MAGPIE: Multi-Task Analysis of Media-Bias **Generalization with Pre-Trained Identification of** Expressions

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LREC-COLING 2024



Presentation plan

- 1. Motivation
- 2. Media Bias detection
- 3. Methodology
- 4. Experimental results
- 5. Conclusion





Media bias

• Media Bias — noun. The tendency of news media to report in a way that reinforces a viewpoint, worldview, preference, political ideology, corporate or financial interests, moral framework, or policy inclination, instead of reporting in an objective way.



Since then, health care has turned out to be a very strong issue for Democrats, who campaigned on the issue aggressively during the 2018 midterms and enjoyed a net gain of 40 seats in the U.S. House of Representatives.



Detecting media bias

- A binary classification problem
- Granularity article vs sentence level
- Main datasets:
 - o BABE (~4k sentences)
 - Basil (~8k sentences)
- There has been a substantial number of efforts in improving the classifiers
- the main issue remains : lack of quality datasets





Multi-task learning

- Media bias is a multifaceted phenomenon
- In this work we use MTL for media bias detection as a solution to the problem of the lack of high quality data
- We base our work on findings of ExT5 and Muppet [1,2]







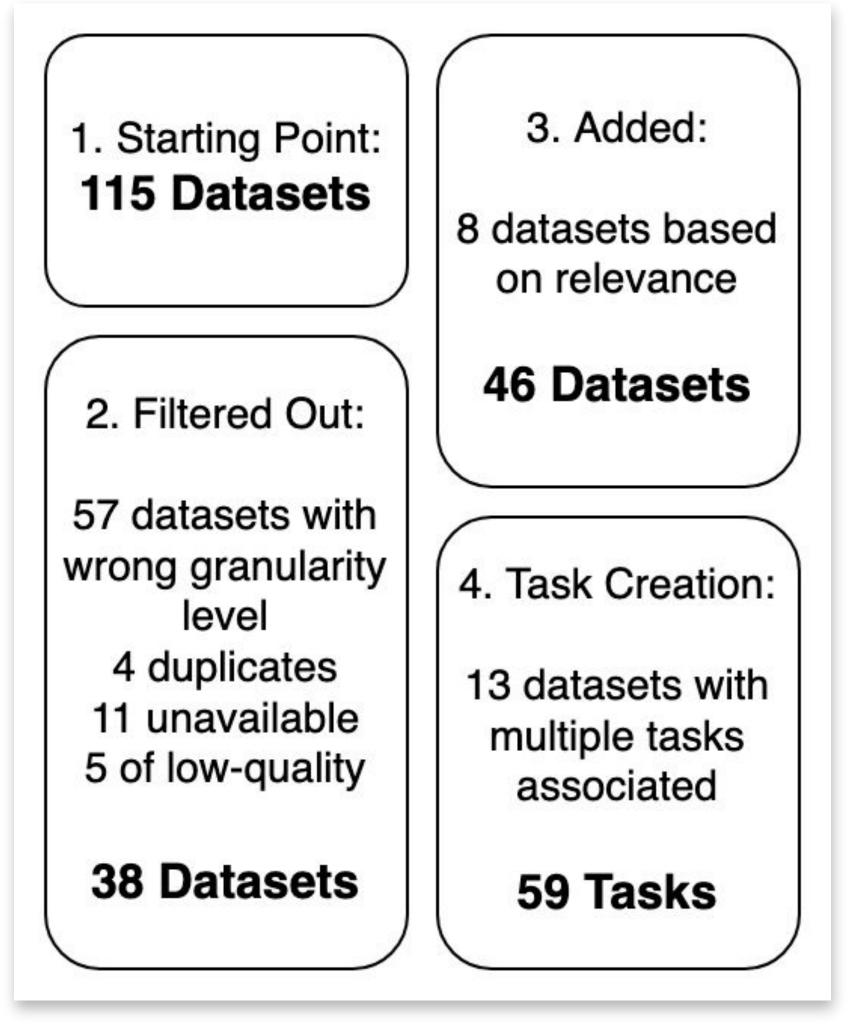
Method



LBM - Large Bias Mixture

- 59 tasks
- over 1.200.000 labeled sentences







LBM - Task families

Task Family	#sentences
News bias	19759
Subjective bias	69610
Hate-speech	485 179
Gender bias	121 983
Sentiment analysis	199 273
Fake news	39063
Group bias	19782
Emotional bias	218 589
Subjective bias	45 686



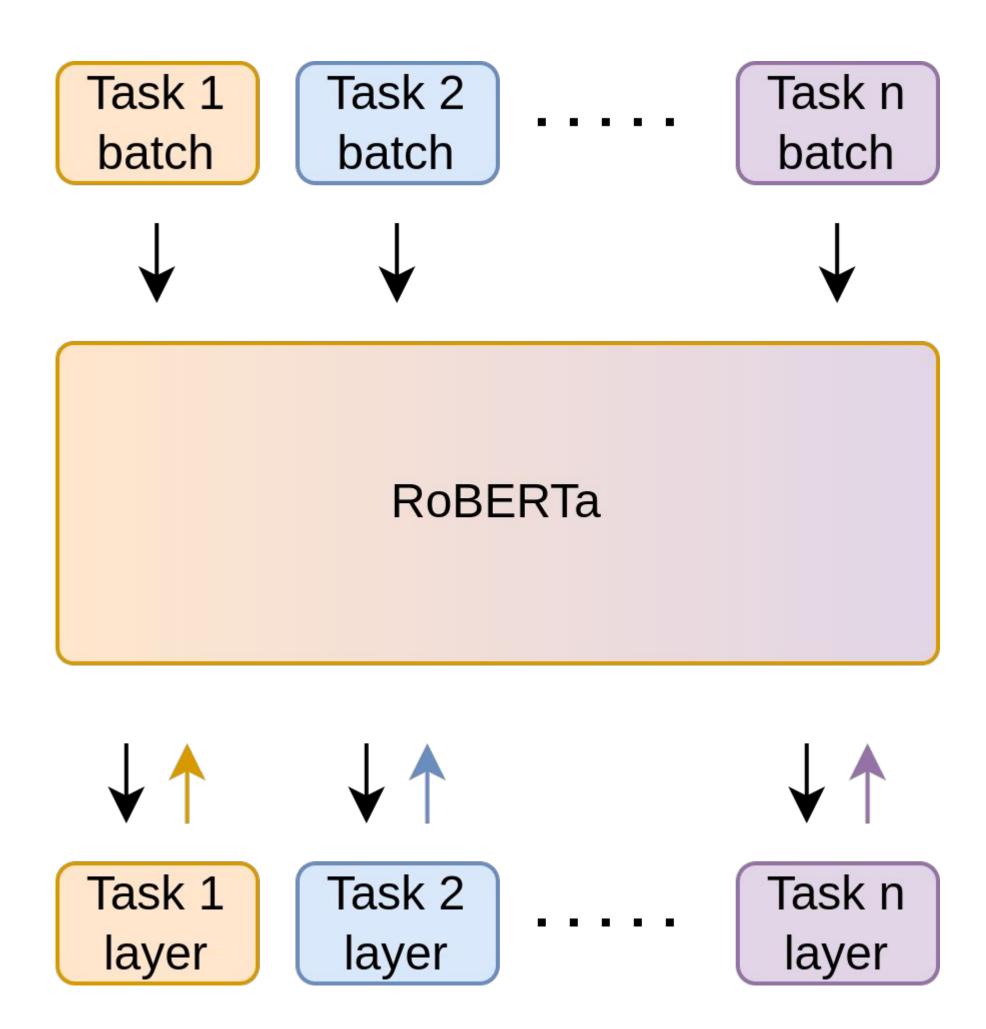




Multi-task Training strategy

- RoBERTa with hard-shared parameters
- Gradient aggregation PCGrad [3]
- Loss scaling Static scaling [2]
- Task selection GradTS [4]







Experiments





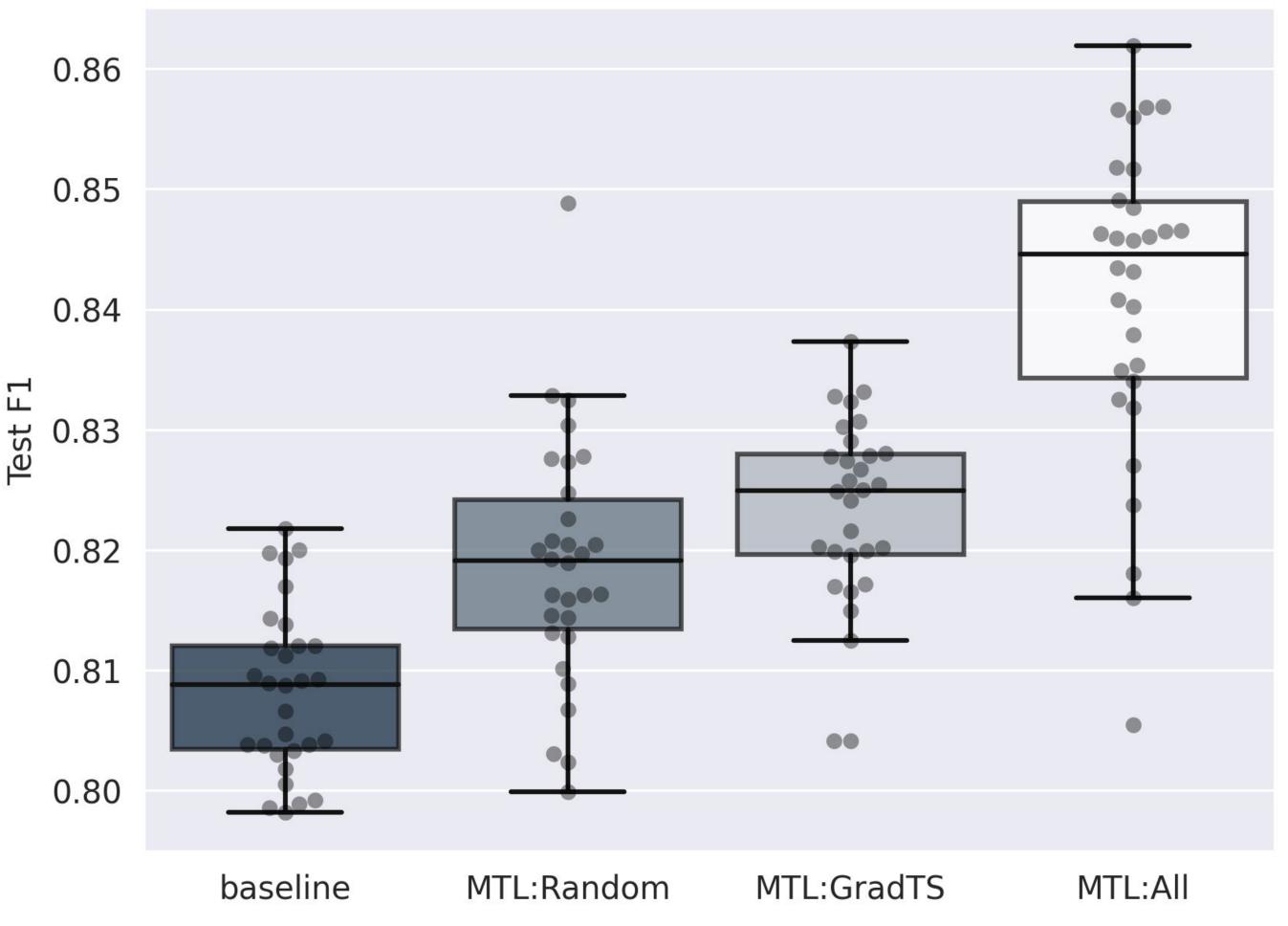
Experiment 1: Evaluation of the MTL model on media bias task

- **Objective**: We want to compare different sets of tasks and its effect on downstream performance on BABE dataset
- We use multi-task learning for pre-training and then fine-tune and evaluate the model on BABE dataset
- All are averaged on 30 random seeds



Experiment 1: Comparison of different task-selection strategies

- **Objective**: We want to compare different sets of tasks and its effect on downstream performance on BABE dataset
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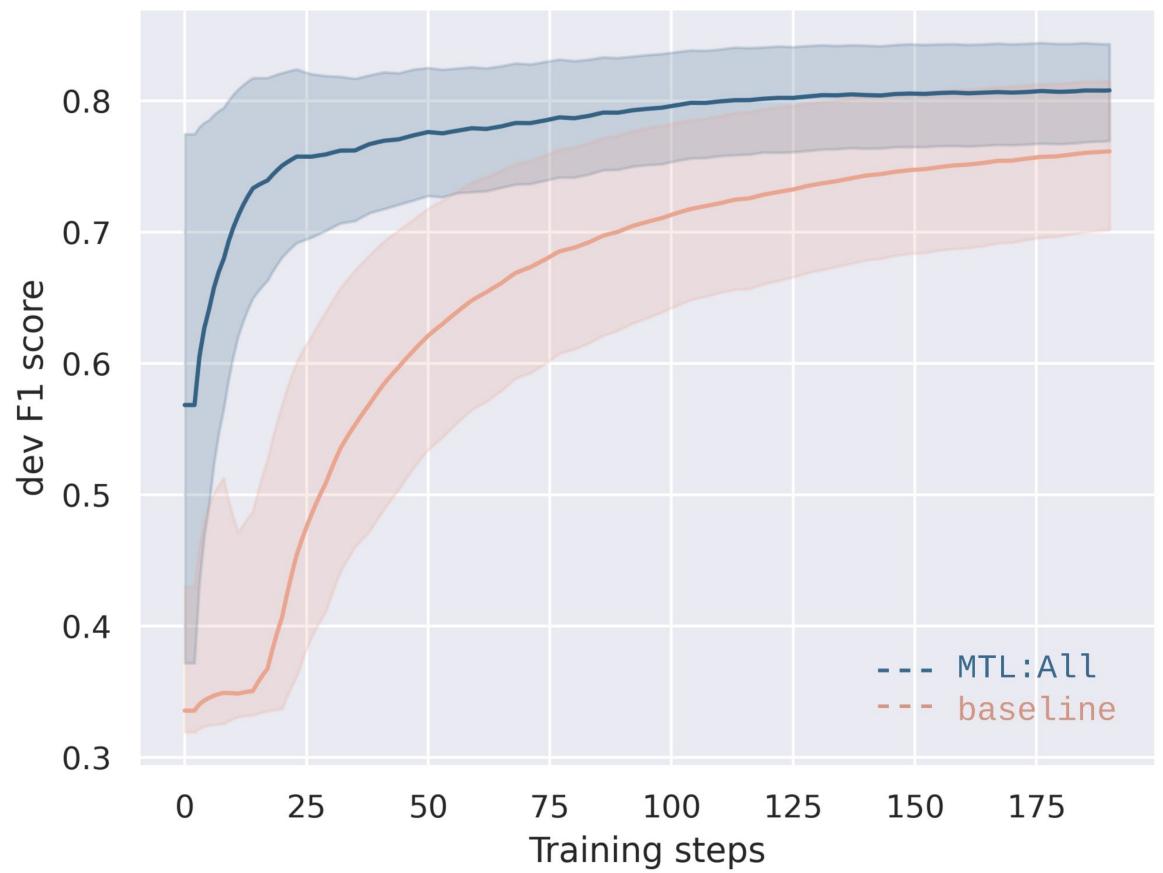
Experiment 1: Downstream performance

Model	F1	Acc	loss
Baseline (RoBERTa base)	80.83 (±0.69)	81.19 (±0.69)	43.6 (±3.54)
DA-RoBERTa	77.83 (±1.4)	78.56 (±1.3)	47.84 (±2.97)
MUPPET	80.56 (±1.3)	81.18 (±1.16)	44.19 (±4.65)
UnifiedM2	81.91 (±0.91)	82.41 (±0.88)	44.86 (±3.99)
MTL:Random	81.88 (±1.02)	82.28 (±0.97)	40.35 (±1.73)
MTL:GradTS	82.32 (±0.79)	82.64 (±0.8)	40.96 (±2.36)
MTL:All	84.1 (±1.33)	84.44 (±1.25)	39.46 (±2.41)



Experiment 1: Downstream performance

• 15% steps are required to match the single-task performance





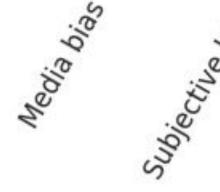
Experiment 2: Can we improve the performance further?

- How do task families affect each other?
- Can we exploit the task families for more focused subset of tasks?
- We pairwise train task families together and report and average improvement within the task families

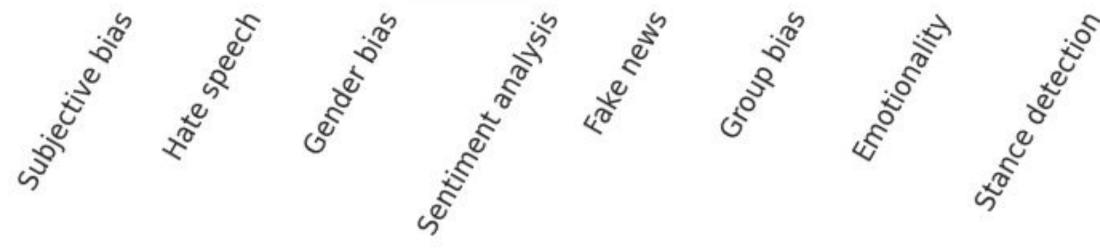


Experiment 3: How do task families affect each other?

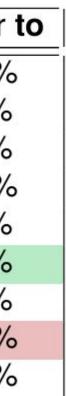
Media bias	0	-0.35	-1.4	-0.23	-1.5	-0.67	-0.31	-1.4	-1.7
Subjective bias	0.03	0	0.68	0.04	0.8	2.1	1.6	1.5	0.49
Hate speech	-2.1	0.15	0	0.17	0.58	0.86	1.5	0.76	-0.53
Gender bias	-2.4	-0.67	-0.43	0	-0.04	0.47	-2.3	-1.9	-1.4
Sentiment analysis	0.02	0.6	1.1	0.89	0	0.76	-0.02	1.3	1
Fake news	0.33	1.9	0.54	2	2.2	0	1.7	3.5	2
Group bias	-2.3	0.17	-0.23	0.24	1.3	1	0	0.5	-0.01
Emotionality	-7	-11	-6.5	-9.5	-1.4	-2	-9.3	0	-6.3
Stance detection	-3.2	-1.3	-0.8	-1.7	-1.1	-3.6	-1.2	-1.6	0
	bias	bias	sech	bias	Vsis	SMa	bias	lity	tion







Task Family	Transfer from	Transfer
media bias	-2.07%	-0.94%
subjective bias	-1.26%	0.89%
hate speech	-0.87%	0.17%
gender bias	-1.01%	-1.07%
sentiment analysis	0.11%	0.72%
fake news	-0.13%	1.79%
group bias	-1.04%	0.09%
emotionality	0.34%	-6.56%
stance detection	-0.79%	-1.83%



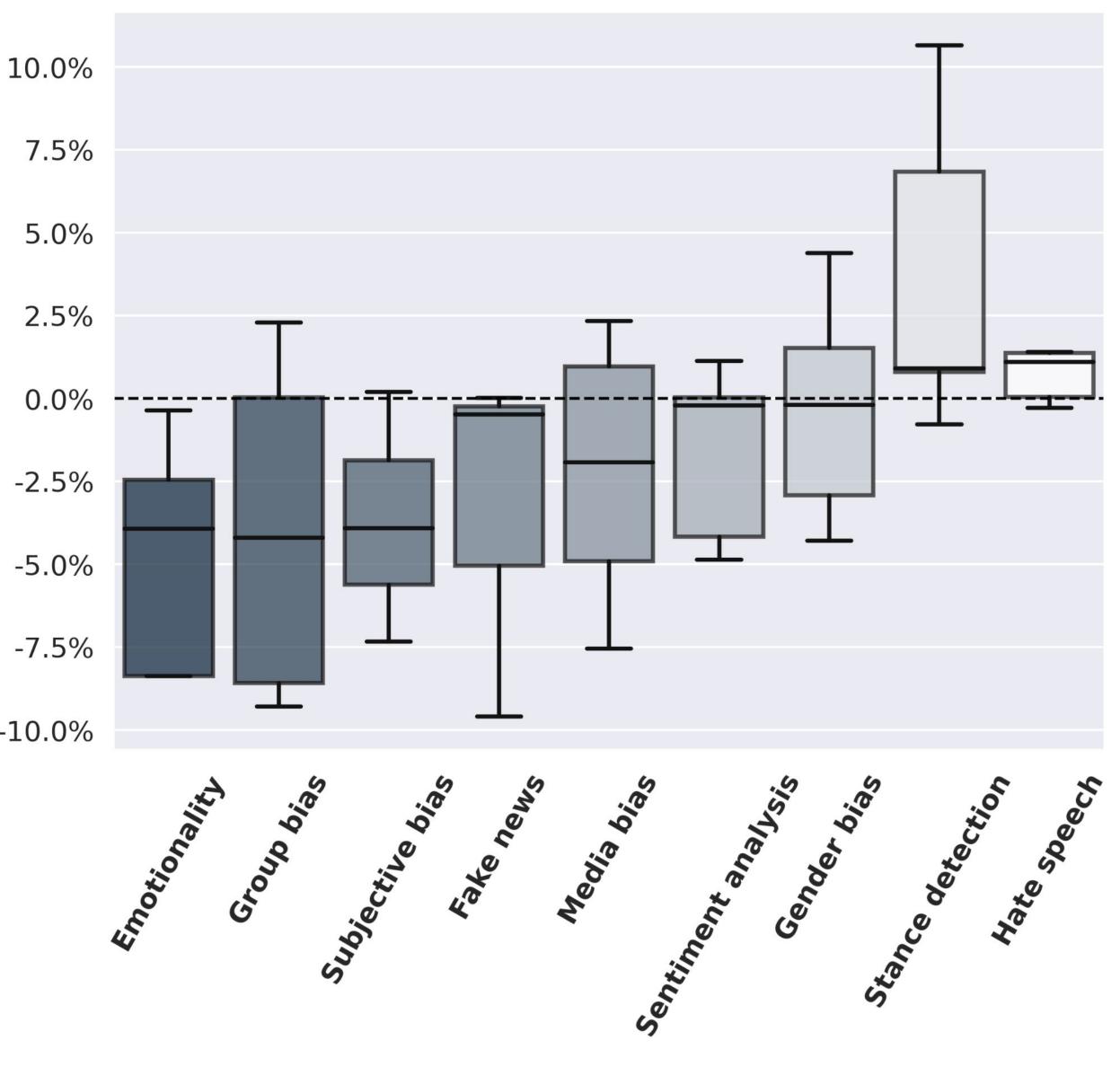


Experiment 3: How do task families affect each other?

Almost all task families	7.5%
underperform in MTL setting	5.0%
The negative transfer is not a	2.5%
reliable measure for large-scale	0.0%
MTL performance	
	-2.5%
	-5.0%

-7.5%

-10.0%





Summary : contributions

- We release an LBM a curated set of datasets for multi-task pre-training
- We release a pre-trained model for downstream tasks
- We show a new state-of-the-art method for media bias dataset, surpassing previous efforts by 3.3%

mediabiasgroup/magpie-babe-ft mediabiasgroup/magpie-pt github.com/magpie-multi-task





Thank you for your attention





References

[1] Aribandi, Vamsi, et al. "Ext5: Towards extreme multi-task scaling for transfer learning." arXiv preprint arXiv:2111.10952 (2021).

[2] Aghajanyan, Armen, et al. "Muppet: Massive multi-task representations with pre-finetuning." arXiv preprint arXiv:2101.11038 (2021).§

[3] Yu, Tianhe, et al. "Gradient surgery for multi-task learning." Advances in Neural Information Processing Systems 33 (2020): 5824-5836.

[4] Ma, Weicheng, et al. "GradTS: a gradient-based automatic auxiliary task selection method based on transformer networks." arXiv preprint arXiv:2109.05748 (2021).



