A Details of Robustness Tests

Table 1 tells more detailed numbers about stress test results with different aspects in Figure 4. (Section 3.2)

B Details of Choice-only test

In Table 2, we show specific numbers for Figure 5 which describe the choice-only results. (Section 3.3)

C Extra Cases

We have shown an example in Section 3.4 for the case study. In this section of the appendix, we provide extra 3 cases for further illustrating that *crossover* and *mutation* encourage models to build contextual reasoning by attending to relevant concepts in the premise.

Example 1 *An MCQ from ROC:*

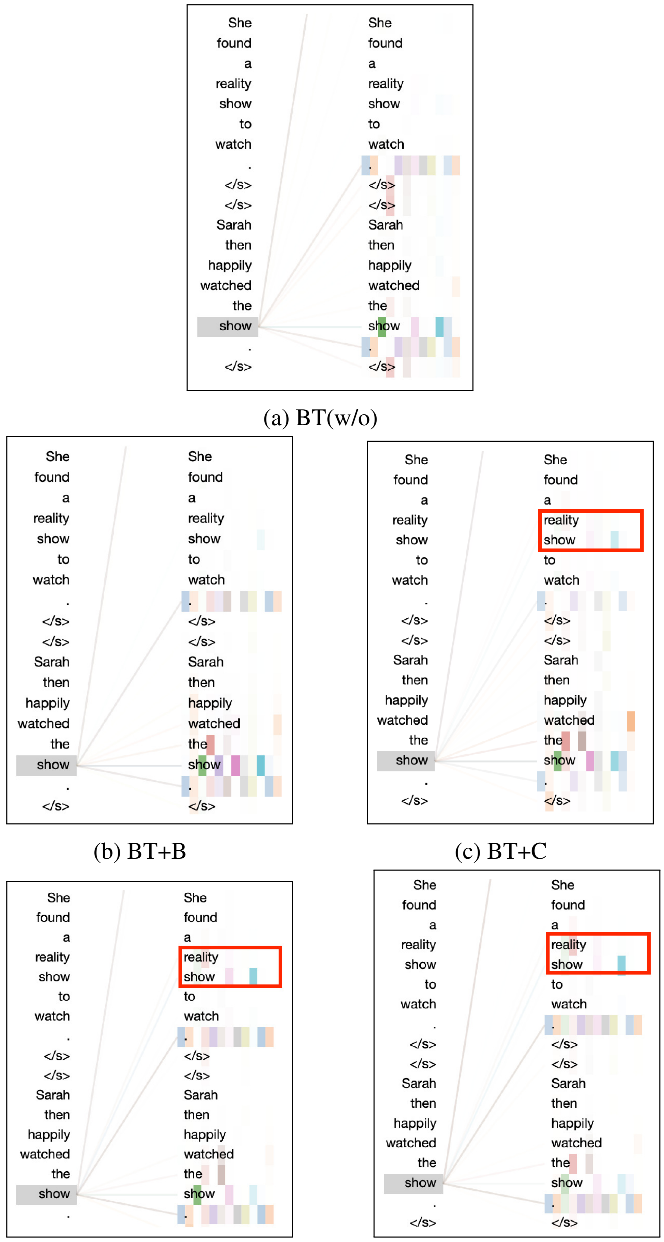
Premise: *Sarah was home alone. She wanted to stay busy. She turned on the TV. She found a reality show to watch.*
Choice 1: *Sarah then happily watched the show.* ✓
Choice 2: *Sarah could not find anything to watch.* ✗

In Example 1, we explore BERT-based models by analyzing their attention maps on this question in Figure 1. There is no positive attention value in front of the fourth sentence, so we intercept it from where it is worth. BERT trained on the original training set fails to pick up the right choice likely due to there being virtually no attention connection between words in the choice and words in the premise. After training with *crossover* data augmentation, the model learns to pay attention to premise and the relationship between premise and choices. i.e., "show" in this example. The rationale behind such a change of attention pattern is that, in an MCQ created by *crossover* operation (Figure 1c), *mutation*(Figure 1d), and the combination of them (Figure 1e) the model needs to combine the information in the premise to effectively distinguish the true "right" choice from the wrong one. However, the light and sparse attention color blocks on the attention map for back-translation in Figure 1b indicate back-translation can not help BERT connect the choice and premise very well in this question.

Example 2 *An MCQ from COPA:*

Premise: *I was furious.*
Choice 1: *I slammed the door upon leaving the house.* ✓
Choice 2: *I checked the mailbox upon leaving the house.* ✗

In human cognition, the word "furious" in premise and "slammed" in the right choice have a strong causal relationship in Example 2. However, from the attention map of the vanilla XLNet model in Figure 2, it is difficult to observe that they are related. In Figure 2, we also observe that the ability of XLNet to use relationships has been strengthened by adding augmented data with all methods we mentioned. Back-translation is worse than the other methods with lighter color blocks.



(a) BT(w/o)

(b) BT+B

(c) BT+C

(d) BT+M

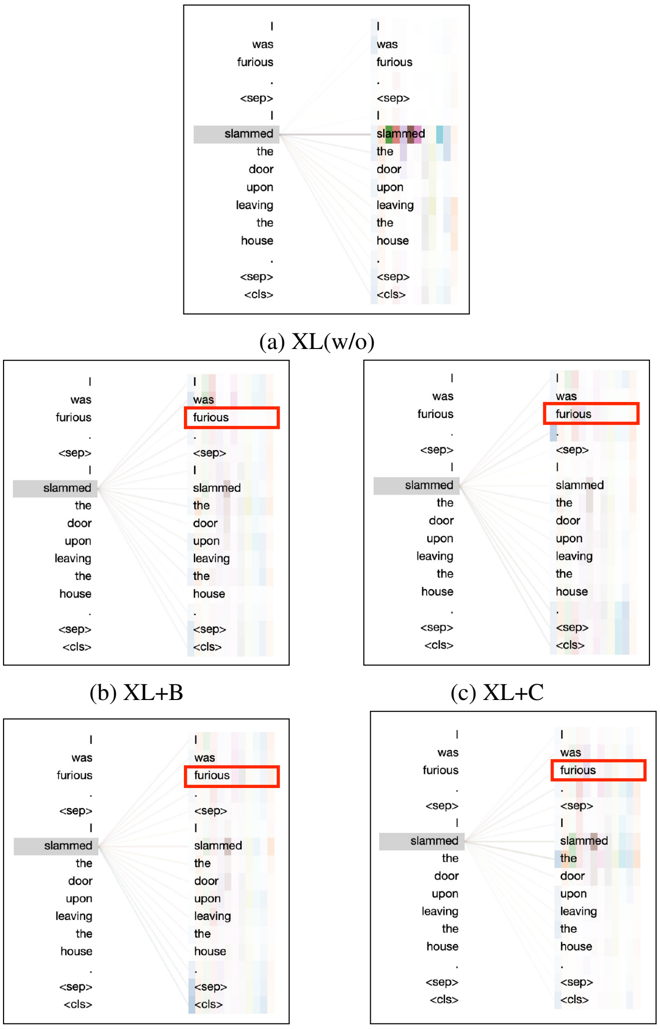
(e) BT+C+M

Figure 1: Attention map on a ROC example for BERT-based models.

Example 3 *An MCQ from ARCT:*

Premise: *I would be happy to support free community college so those who can't afford it can get educated. College should be free.*
Choice 1: *I would be happy to pay tuition for everyone , even some rich kids.* ✓
Choice 2: *I would not be happy to pay for some rich kids tuition at the same time.* ✗

In Example 3, the claim and reason are "College should be



(a) XL(w/o)

(b) XL+B

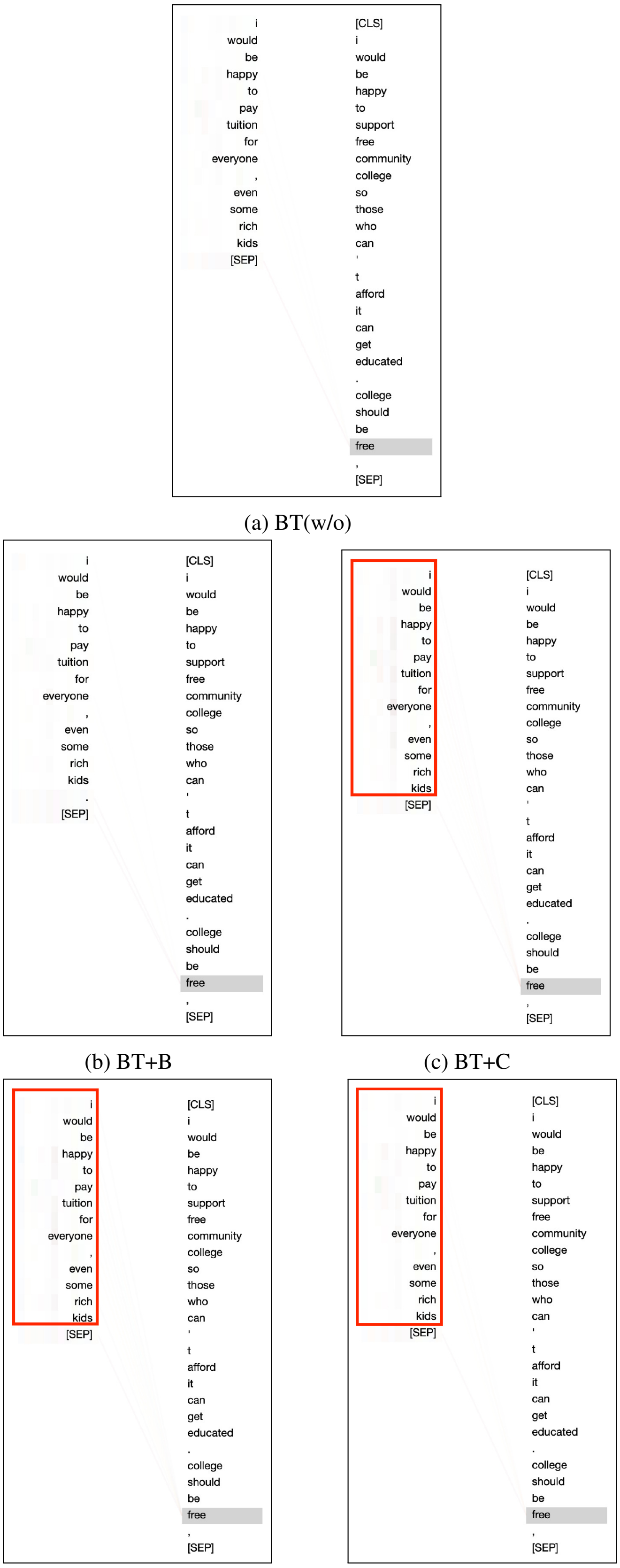
(c) XL+C

(d) XL+M

(e) XL+C+M

Figure 2: Attention map on a COPA example for XLNet-based models.

free" and "I would be happy to support ... who can't afford it can get educated" separately. The word "free" is very important for the claim. It should be very related to the information in the correct warrant, such as "tuition" or "pay" from the knowledge of commonsense reasoning. Unfortunately, "free" has little relationship with the warrant in Figure 3a through the vanilla BERT model. Consistent with our previous conclusion, the improvement effect of *crossover* and *mutation* is more obvious than back-translation. Besides, we also observe that the performance of data augmentation methods is not as obvious as the first two examples. One reason may be that analyzing with this white-box method is not completely reliable. The other may be that the ability of these data augmentation methods to reduce short circuits and to improve the stability of the model is limited. We will continue to study the reason in the future.



(a) BT(w/o)

(b) BT+B

(c) BT+C

(d) BT+M

(e) BT+C+M

Figure 3: Attention map on an ARCT example for BERT-based models.

Dataset	Model	Original	Neg+	Neg-	NER	PR	PI	Voice	All
ROC	BT(w/o)	86.58	82.19	59.57	78.18	76.61	90.48	70.22	79.39
	BT+B	86.75	86.14	60.64	86.46	78.66	94.31	70.22	82.41
	BT+C	87.07	80.08	62.77	97.79	88.07	95.93	70.12	83.33
	BT+M	86.48	81.86	79.79	93.09	85	96.75	96.35	88.54
	BT+C+M	86.75	83.36	77.66	97.24	93.2	97.79	97.53	91.40
	XL(w/o)	90.81	88.65	55.32	86.74	50.89	93.5	51.58	73.70
	XL+B	90.43	87.09	60.64	90.88	65.24	94.54	61.24	78.56
	XL+C	89.47	85.7	60.64	99.17	91.61	99.65	64.6	85.60
	XL+M	90.17	87.37	80.85	96.69	74.09	98.84	98.62	89.25
	XL+C+M	90.22	85.53	81.91	99.17	93.38	99.88	98.22	92.88
	RB(w/o)	92.73	85.7	69.15	75.97	67.94	87.34	60.36	76.39
	RB+B	92.46	88.26	62.77	65.19	58.62	77.93	43.79	69.70
	RB+C	91.18	87.76	74.47	99.17	90.49	96.75	75.64	88.00
	RB+M	92.62	86.7	80.85	86.46	76.14	93.73	99.51	88.06
	RB+C+M	91.88	84.97	86.17	99.45	88.35	98.95	99.21	91.79
COPA	BT(w/o)	62	51.42	-	-	55.79	63.47	56.91	55.64
	BT+B	68.6	64.02	-	-	71.95	69.86	72.36	68.64
	BT+C	72.8	69.72	-	-	93.6	77.17	89.43	80.86
	BT+M	70.4	72.15	-	-	83.23	80.37	99.59	81.63
	BT+C+M	72.4	74.8	-	-	87.5	79.91	95.12	82.80
	XL(w/o)	61.4	34.15	-	-	54.88	60.27	79.67	52.61
	XL+B	63.2	88.62	-	-	55.49	64.84	24.8	63.89
	XL+C	67.8	60.16	-	-	83.84	97.26	79.67	76.26
	XL+M	62.2	59.96	-	-	56.4	94.52	100	72.61
	XL+C+M	67.2	82.32	-	-	76.83	98.17	100	87.00
	RB(w/o)	76.4	80.69	-	-	71.04	76.71	67.07	74.94
	RB+B	77	79.67	-	-	82.62	90.87	77.64	81.94
	RB+C	79	79.47	-	-	88.41	97.72	76.83	84.36
	RB+M	72.6	78.46	-	-	86.89	98.63	100	88.17
	RB+C+M	74	87.2	-	-	93.9	100	99.59	93.46
ARCT	BT(w/o)	63.96	31.65	88.16	80	53.52	60.71	36.78	48.74
	BT+B	68.47	37.04	83.55	60	40.85	48.21	29.31	45.96
	BT+C	68.92	36.7	85.53	100	70.42	76.79	50.57	56.29
	BT+M	67.79	32.32	91.45	80	74.65	82.14	91.95	65.96
	BT+C+M	67.57	36.36	94.08	100	85.92	83.93	91.38	69.27
	XL(w/o)	75.45	39.39	72.37	20	30.99	51.79	38.51	45.83
	XL+B	79.05	45.12	80.26	40	64.79	57.14	46.55	55.23
	XL+C	74.55	39.73	84.21	60	69.01	82.14	54.6	58.15
	XL+M	74.1	41.75	92.11	40	70.42	80.36	95.4	69.80
	XL+C+M	77.03	45.12	95.39	60	85.92	92.86	95.98	74.44
	RB(w/o)	78.83	48.82	78.29	60	46.48	42.86	44.83	53.25
	RB+B	81.31	48.82	76.32	60	47.89	58.93	44.25	54.04
	RB+C	77.93	45.12	79.61	60	64.79	69.64	38.51	54.31
	RB+M	77.03	56.57	88.16	40	78.87	85.71	96.55	76.29
	RB+C+M	75	42.42	93.42	60	74.65	87.5	93.68	70.99
RECLOR	BT(w/o)	45.6	21.87	39.5	-	17.39	42.22	11.45	22.83
	BT+B	48.6	26.93	42.86	-	15.22	42.22	10.69	24.94
	BT+C	47	27.47	56.3	-	63.04	95.56	59.54	49.89
	BT+M	46.8	26.13	53.78	-	56.52	55.56	64.89	46.08
	BT+C+M	43.6	22.13	55.46	-	78.26	77.78	80.92	53.14
	XL(w/o)	56	25.07	44.54	-	30.43	26.67	13.74	24.93
	XL+B	57	39.2	39.5	-	28.26	42.22	20.61	33.37
	XL+C	54.4	28.53	60.5	-	73.91	91.11	51.15	48.87
	XL+M	53.6	29.33	66.39	-	63.04	68.89	77.86	54.55
	XL+C+M	54.2	33.07	64.71	-	65.22	75.56	77.1	56.47
	RB(w/o)	50.4	19.47	36.97	-	20.65	20.88	6.46	18.25
	RB+B	51	22.13	39.5	-	28.26	28.89	9.92	22.03
	RB+C	50.4	33.07	60.5	-	89.13	82.22	54.2	51.91
	RB+M	52	31.47	68.91	-	73.91	80	87.79	60.53
	RB+C+M	48.4	26.4	67.23	-	67.39	77.78	81.68	55.77

Table 1: Detailed Breakdown of Robustness Tests on 4 models with or without(w/o) data augmentation. +B = augmented with backtranslation, +C = augmented with crossover, +M = augmented with mutation. Robustness Tests includes the following stress tests: Neg+=negation-add, Neg-=negation-remove, NER, PR=pronoun-replacement, PI=Pronoun-instantiation, Adv=adverbial, Voice, Syn=synonym.

Model	**ROC**	**COPA**	**ARCT**	**RECLOR**
BT (w/o)	54.62	51.4	61.94	42.8
BT+B	58.26	50.8	64.41	39.2
BT+C	51.2	48.2	55.63	30.8
BT+M	51.79	48.8	55.18	38
BT+C+M	43.56	49.4	52.03	33.8
XL (w/o)	71.14	57	65.99	42.2
XL+B	73.17	60	66.89	41.4
XL+C	65.63	55	55.86	34.2
XL+M	71.94	57.8	66.22	42
XL+C+M	66.22	58.4	62.84	35
RB (w/o)	73.97	59.4	67.79	30.2
RB+B	74.77	61.4	69.37	42.2
RB+C	73.06	58.4	68.47	34.6
RB+M	70.34	56	61.49	40
RB+C+M	71.3	54.8	67.79	32.2

Table 2: Choice-only test for transformer-based models on 4 datasets. All numbers are percentages (%)