/N19-1423.

Dodge, J.; Gururangan, S.; Card, D.; Schwartz, R.; and Smith, N. A. 2019. Show Your Work: Improved Reporting of Experimental Results. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2185–2194. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/D19-1224. URL https://www.aclweb.org/anthology/D19-1224.

Dolan, W. B.; and Brockett, C. 2005. Automatically constructing a corpus of sentential paraphrases. In Proceedings of the International Workshop on Paraphrasing.

Giampiccolo, D.; Magnini, B.; Dagan, I.; and Dolan, B. 2007. The third PASCAL recognizing textual entailment challenge. In Proceedings of the ACL–PASCAL workshop on textual entailment and paraphrasing, 1–9. Association for Computational Linguistics.

Gordon, J.; and Van Durme, B. 2013. Reporting bias and knowledge acquisition. In Proceedings of the 2013 workshop on Automated knowledge base construction, 25–30. ACM.

Gururangan, S.; Swayamdipta, S.; Levy, O.; Schwartz, R.; Bowman, S.; and Smith, N. A. 2018. Annotation Artifacts in Natural Language Inference Data. In NAACL. URL https://www.aclweb.org/anthology/N18-2017/.

Hestness, J.; Narang, S.; Ardalani, N.; Diamos, G. F.; Jun, H.; Kianinejad, H.; Pottery, M. M. A.; Yang, Y.; and Zhou, Y. 2017. Deep Learning Scaling is Predictable, Empirically. ArXiv abs/1712.00409.

Huang, L.; Le Bras, R.; Bhagavatula, C.; and Choi, Y. 2019. Cosmos QA: Machine Reading Comprehension with Contextual Commonsense Reasoning. In EMNLP-IJCNLP.

Kaplan, J.; McCandlish, S.; Henighan, T.; Brown, T. B.; Chess, B.; Child, R.; Gray, S.; Radford, A.; Wu, J.; and Amodei, D. 2020. Scaling laws for neural language models. arXiv preprint arxiv:2001.08361.

Khashabi, D.; Chaturvedi, S.; Roth, M.; Upadhyay, S.; and Roth, D. 2018. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In Proceedings of the
Speer, R.; Chin, J.; and Havasi, C. 2017. ConceptNet 5.5: An Open Multilingual Graph of General Knowledge. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, AAAI’17, 4444–4451. AAAI Press.

Sun, C.; Shrivastava, A.; Singh, S.; and Gupta, A. 2017. Revisiting unreasonable effectiveness of data in deep learning era. In Proceedings of the IEEE international conference on computer vision, 843–852.

Sutton, R. S. 2019. The Bitter Lesson. URL http://incompleteideas.net/IncIdeas/BitterLesson.html.

Talmor, A.; Herzig, J.; Lourie, N.; and Berant, J. 2019. CommonsenseQA: A Question Answering Challenge Targeting Commonsense Knowledge. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4149–4158. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1421. URL https://www.aclweb.org/anthology/N19-1421.

Tange, O. 2011. GNU Parallel - The Command-Line Power Tool. ;login: The USENIX Magazine 36(1): 42–47. doi:10.5281/zenodo.16303. URL http://www.gnu.org/s/parallel.

Trinh, T. H.; and Le, Q. V. 2018. A simple method for commonsense reasoning. arXiv preprint arXiv:1806.02847.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In Advances in neural information processing systems, 5998–6008.

Vu, T.; Wang, T.; Munkhdalai, T.; Sordoni, A.; Trischler, A.; Mattarella-McKe, A.; Maji, S.; and Iyyer, M. 2020. Exploring and predicting transferability across nlp tasks. arXiv preprint arXiv:2005.00770.

Wang, A.; Pruksachatkun, Y.; Nangia, N.; Singh, A.; Michael, J.; Hill, F.; Levy, O.; and Bowman, S. R. 2019a. SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems. arXiv preprint 1905.00537.

Wang, A.; Singh, A.; Michael, J.; Hill, F.; Levy, O.; and Bowman, S. R. 2019b. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In the Proceedings of ICLR.

Warstadt, A.; Singh, A.; and Bowman, S. R. 2018. Neural Network Acceptability Judgments. arXiv preprint 1805.12471.

Williams, A.; Nangia, N.; and Bowman, S. R. 2018. A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference. In Proceedings of NAACL-HLT.

Williams, R. J.; and Zipser, D. 1989. A Learning Algorithm for Continually Running Fully Recurrent Neural Networks. Neural Computation 1(2): 270–280.

Winograd, T. 1972. Understanding natural language. Cognitive psychology 3(1): 1–191.

Yang, Z.; Dai, Z.; Yang, Y.; Carbonell, J.; Salakhutdinov, R. R.; and Le, Q. V. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems, 5753–5763.

Zellers, R.; Bisk, Y.; Schwartz, R.; and Choi, Y. 2018. SWAG: A Large-Scale Adversarial Dataset for Grounded Commonsense Inference. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP).

Zellers, R.; Holtzman, A.; Bisk, Y.; Farhadi, A.; and Choi, Y. 2019. HellaSwag: Can a Machine Really Finish Your Sentence? In ACL.
A Cost Equivalent Curves

Section 2 discusses the intuitions, assumptions, and visualization of cost equivalent curves at a high level. This appendix provides additional discussion as well as technical details for implementing cost equivalent curves.

The aim of cost equivalent curves is to visualize how an innovation impacts a cost-benefit trade-off, in a compact and intuitive way. Since cost equivalent curves are more general than the use case explored in this work (dataset size/performance trade-offs), we’ll introduce more general terminology for discussing them, borrowing from the experimental design literature. The control is the baseline approach (e.g., single task training), while the treatment is the new approach or innovation (e.g., multitask or sequential training). Benefit is a quantitative measure of how good the outcome is, like accuracy, while cost measures what we pay to get it, such as dataset size or even dollars. Thus, cost equivalent curves can visualize how sequential training (the treatment) reduces data usage (the cost) compared to single task training (the control) when trying to achieve high accuracy (the benefit).

Similarly, cost equivalent curves could visualize how Gaussian process optimization reduces hyper-parameter evaluations compared to random search when trying to achieve low perplexity on a language modeling task.

To construct cost equivalent curves, the main assumption is that the cost and benefit have a continuous, strictly monotonic (most often increasing) relationship. For machine learning, this assumption is satisfied empirically when using measures like expected cross-entropy against parameters, data, and compute (Kaplan et al. 2020). Since the cost and benefit share a monotonic relationship, we estimate the cost-benefit trade-offs using isotonic regression (Barlow et al. 1972). Concretely, we test the control and the treatment at a bunch of different costs, and measure the benefit. Then, we fit a curve to the control’s results, \( f_c \), and a curve to the treatment’s results, \( f_t \). Since the cost equivalent curve, \( \hat{g} \), maps the control costs to the treatment costs achieving the same benefit, we can estimate it as:

\[
\hat{g} = f_t^{-1} \circ f_c
\]

That is, we compose the inverse cost-benefit curve for the treatment with the cost-benefit curve for the control. The inverse is guaranteed to exist because we assumed that the cost-benefit trade-offs are strictly monotonic.

Our implementation uses isotonic regression as implemented in scikit-learn (Pedregosa et al. 2011). To estimate the inverse curve, we switch the inputs and the outputs in the regression. The code may be found at https://github.com/allenai/rainbow.

B Datasets

Our empirical study investigates transferring common sense from multisets (dataset collections) to various end tasks. Section 3 presented a new multiset, RAINBOW, for common sense transfer. In this appendix, Appendix B.1 describes each end task we evaluated, Appendix B.2 expands on RAINBOW and the other multisets we tried, and Appendix B.3 details the knowledge graphs we used.

B.1 Tasks

Six tasks, \( \alpha \)NLI, COSMOSQA, HELLASWAG, PIQA, SOCIALIQ, and WINOGRADE, compose RAINBOW, as discussed in Section 3. Our experiments also use all six of these datasets as end tasks. In addition, we evaluated on COMMONSENSEQA, JOCI, and CYCIC. Each dataset is described below:

\( \alpha \)NLI (Bhagavatula et al. 2020) challenges models to infer the best explanation connecting the beginning and ending of a story. Concretely, \( \alpha \)NLI presents models with the first and last sentences of a three sentence story. The model must choose among two alternative middles based on which provides the most plausible explanation.

COSMOSQA (Huang et al. 2019) tests models’ reading comprehension by asking them to read in-between the lines. Each example presents a short passage along with a question dealing with commonsense causes, effects, inferences and counterfactuals drawn from the passage. To solve the task, models must choose the best answer among four candidates.

HELласWAG (Zellers et al. 2019) takes a context sentence and generates multiple completions using a language model. The machine generated endings often break commonsense world understanding, making it easy for humans to distinguish them from the original ending. In addition, HELласWAG uses adversarial filtering (Zellers et al. 2018) to select the three distractor endings only from among those difficult for models to detect.

PIQA (Bisk et al. 2020) probes models’ physical commonsense knowledge through goal-oriented question answering problems. The questions often explore object affordances, presenting a goal (e.g., “How do I find something lost on a carpet?”) and then offering two solutions (such as “Put a solid seal on the end of your vacuum and turn it on” vs. “Put a hair net on the end of your vacuum and turn it on”). Models choose the best solution to solve the problem.

SOCIALIQ (Sap et al. 2019b) leverages ATOMIC (Sap et al. 2019a) to crowdsourced a three-way multiple-choice benchmark evaluating the social and emotional common sense possessed by models. Questions explore people’s motivations and reactions in a variety of social situations.

WINOGRADE (Sakaguchi et al. 2020) takes inspiration from winograd schemas (Winograd 1972; Levesque, Davis, and Morgenstern 2011) to create a large-scale dataset of coreference resolution problems requiring both physical and social common sense. Each question presents a sentence with a blank where a pronoun might be and two options to fill it. The questions often come in pairs where a single word changes between them, flipping which option is correct.

\(^8\)Also known as abductive reasoning.
**COMMONSENSEQA** (Talmor et al. 2019) offers general, challenging, common sense questions in a multiple-choice format. By construction, each question requires fine-grained world knowledge to distinguish between highly similar concepts. In particular, COMMONSENSEQA crowdsources questions by presenting annotators with three related concepts drawn from CONCEPTNET (Speer, Chin, and Havasi 2017). The annotators then create three questions, each picking out one of the concepts as the correct answer. To increase the dataset’s difficulty, an additional distractor from CONCEPTNET as well as one authored by a human were added to each question, for a total of five options.

**CycIC** offers five-way multiple-choice questions that touch on both common sense reasoning and knowledge over topics such as arithmetic, logic, time, and locations.

**JOCI** (Zhang et al. 2017) (JHU Ordinal Commonsense Inference) generalizes natural language inference (NLI) to likely implications. Each problem presents a context followed by a hypothesis. In contrast to traditional NLI which explores hard, logical implications, JOCI instead explores likely inferences from the context. Thus, each example comes with an ordinal label of the likelihood: very likely, likely, plausible, technically possible, or impossible. In contrast to Zhang et al. (2017), we treat the task as five-way classification and evaluate it with accuracy in order to make it uniform with other end tasks we explore.

**B.2 Multisets**

In addition to RAINBOW, we use two other multisets for transfer. All three are described below.

**GLUE** (Wang et al. 2019b) measures natural language understanding by evaluating models on a suite of classification tasks. In particular, GLUE contains tasks for linguistic acceptability (Warstadt, Singh, and Bowman 2018), sentiment analysis (Socher et al. 2013), paraphrase (Dolan and Brockett 2005; Agirre, Márquez, and Wicentowski 2007)\(^9\), natural language inference (sometimes constructed from other datasets) (Williams, Nangia, and Bowman 2018; Rujpurkar et al. 2016; Dagan, Glickman, andMagnini 2006; Bar Haim et al. 2006; Giampiccolo et al. 2007; Bentivogli et al. 2009; Levesque, Davis, and Morgenstern 2011), and general diagnostics.

**SUPERGLUE** (Wang et al. 2019a) provides a more challenging successor to GLUE, measuring natural language understanding with a broader range of more complex tasks. Specifically, SUPERGLUE comprises tasks for identifying when speakers implicitly assert something (De Marneffe, Simons, and Tonhauser 2019), determining cause-effect relationships (Roemmele, Bejan, and Gordon 2011), reading comprehension (Khashabi et al. 2018; Zhang et al. 2018), natural language inference (Dagan, Glickman, and Magnini 2006; Bar Haim et al. 2006; Giampiccolo et al. 2007; Bentivogli et al. 2009; Poliak et al. 2018), word sense disambiguation (Pilehvar and Camacho-Collados 2019), winograd schemas (Levesque, Davis, and Morgenstern 2011), true-false question answering (Clark et al. 2019), and gender bias diagnostics (Rudinger et al. 2018).

**RAINBOW** combines the six common sense benchmarks as we proposed in Section 3: αNLI (Bhagavatula et al. 2020), COSMOSQA (Huang et al. 2019), HELLASWAG (Zellers et al. 2019), PIQA (Bisk et al. 2020), SOCIALIQA (Sap et al. 2019b), and WINOGRANDE (Sakaguchi et al. 2020). These multiple-choice datasets each measure different aspects of common sense, from likely sequences of events, to instrumental knowledge in physical situations, to theory of mind and social common sense.

**B.3 Knowledge Graphs**

In addition to multisets, we explored common sense transfer from the following knowledge graphs in Section 4.4:

**CONCEPTNET** (Speer, Chin, and Havasi 2017) combines both expert curated and crowdsourced knowledge from various sources into a graph of concepts and relations. A concept is a short natural language word or phrase, such as “water”. Connecting concepts, there’s a commonly used set of canonical relations like ATLOCATION. For example, CONCEPTNET contains the triple: “water” ATLOCATION “river”. CONCEPTNET contains a significant amount of information beyond common sense; however, the common sense subset tends to focus on knowledge about objects and things.

**ATOMIC** (Sap et al. 2019a) offers a rich source of knowledge about the relationships between events and common sense inferences about them. ATOMIC connects events described in natural language using relations that express things like pre-conditions, post-conditions, and plausible inferences based on the event. For example, ATOMIC contains the triple: “PersonX makes PersonY’s coffee” oREACT “PersonY will be grateful”, where oREACT denotes the patient’s (PersonY’s) reaction.

**C Training and Evaluation**

This appendix describes the technical details of our training and evaluation setup, to help reproduce our experiments.

**C.1 Model and Implementation**

All of our experiments are run with the state-of-the-art T5 model (Raffel et al. 2019). T5 is a text-to-text model built on top of the transformer architecture (Vaswani et al. 2017). It has an encoder-decoder structure and is pretrained using a combination of masked language modeling (Devlin et al. 2019) and multitask training on a large collection of NLP datasets. As a text-to-text model, T5 frames every NLP...
problem as mapping input text to output text. All structural information in the input is linearized into a sequence of text, similarly to Radford et al. (2018), and all output is generated as a string when making predictions. For training, T5 uses teacher forcing (Williams and Zipser 1989), i.e. maximum likelihood; for testing, T5 greedily decodes the generated text. Thus, for T5 to solve a task, one must first apply some straightforward preprocessing to frame it as text-to-text. Appendix C.2 describes the preprocessing we performed in more detail. Lastly, T5 is available in several model sizes: small (60M parameters), base (220M parameters), large (770M parameters), 3B (3B parameters), and 11B (11B parameters). For more information on T5 and its pretraining, see Raffel et al. (2019).

Our experiments use the original implementation, code, and weights for T5, which are publicly available at https://github.com/google-research/text-to-text-transfer-transformer. Our code uses the original T5 implementation unmodified, only extending it with our own dataset preprocessing, reading, and task mixing. For deep learning operations, the implementation uses tensorflow (Abadi et al. 2015). For leaderboard submissions, the implementation uses tensorflow (Abadi et al. 2015). Our code is available at https://github.com/allenai/rainbow. To facilitate reproducibility and future research, we released results for all of our experiments, including hyper-parameter tuning. Download the results at https://github.com/allenai/rainbow. These tables contain all model evaluations and all hyper-parameter combinations tried in any given experiment.

C.2 Preprocessing

To model tasks as text-to-text, we need to convert their inputs and outputs into strings. Our preprocessing first prepends a string to each example signifying its dataset, e.g. [socialiqa]: for the SOCIALIQ task. Next, it wraps each feature in XML-like brackets with a unique tag identifying the feature, then joins them all together with newline characters. Figure 6 depicts an example from WINOGRANDE. Preprocessing for other tasks is similar.

```
WinoGrande
Sentence: Katrina could afford a new car while Monica couldn't, since _ had a high paying job. 
Option1: Katrina
Option2: Monica
```

Figure 6: An example of the dataset preprocessing applied to an instance from WINOGRANDE.

C.3 Training and Hyper-parameter Tuning

Following Raffel et al. (2019), we converted all tasks to text-to-text and used teacher forcing (Williams and Zipser 1989) as the training objective, with greedy decoding for predictions. Our implementation reused the training and evaluation code from the original T5 paper. For leaderboard submissions and test set evaluations, we built UNICORN off of T5-11B. For all other experiments, we used T5-LARGE except when experiments specifically explore the impact of size, in which case the model size was explicitly indicated.

Hyper-parameters which were not set manually were tuned via grid search. In general, the fixed hyper-parameters and the grid used for search depended on the group of experiments, as outlined below. All hyper-parameters not mentioned were identical to those used in Raffel et al. (2019).

**Leaderboard Submissions** For leaderboard submissions and test set evaluations, T5-11B was initially multitasked on RAINBOW with an equal task mixing rate for 25,000 gradient updates using different hyper-parameter combinations to produce the UNICORNs. We then trained each on the end tasks separately for 25,000 gradient updates, saving a checkpoint every 2,500. The 10 most recent checkpoints were kept for early stopping, using dev set accuracy to choose the best checkpoint for evaluation. The grid search explored learning rates of 4e-3, 2e-3, 1e-3, and 5e-4 as well as batch sizes of 16 and 32.

**Investigatory Experiments** Experiments which were not evaluated on the test set or submitted to a leaderboard used the T5-LARGE model as a starting point, unless explicitly noted otherwise (e.g., in experiments exploring the impact of model size). Training was carried out for 50,000 gradient updates, saving a checkpoint every 5,000 and keeping the 10 most recent. The batch size was fixed to 16. Grid search explored learning rates of 4e-3, 1e-3, and 2.5e-4. Depending on the specific experiment, other hyper-parameters were explored as well. For models trained on full datasets (rather than learning curves), we explored equal and dataset size-weighted mixing rates when multitasking. In sequential training, this meant that these rates were tried during the initial multitask training before training on the end task alone. For transferring knowledge graphs, we also explored predicting the subject-relation-object tuples in forward, backward, and bidirectional configurations. When producing learning curves, i.e. training the model on subsets of the full data, we used the equal mixing rate for all mixtures and the forward direction for knowledge graph transfer. Given the extensiveness of these experiments, we chose not to evaluate these models on the test sets to avoid test leakage; thus, reported results for these experiments are always the best score on dev.

For transfer techniques requiring two stages of training (i.e. multitask fine-tune and sequential training), we reused the hyper-parameters from the first stage of training in the second stage. For all tasks, we used accuracy as the evaluation metric.

To facilitate reproducibility and future research, we released results for all of our experiments, including hyper-parameter tuning. Download the results at https://github.com/allenai/rainbow. These tables contain all model evaluations and all hyper-parameter combinations tried in any given experiment.

C.4 Hardware, Software, and Compute

All experiments were run on Google Cloud using two Google Compute Engine virtual machine (VM) instances communicating with various TPUs. Experimental results were saved into Google Cloud Storage. Each VM had 20 vCPUs with 75GB of memory and ran Debian 9 (Stretch).
One VM used Intel Skylake vCPUs while the other used Intel Haswell. Specific versions of libraries and other dependencies used are available and tracked in the code repository.

For hardware acceleration, we ran all the experiments using v3-8 TPUs when building off of T5-LARGE or smaller. For T5-SMALL and T5-LARGE we used a model parallelism of 8, while for T5-BASE we used 4. The T5-11B models were trained using TPU v2-256 and v3-256s with a model parallelism of 16. Training times usually took several hours per run, so we ran many experiments in parallel on the VMs using GNU Parallel (Tange 2011).

D Leaderboards

As discussed in Section 5, Unicorn achieves state-of-the-art performance across a number of popular commonsense benchmarks. This appendix collects those results along with the leaderboards’ previous state-of-the-art and other useful baseline submissions for comparison.

\[\alpha\text{NLI}\]

| Model                        | Accuracy |
|------------------------------|----------|
| BERT-LARGE (Devlin et al. 2019) | 66.8%    |
| RoBERTA-LARGE (Liu et al. 2019b)  | 83.9%    |
| L2R² (Zhu et al. 2020)       | 86.8%    |
| UNICORN                      | 87.3%    |
| HUMAN                         | 92.9%    |

Table 4: \(\alpha\text{NLI}\) leaderboard submissions.

\[\text{COSMOSQA}\]

| Model                        | Accuracy |
|------------------------------|----------|
| RoBERTA-LARGE (Liu et al. 2019b)  | 83.5%    |
| ALBERT-XX-LARGE (Lan et al. 2019)| 85.4%    |
| T5-11B (Raffel et al. 2019)    | 90.3%    |
| UNICORN                      | 91.8%    |
| HUMAN                         | 94.0%    |

Table 5: COSMOSQA leaderboard submissions.

\[\text{HELLASWAG}\]

| Model                        | Accuracy |
|------------------------------|----------|
| RoBERTA-LARGE (Liu et al. 2019b)  | 81.7%    |
| HYKAS+CSKG (Ma et al. 2019)    | 85.0%    |
| RoBERTA-LARGE ENSEMBLE (Liu et al. 2019b) | 85.5%    |
| UNICORN                      | 93.9%    |
| HUMAN                         | 95.6%    |

Table 6: HELLASWAG leaderboard submissions.

Since COMMONSENSEQA used CONCEPTNET in its construction, its authors have split leaderboard submissions for comparison.

\[\text{PIQA}\]

| Model                        | Accuracy |
|------------------------------|----------|
| BERT-LARGE (Devlin et al. 2019) | 66.7%    |
| RoBERTA-LARGE (Liu et al. 2019b)  | 79.4%    |
| UNIFIEDQA-3B (Khashabi et al. 2020) | 85.3%    |
| UNICORN                      | 90.1%    |
| HUMAN                         | 94.9%    |

Table 7: PIQA leaderboard submissions.

\[\text{SOCIALIQA}\]

| Model                        | Accuracy |
|------------------------------|----------|
| RoBERTA-LARGE (Liu et al. 2019b)  | 76.7%    |
| UNIFIEDQA-3B (Khashabi et al. 2020) | 79.8%    |
| UGAMIX                        | 80.0%    |
| UNICORN                      | 83.2%    |
| HUMAN                         | 88.1%    |

Table 8: SOCIALIQA leaderboard submissions.

\[\text{WINOGRANDE}\]

| Model                        | AUC  |
|------------------------------|------|
| BERT-LARGE (Devlin et al. 2019) | 52.9% |
| RoBERTA-LARGE (Liu et al. 2019b)  | 66.4% |
| UNIFIEDQA-11B (Khashabi et al. 2020) | 85.7% |
| UNICORN                      | 86.6% |
| HUMAN                         | 94.0% |

Table 9: WINOGRANDE leaderboard submissions. AUC is the area under the dataset-size vs. accuracy learning curve.

\[\text{CICIC}\]

| Model                        | Accuracy |
|------------------------------|----------|
| RoBERTA-LARGE (Liu et al. 2019b)  | 91.3%    |
| PRV2                         | 91.4%    |
| UNICORN                      | 94.0%    |
| HUMAN                         | 90.0%    |

Table 10: CICIC leaderboard submissions.

\[\text{COMMONSENSEQA}\]

| Model                        | Accuracy |
|------------------------------|----------|
| RoBERTA-LARGE (Liu et al. 2019b)  | 72.1%    |
| T5-11B (Raffel et al. 2019)    | 78.1%    |
| UNIFIEDQA-11B (Khashabi et al. 2020) | 79.1%    |
| UNICORN                      | 79.3%    |
| HUMAN                         | 88.9%    |

Table 11: COMMONSENSEQA leaderboard submissions.
into two categories: models that do and that do not use CONCEPTNET. Models using CONCEPTNET can gain an advantage by eliminating the human authored distractor options. UNICORN holds the current state-of-the-art among models which do not use CONCEPTNET. The state-of-the-art model using CONCEPTNET combines the knowledge graph with ALBERT (Lan et al. 2019)\textsuperscript{11} and scores 79.5% accuracy.

Hyper-parameters For each of the submissions, we used the following hyper-parameters. αNLI used a learning rate of 5e-4 and a batch size of 16. COSMOSQA used a learning rate of 2e-3 and a batch size of 32. HELLASWAG used a learning rate of 2e-3 and a batch size of 32. PIQA used a learning rate of 2e-3 and a batch size of 32. SOCIALIQA used a learning rate of 5e-4 and a batch size of 32. WINOGRANDE-xs used a learning rate of 2e-3 and a batch size of 32. WINOGRANDE-s used a learning rate of 5e-4 and a batch size of 32. WINOGRANDE-m used a learning rate of 5e-4 and a batch size of 32. WINOGRANDE-l used a learning rate of 1e-3 and a batch size of 16, and WINOGRANDE-xl used a learning rate of 2e-3 and a batch size of 16. CycIC had a learning rate of 5e-4 and a batch size of 32, while COMMONSENSEQA had a learning rate of 1e-3 and a batch size of 32.

E. Experiments
This appendix provides additional figures illustrating the findings as well as tables for all the experiments. In addition, the code used to run these experiments may be found at https://github.com/allenai/rainbow, and the models, experimental results (in CSV format) and even more figures, may be downloaded there as well.

E.1 Transferring to the RAINBOW Tasks
These figures and tables use RAINBOW for the end tasks:

- **Figure 7** A comparison of different multisets using multitask training
- **Figure 8** A comparison of different multisets using sequential training
- **Figure 9** A comparison of different multisets using multitask fine-tune training
- **Figure 10** A comparison of transfer methods on GLUE
- **Figure 11** A comparison of transfer methods on SUPERGLUE
- **Figure 12** A comparison of transfer methods on CONCEPTNET

- **Table 12** Single task baselines using the full training data
- **Table 13** The performance using transfer and the full training data
- **Table 14** Single task learning curves
- **Table 15** αNLI learning curves with transfer
- **Table 16** COSMOSQA learning curves with transfer

E.2 Transferring to Other Tasks
These experiments target COMMONSENSEQA and JOCI.

- **Figure 13** A comparison of different multisets using multitask training
- **Table 21** Single task baselines using the full training data
- **Table 22** The performance using transfer and the full training data
- **Table 23** Single task learning curves
- **Table 24** Learning curves using transfer

E.3 Effect of Size
These experiments explore the impact of model size on transfer using COMMONSENSEQA as the target dataset.

- **Figure 14** A comparison of transfer methods across different model sizes
- **Table 25** Full task performance for the initial multitask models used in sequential training and multitask fine-tune training experiments comparing model size
- **Table 26** Single task learning curves across different model sizes
- **Table 27** Learning curves using transfer across different model sizes

E.4 Transferring Knowledge Graphs
These experiments explore transferring knowledge graphs via multitask training, using RAINBOW for the end tasks.

- **Figure 15** A comparison of transfer from different knowledge graphs
- **Figure 16** A comparison of transfer from different knowledge graphs when also multitasking with RAINBOW
- **Figure 17** A comparison of transfer from ATOMIC with and without multitasking RAINBOW
- **Figure 18** A comparison of transfer from CONCEPTNET with and without multitasking RAINBOW
- **Figure 19** A comparison of transfer from both ATOMIC and CONCEPTNET with and without multitasking RAINBOW

- **Table 28** The performance using transfer and the full training data
- **Table 29** αNLI learning curves with transfer
- **Table 30** COSMOSQA learning curves with transfer
- **Table 31** HELLASWAG learning curves with transfer
- **Table 32** PIQA learning curves with transfer
- **Table 33** SOCIALIQA learning curves with transfer
- **Table 34** WINOGRANDE learning curves with transfer

\textsuperscript{11}For more, see https://github.com/jessionlin/csqa/blob/master/Model_details.md
Figure 7: A comparison of multisets for transfer to the RAINBOW tasks using multitask training with T5-LARGE. Performance is dev accuracy.

Figure 8: A comparison of multisets for transfer to the RAINBOW tasks using sequential training with T5-LARGE. Performance is dev accuracy.
Figure 9: A comparison of multisets for transfer to the RAINBOW tasks using multitask fine-tune training with T5-LARGE. Performance is dev accuracy.

Figure 10: A comparison of methods for transferring GLUE to the RAINBOW tasks with T5-LARGE. Performance is dev accuracy.
Figure 11: A comparison of methods for transferring SUPERGLUE to the RAINBOW tasks with T5-LARGE. Performance is dev accuracy.

Figure 12: A comparison of methods for transferring the RAINBOW tasks to the RAINBOW tasks with T5-LARGE. Each plot treats its end task as held out from RAINBOW, using the other five tasks for transfer. Performance is dev accuracy.
| model | αNLI | CosmosQA | HELLASWAG | PIQA | SOCIALIQ | WinoGrande |
|-------|------|----------|-----------|------|----------|------------|
| large | 77.8 | 81.9     | 82.8      | 80.2 | 73.8     | 77.0       |

Table 12: Single task baselines using the full training data.

| multiset transfer | Task | αNLI | CosmosQA | HELLASWAG | PIQA | SOCIALIQ | WinoGrande |
|-------------------|------|------|----------|-----------|------|----------|------------|
| GLUE              | fine-tune | 78.5 | 82.4     | 82.9      | 80.1 | 74.3     | 78.4       |
|                   | multitask | 77.2 | 80.8     | 81.8      | 77.6 | 74.7     | 76.0       |
|                   | sequential | 78.5 | 81.4     | 82.3      | 80.8 | 74.3     | 77.9       |
| RAINBOW           | fine-tune | 79.2 | 82.6     | 83.1      | 82.2 | 75.2     | 78.2       |
|                   | multitask | 78.4 | 81.1     | 81.3      | 80.7 | 74.8     | 72.1       |
|                   | sequential | 79.5 | 83.2     | 83.0      | 82.2 | 75.5     | 78.7       |
| SUPERGLUE         | fine-tune | 78.5 | 81.7     | 82.8      | 80.0 | 74.7     | 78.5       |
|                   | multitask | 77.7 | 78.9     | 80.5      | 70.7 | 72.3     | 69.8       |
|                   | sequential | 79.1 | 82.2     | 82.5      | 80.7 | 74.6     | 77.6       |

Table 13: The performance using transfer and the full training data.

| task | 4 | 10 | 30 | 91 | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
|------|---|----|----|----|-----|-----|------|------|------|--------|--------|-------|
| αNLI | 49.2 | 53.1 | 54.8 | 61.1 | 65.6 | 68.4 | 72.3 | 72.1 | 76.1 | 73.4 | 74.4 | 74.9 |
| CosmosQA | 24.6 | 31.0 | 26.2 | 31.9 | 43.0 | 43.6 | 48.6 | 46.4 | 72.5 | 75.8 | 77.5 | 78.2 |
| HELLASWAG | 24.6 | 26.6 | 26.0 | 32.6 | 48.6 | 44.6 | 64.6 | 72.5 | 75.8 | 77.5 | 78.2 | 79.2 |
| PIQA | 50.1 | 50.7 | 51.7 | 52.8 | 52.7 | 59.8 | 70.7 | 76.3 | 77.0 | 78.4 | 80.0 | 80.0 |
| SOCIALIQ | 33.6 | 34.7 | 34.4 | 34.7 | 35.3 | 54.0 | 66.4 | 64.7 | 68.6 | 70.6 | 70.9 | 71.0 |
| WinoGrande | 50.1 | 50.7 | 52.9 | 50.7 | 51.7 | 57.9 | 64.2 | 67.4 | 69.9 | 71.4 | 72.2 | 73.1 |

Table 14: Learning curves for the single task baselines.

| multiset transfer | Task | 4 | 10 | 30 | 91 | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
|-------------------|------|---|----|----|----|-----|-----|------|------|------|--------|--------|-------|
| GLUE              | fine-tune | 49.2 | 53.7 | 60.1 | 61.9 | 66.2 | 69.2 | 72.6 | 72.7 | 75.4 | 73.2 | 74.2 | 74.6 |
|                   | multitask | 49.2 | 53.3 | 59.3 | 61.7 | 66.1 | 69.5 | 72.6 | 72.4 | 74.5 | 73.2 | 74.2 | 74.3 |
|                   | sequential | 49.1 | 57.1 | 63.1 | 63.8 | 67.4 | 70.0 | 72.8 | 73.4 | 75.8 | 74.3 | 74.3 | 75.4 |
| RAINBOW           | fine-tune | 61.0 | 63.4 | 69.6 | 71.3 | 72.6 | 73.9 | 76.6 | 75.8 | 76.7 | 75.8 | 76.4 | 76.7 |
|                   | multitask | 61.9 | 62.9 | 69.6 | 71.4 | 73.0 | 74.3 | 76.4 | 76.7 | 76.9 | 76.8 | 77.5 | 77.2 |
|                   | sequential | 61.4 | 65.3 | 70.9 | 71.0 | 73.6 | 73.8 | 75.8 | 75.7 | 76.6 | 76.6 | 76.6 | 76.5 |
| SUPERGLUE         | fine-tune | 49.1 | 57.0 | 59.9 | 63.6 | 66.1 | 69.1 | 71.3 | 71.9 | 75.3 | 73.6 | 73.3 | 74.5 |
|                   | multitask | 49.1 | 57.0 | 59.5 | 63.7 | 65.5 | 67.9 | 71.3 | 71.6 | 74.3 | 72.8 | 72.7 | 74.5 |
|                   | sequential | 49.2 | 61.5 | 62.6 | 64.8 | 66.3 | 70.2 | 72.2 | 72.3 | 76.1 | 73.6 | 74.0 | 75.2 |

Table 15: Learning curves on αNLI using transfer.
### Table 16: Learning curves on COSMOSQA using transfer.

| multiset | transfer     | Size       |        |        |        |        |        |        |        |        |        |        |
|----------|--------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| GLUE     | fine-tune    | 4 10 30 91 | 280    | 865    | 2667   | 5334   | 8000   | 10000  | 13334  | 16000  |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| RAINBOW  | fine-tune    | 54.9 61.9  | 57.4   | 60.9   | 62.1   | 64.7   | 74.7   | 78.2   | 79.1   | 80.1   |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| SUPERGLUE| fine-tune    | 24.6 35.3  | 25.8   | 36.1   | 48.0   | 63.8   | 72.2   | 75.3   | 75.6   | 77.7   |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |

### Table 17: Learning curves on HELLASWAG using transfer.

| multiset | transfer     | Size       |        |        |        |        |        |        |        |        |        |        |
|----------|--------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| GLUE     | fine-tune    | 25.3 26.4  | 26.7   | 35.3   | 50.2   | 64.3   | 72.7   | 75.2   | 77.0   | 77.9   | 78.8   | 79.6   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| RAINBOW  | fine-tune    | 53.7 49.1  | 47.0   | 55.4   | 63.5   | 67.0   | 74.0   | 76.4   | 77.9   | 78.5   | 79.7   | 80.2   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| SUPERGLUE| fine-tune    | 25.3 26.5  | 25.9   | 35.1   | 48.0   | 63.3   | 71.5   | 74.4   | 76.5   | 77.0   | 77.7   | 78.7   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |

### Table 18: Learning curves on PIQA using transfer.

| multiset | transfer     | Size       |        |        |        |        |        |        |        |        |        |        |
|----------|--------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| GLUE     | fine-tune    | 33.6 34.1  | 35.2   | 35.1   | 34.4   | 48.1   | 66.6   | 67.5   | 68.7   | 71.8   | 71.2   | 72.8   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| RAINBOW  | fine-tune    | 33.6 48.2  | 58.1   | 63.9   | 64.7   | 66.6   | 70.2   | 70.6   | 73.1   | 72.7   | 73.6   | 73.6   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| SUPERGLUE| fine-tune    | 33.6 34.1  | 34.1   | 35.2   | 34.9   | 58.1   | 67.7   | 70.2   | 70.6   | 71.6   | 72.3   | 72.4   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |

### Table 19: Learning curves on SOCIALIQA using transfer.

| multiset | transfer     | Size       |        |        |        |        |        |        |        |        |        |        |
|----------|--------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| GLUE     | fine-tune    | 33.6 34.1  | 34.6   | 34.6   | 35.9   | 58.9   | 67.0   | 68.7   | 69.4   | 71.8   | 72.2   | 72.6   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| RAINBOW  | fine-tune    | 33.6 34.1  | 34.1   | 35.2   | 34.9   | 58.1   | 67.7   | 70.2   | 70.6   | 71.6   | 72.3   | 72.4   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| SUPERGLUE| fine-tune    | 33.6 34.1  | 34.6   | 35.2   | 35.4   | 57.3   | 66.3   | 69.7   | 70.9   | 70.5   | 70.0   | 70.9   |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
|          |              |            |        |        |        |        |        |        |        |        |        |        |
| multiset | transfer  | Size       |
|---------|-----------|------------|
|         |           | 4          | 10 | 30 | 91 | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
| GLUE    | fine-tune | 48.5       | 50.5 | 52.3 | 50.4 | 51.5 | 59.4 | 64.8 | 67.2 | 69.9 | 71.3 | 72.5 | 74.2 |
|         | multitask | 49.2       | 50.8 | 51.9 | 51.7 | 51.7 | 59.5 | 63.8 | 66.1 | 68.7 | 69.4 | 71.0 | 71.7 |
|         | sequential| 48.6       | 50.5 | 52.3 | 49.9 | 52.2 | 58.8 | 65.4 | 67.2 | 69.6 | 71.1 | 72.8 | 73.0 |
| RAINBOW | fine-tune | 52.6       | 52.6 | 52.6 | 53.0 | 56.5 | 63.2 | 66.5 | 69.2 | 71.3 | 72.5 | 73.8 | 73.9 |
|         | multitask | 51.8       | 52.7 | 52.9 | 53.5 | 55.8 | 62.6 | 64.9 | 67.9 | 69.4 | 70.1 | 70.6 | 70.3 |
|         | sequential| 51.0       | 53.2 | 54.1 | 54.7 | 58.8 | 63.3 | 66.9 | 68.4 | 70.5 | 72.5 | 73.4 | 74.9 |
| SUPERGLUE| fine-tune | 49.3       | 50.7 | 52.2 | 50.7 | 52.9 | 61.7 | 65.2 | 67.2 | 70.1 | 72.1 | 73.5 | 73.5 |
|         | multitask | 50.7       | 50.7 | 52.1 | 51.6 | 52.2 | 60.1 | 64.3 | 64.9 | 68.0 | 68.5 | 70.0 | 69.8 |
|         | sequential| 48.8       | 50.4 | 52.4 | 51.7 | 52.9 | 60.6 | 64.5 | 66.6 | 69.0 | 71.3 | 72.1 | 73.2 |

Table 20: Learning curves on WINOGRANDE using transfer.

Figure 13: A comparison of transfer from different multisets to COMMONSENSEQA and JOCI with T5-LARGE via multitask training. Performance is dev accuracy.

| Task     | model | COMMONSENSEQA | JOCI |
|----------|-------|---------------|------|
|          | large | 71.6          | 58.0 |

Table 21: Single task baselines using the full training data.

| Task     | multiset       | COMMONSENSEQA | JOCI |
|----------|----------------|---------------|------|
|          | GLUE           | 70.8          | 57.8 |
|          | RAINBOW        | 72.6          | 57.5 |
|          | SUPERGLUE      | 70.5          | 58.3 |

Table 22: The performance on COMMONSENSEQA and JOCI using transfer via multitask training.

| Task     | Size         |
|----------|--------------|
|          | 4            | 10 | 30 | 91 | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
| COMMONSENSEQA | 19.9   | 35.1 | 45.6 | 53.6 | 58.3 | 63.2 | 66.3 | 70.8 | 71.4 | 72.0 | –   | –       | –     |
| JOCI     | 21.8   | 24.6 | 29.3 | 28.8 | 43.3 | 48.7 | 52.0 | 53.5 | 55.4 | –   | 55.3 | 56.0 | 57.4  |

Table 23: Learning curves for the single task baselines on COMMONSENSEQA and JOCI.
Table 24: Learning curves using multitask training on COMMONSENSEQA and JOCI.

Table 25: Full task performance for UNICORN on RAINBOW after multitask training and before training on the target dataset (COMMONSENSEQA) across different model sizes.

Table 26: Learning curves for single task baselines on COMMONSENSEQA at different model sizes.
| model | transfer | Size    |
|-------|----------|---------|
|       |          | 4       | 10    | 30    | 91    | 280   | 865   | 2667  | 5334  | 8000  | 9741  |
| base  | fine-tune | 37.5    | 47.1  | 46.5  | 47.9  | 49.2  | 51.0  | 55.1  | 59.2  | 59.9  | 60.6  |
|       | multitask | 36.4    | 47.7  | 46.9  | 48.9  | 49.2  | 52.7  | 55.4  | 58.3  | 59.5  | 60.0  |
|       | sequential| 38.4    | 45.4  | 45.6  | 48.1  | 50.2  | 52.7  | 56.1  | 59.7  | 61.6  | 61.6  |
| large | fine-tune | 47.4    | 64.0  | 63.8  | 63.0  | 65.7  | 66.5  | 68.8  | 71.6  | 71.8  | 72.6  |
|       | multitask | 41.7    | 63.2  | 63.7  | 63.9  | 65.7  | 66.7  | 68.3  | 71.8  | 72.1  | 73.0  |
|       | sequential| 59.5    | 63.3  | 63.0  | 64.0  | 65.9  | 68.1  | 69.8  | 72.9  | 73.1  | 72.6  |
| small | fine-tune | 26.3    | 30.9  | 30.3  | 27.7  | 29.7  | 31.1  | 33.5  | 36.6  | 37.8  | 40.2  |
|       | multitask | 26.3    | 30.7  | 29.7  | 28.9  | 29.9  | 31.7  | 33.0  | 36.6  | 40.5  | 40.1  |
|       | sequential| 25.1    | 28.7  | 29.1  | 27.8  | 29.8  | 31.0  | 32.7  | 38.0  | 39.3  | 41.0  |

Table 27: Learning curves for UNICORN on COMMONSENSEQA at different model sizes, with different transfer approaches.

Figure 15: A comparison of transfer from different knowledge graphs to the RAINBOW tasks using multitask training. Performance is dev accuracy.
Figure 16: A comparison of transfer from different knowledge graphs and RAINBOW to the RAINBOW tasks using multitask training. Performance is dev accuracy.

Figure 17: A comparison of transfer from ATOMIC to the RAINBOW tasks via multitask training when also and not also multitasking with RAINBOW.
Figure 18: A comparison of transfer from CONCEPTNET to the RAINBOW tasks via multitask training when also and not also multitasking with RAINBOW.

Figure 19: A comparison of transfer from both ATOMIC and CONCEPTNET to the RAINBOW tasks via multitask training when also and not also multitasking with RAINBOW.
| multiset knowledge | direction | oNLI | COSMOSQA | HELLASWAG | PIQA | SOCIALIQ | WINOGRANDE |
|---------------------|-----------|------|----------|----------|------|----------|------------|
| ATOMIC              | backward  | 78.3 | 81.8     | 82.5     | 79.5 | 74.3     | 76.9       |
|                     | bidirectional | 77.9 | 81.0     | 82.8     | 79.3 | 75.0     | 78.2       |
|                     | forward    | 77.7 | 81.0     | 82.4     | 79.9 | 74.4     | 76.8       |
| NONE                | backward  | 78.0 | 81.8     | 82.5     | 79.4 | 74.3     | 76.3       |
|                     | bidirectional | 77.8 | 81.5     | 82.3     | 80.5 | 74.1     | 76.3       |
|                     | forward    | 77.0 | 81.6     | 82.4     | 80.0 | 73.7     | 76.2       |
| BOTH                | backward  | 78.0 | 81.2     | 82.4     | 81.1 | 74.4     | 75.7       |
|                     | bidirectional | 77.6 | 81.0     | 82.6     | 80.1 | 74.7     | 76.4       |
|                     | forward    | 77.5 | 81.8     | 82.7     | 79.8 | 74.8     | 76.6       |
| ATOMIC              | backward  | 78.3 | 81.4     | 81.3     | 80.5 | 75.0     | 73.2       |
|                     | bidirectional | 77.7 | 81.4     | 81.2     | 80.4 | 74.9     | 71.5       |
|                     | forward    | 77.9 | 81.3     | 81.6     | 80.4 | 75.0     | 73.6       |
| RAINBOW             | backward  | 78.7 | 81.8     | 81.6     | 81.3 | 75.0     | 73.5       |
|                     | bidirectional | 78.3 | 80.6     | 81.5     | 81.0 | 74.7     | 72.9       |
|                     | forward    | 78.3 | 81.6     | 81.3     | 80.6 | 75.5     | 73.4       |
| BOTH                | backward  | 77.1 | 80.9     | 81.6     | 81.2 | 74.3     | 71.6       |
|                     | bidirectional | 76.9 | 81.4     | 81.0     | 80.3 | 75.0     | 72.2       |
|                     | forward    | 77.7 | 81.9     | 81.7     | 80.8 | 74.8     | 72.1       |

Table 28: The performance when transferring different knowledge graphs to RAINBOW with multitask training using the full training data.

| multiset knowledge | size | 4   | 10  | 30  | 91  | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
|---------------------|------|-----|-----|-----|-----|-----|-----|------|------|------|------|-------|-------|
| ATOMIC              |      | 49.3| 52.3| 54.6| 61.6| 65.8| 68.5| 71.6  | 72.5 | 75.3 | 73.4  | 74.1  | 74.8  |
| CONCEPTNET          |      | 49.2| 54.6| 53.5| 60.2| 65.5| 68.6| 72.2  | 71.7 | 74.4 | 73.1  | 74.0  | 74.9  |
| BOTH                |      | 49.3| 54.0| 52.9| 59.6| 66.3| 68.5| 72.4  | 71.6 | 74.7 | 73.6  | 74.0  | 75.0  |
| RAINBOW             |      | 55.0| 67.0| 73.0| 72.0| 73.8| 74.9| 76.2  | 76.4 | 76.6 | 76.8  | 76.6  | 77.0  |
| CONCEPTNET          |      | 56.7| 66.4| 64.5| 72.7| 75.2| 75.1| 76.2  | 76.4 | 77.1 | 76.3  | 76.4  | 76.6  |
| BOTH                |      | 58.3| 64.7| 65.4| 72.1| 73.2| 74.5| 76.2  | 76.0 | 76.6 | 76.6  | 77.0  | 76.7  |

Table 29: Learning curves on oNLI using transfer from knowledge graphs via multitask training.

| multiset knowledge | size | 4   | 10  | 30  | 91  | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
|---------------------|------|-----|-----|-----|-----|-----|-----|------|------|------|------|-------|-------|
| ATOMIC              |      | 25.5| 26.4| 26.0| 37.4| 46.8| 64.8| 72.5  | 75.5 | 77.3 | 78.2  | 78.8  | 79.4  |
| CONCEPTNET          |      | 25.2| 26.1| 25.7| 35.7| 46.6| 64.7| 72.4  | 75.6 | 77.2 | 78.3  | 78.9  | 79.7  |
| BOTH                |      | 25.9| 26.1| 26.5| 37.4| 47.8| 64.4| 72.5  | 75.7 | 77.1 | 78.1  | 78.8  | 79.6  |
| RAINBOW             |      | 54.1| 45.9| 49.3| 55.5| 61.9| 66.5| 73.1  | 75.7 | 77.1 | 77.7  | 78.8  | 79.8  |
| CONCEPTNET          |      | 53.9| 47.2| 47.4| 54.6| 62.8| 66.7| 73.2  | 76.0 | 77.4 | 77.9  | 78.9  | 79.2  |
| BOTH                |      | 54.4| 45.0| 49.1| 55.0| 63.0| 66.3| 73.3  | 75.6 | 77.3 | 77.6  | 78.3  | 79.3  |

Table 30: Learning curves on COSMOSQA using transfer from knowledge graphs via multitask training.

| multiset knowledge | size | 4   | 10  | 30  | 91  | 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
|---------------------|------|-----|-----|-----|-----|-----|-----|------|------|------|------|-------|-------|
| ATOMIC              |      | 25.5| 26.4| 26.0| 37.4| 46.8| 64.8| 72.5  | 75.5 | 77.3 | 78.2  | 78.8  | 79.7  |
| CONCEPTNET          |      | 25.2| 26.1| 25.7| 35.7| 46.6| 64.7| 72.4  | 75.6 | 77.2 | 78.3  | 78.9  | 79.7  |
| BOTH                |      | 25.9| 26.1| 26.5| 37.4| 47.8| 64.4| 72.5  | 75.7 | 77.1 | 78.1  | 78.8  | 79.6  |
| RAINBOW             |      | 54.1| 45.9| 49.3| 55.5| 61.9| 66.5| 73.1  | 75.7 | 77.1 | 77.7  | 78.8  | 79.8  |
| CONCEPTNET          |      | 53.9| 47.2| 47.4| 54.6| 62.8| 66.7| 73.2  | 76.0 | 77.4 | 77.9  | 78.9  | 79.2  |
| BOTH                |      | 54.4| 45.0| 49.1| 55.0| 63.0| 66.3| 73.3  | 75.6 | 77.3 | 77.6  | 78.3  | 79.3  |

Table 31: Learning curves on HELLASWAG using transfer from knowledge graphs via multitask training.
| multiset | knowledge | Size     |
|----------|-----------|----------|
|          |           | 4 10 30 | 91 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
| **NONE** | ATOMIC    | 51.0 54.0 50.8 53.2 54.7 66.0 71.6 76.9 77.7 79.4 79.9 |
|          | CONCEPTNet | 50.4 50.2 54.0 51.0 54.5 52.0 65.7 76.0 76.4 78.1 78.8 79.5 |
|          | BOTH      | 50.5 50.1 53.9 51.1 54.4 56.6 63.9 73.6 75.2 77.1 79.4 79.5 |
| **RAINBOW** | ATOMIC    | 50.0 48.9 50.5 56.7 69.4 72.7 77.6 78.2 78.4 79.3 80.2 80.6 |
|          | CONCEPTNet | 49.8 49.0 53.6 54.2 68.4 73.7 76.4 77.6 78.2 80.0 80.8 80.4 |
|          | BOTH      | 50.1 49.1 50.0 59.5 70.5 73.8 77.4 78.3 78.8 79.8 80.4 80.4 |

Table 32: Learning curves on PIQA using transfer from knowledge graphs via multitask training.

| multiset | knowledge | Size     |
|----------|-----------|----------|
|          |           | 4 10 30 | 91 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
| **NONE** | ATOMIC    | 33.6 34.2 33.5 35.0 34.5 56.0 67.1 68.3 71.0 72.0 72.6 73.2 |
|          | CONCEPTNet | 33.6 34.6 34.0 34.7 34.7 37.2 66.6 67.9 69.7 71.8 72.4 71.7 |
|          | BOTH      | 33.6 34.4 33.7 35.1 34.1 50.6 67.3 68.4 70.2 71.5 72.1 72.3 |
| **RAINBOW** | ATOMIC    | 33.6 34.8 64.3 65.0 65.8 66.0 70.4 70.5 71.8 72.2 73.2 73.8 |
|          | CONCEPTNet | 33.6 55.0 64.3 63.1 65.7 66.4 69.7 71.1 72.3 72.5 72.6 73.5 |
|          | BOTH      | 33.6 61.4 62.3 65.5 65.9 67.5 70.6 71.1 71.8 72.5 73.5 74.4 |

Table 33: Learning curves on SOCIALIQA using transfer from knowledge graphs via multitask training.

| multiset | knowledge | Size     |
|----------|-----------|----------|
|          |           | 4 10 30 | 91 280 | 865 | 2667 | 5334 | 8000 | 10667 | 13334 | 16000 |
| **NONE** | ATOMIC    | 50.4 50.5 52.3 49.6 49.6 54.1 64.4 66.5 68.6 71.3 71.7 72.8 |
|          | CONCEPTNet | 50.1 50.4 52.4 49.9 50.2 54.5 62.8 66.1 69.7 69.9 71.6 72.5 |
|          | BOTH      | 50.7 50.3 51.9 50.4 49.9 53.9 63.4 66.1 67.7 70.3 70.5 72.1 |
| **RAINBOW** | ATOMIC    | 51.9 53.5 52.8 52.9 54.1 61.2 64.4 67.6 68.7 70.0 71.0 70.8 |
|          | CONCEPTNet | 51.6 52.6 53.7 54.0 57.1 62.6 65.3 66.6 69.0 70.7 71.3 71.3 |
|          | BOTH      | 50.4 52.6 52.0 53.9 56.5 61.5 64.8 66.9 69.3 70.4 70.6 70.9 |

Table 34: Learning curves on WINOGRANDE using transfer from knowledge graphs via multitask training.