

# Appendices

## A Super-Clusters

Table 4 (below) shows our eight super-clusters over TACRED sentence groups described in Section 3.2. Each group appears in exactly one cluster.

## B Re-TACRED Corrected Prediction Errors

Table 5 (below) presents five handpicked sentences showing different types of errors that a SpanBERT model trained on TACRED makes on the Re-TACRED test split, and that the same model trained on Re-TACRED is able to correct on the same split.

## C Effect of Non-Refined Labels

We also examine how models differ based on our *non-refined* label re-annotations. Non-refined relations are any for which we did not alter the TAC KBP relation definitions for (i.e. any label not discussed in Section 3.3). We conduct this analysis by comparing model performance over different combinations of train and test splits from TACRED and Re-TACRED.

We denote train splits using  $[\cdot]_{\text{train}}$  and test splits using  $[\cdot]_{\text{test}}$ , where  $[\cdot]$  is either TACRED or Re-TACRED (e.g.,  $\text{TACRED}_{\text{train}}$ ). All models are then trained on  $\text{TACRED}_{\text{train}}$  or  $\text{Re-TACRED}_{\text{train}}$ , and evaluated on  $\text{TACRED}_{\text{test}}$  or  $\text{Re-TACRED}_{\text{test}}$ . Our results are shown in Table 7.

The results show several interesting differences between TACRED and Re-TACRED. First, all methods trained and evaluated on TACRED obtain significantly higher performance on the non-refined labels than over the full label set. We attribute this increase to the fact that these relations are less ambiguous compared than the refined ones. Second, methods trained on  $\text{TACRED}_{\text{train}}$  achieve better performance on  $\text{Re-TACRED}_{\text{test}}$  than on  $\text{TACRED}_{\text{test}}$ . This is consistent with the findings in Alt, Gabryszak, and Hennig (2020), and suggests that: (i) TACRED may be under-estimating model performance, and (ii) large improvements can be obtained simply by evaluating models on higher quality annotations. Third, methods trained on  $\text{Re-TACRED}_{\text{train}}$  and evaluated on  $\text{TACRED}_{\text{test}}$  perform worse than those evaluated on  $\text{Re-TACRED}_{\text{test}}$ . A deeper inspection of the data reveals that such models exhibit significantly fewer correct positively labeled predictions in  $\text{TACRED}_{\text{test}}$  than in  $\text{Re-TACRED}_{\text{test}}$ , result-

Super-Cluster	Subject Type	Object Types
org2miscmulti org2locmulti org2org org2per	ORGANIZATION	URL, DATE, NUMBER, RELIGION, IDEOLOGY, MISC CITY, COUNTRY, STATE_OR_PROVINCE, LOCATION ORGANIZATION PERSON
per2miscmulti per2locmulti per2org per2per	PERSON	TITLE, DATE, CRIMINAL_CHARGE, RELIGION, NUMBER, CAUSE_OF_DEATH, DURATION, MISC NATIONALITY, COUNTRY, STATE_OR_PROVINCE, CITY, LOCATION ORGANIZATION PERSON

Table 4: Mappings between super-clusters and sentence groups. Sentence groups are defined by the pair, (SUBJECT\_TYPE, OBJECT\_TYPE), which describes the subject and object type of all sentences in the group. The leftmost column denotes each super-cluster name. The middle column lists the two possible subject types (ORGANIZATION and PERSON), while the rightmost column shows the list of object types whose pairing with the corresponding subject type is an element of the respective super-cluster. For instance, (PERSON, TITLE) represents the sentence group where all sentence subject types are PERSON and all object types are TITLE. From the table, this group is an element of the per2miscmulti super-cluster.

Error Type	Sentence	TACRED Prediction	Correct Label
Neg → Pos	"...[Motorola] <sub>OBJ</sub> (where [he] <sub>SUB</sub> was also a VP) ..." "[Filmmaker] <sub>OBJ</sub> and attorney [Sarah Kunstler] <sub>SUB</sub> ..." "...[National Taiwan Symphony Orchestra] <sub>SUB</sub> (NTSO)...an [NTSO] <sub>OBJ</sub> spokesman..."	NO_RELATION NO_RELATION NO_RELATION	PERSON:EMPLOYEE_OF PERSON:TITLE ORGANIZATION:ALTERNATE_NAMES
Pos → Neg	"[His] <sub>SUB</sub> [therapist] <sub>OBJ</sub> told him to politely decline, "which helped."	PERSON:TITLE	NO_RELATION
Pos → Pos	"...[her] <sub>SUB</sub> stepchildren, Susan,..., Stephen and [Maggie] <sub>OBJ</sub> Mailer;..."	PERSON:SIBLINGS	PERSON:CHILDREN

Table 5: Five handpicked sentences from the Re-TACRED test split that a TACRED-trained SpanBERT model misclassifies but a Re-TACRED-trained SpanBERT method correctly classifies. Sentence subjects and objects are defined as in Section 1, and the complete TACRED-trained SpanBERT predictions and gold labels are provided. Additionally, each sentence is marked by a specific "error type" (the leftmost column) describing whether the error is due to predicting a negative sentence label when the correct relation is positive (Neg → Pos), predicting a positive relation when the correct label is negative (Pos → Neg), or inferring the incorrect positive label (Pos → Pos).

Label Origin	Label	Sentence Definition
TAC KBP	PERSON:ALTERNATE_NAMES PERSON:OTHER_FAMILY NO_RELATION	Names used to refer to the assigned person that are distinct from the "official" name. Family other than siblings, parents, children, and spouse (or former spouse). There is no relation between the subject and object entity.
New	PERSON:IDENTITY	Both entities refer to the same person.

Table 6: TAC KBP sentence definitions of PERSON:OTHER\_FAMILY, PERSON:ALTERNATE\_NAMES, and NO\_RELATION, and the definition of our new PERSON:IDENTITY label.

Model	(Train Split, Test Split)	Metrics		
		F1	Precision	Recall
PA-LSTM	(TACRED <sub>train</sub> , TACRED <sub>test</sub> )	72.3	71.3	73.3
	(TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	74.8	80.1	70.2
	(Re-TACRED <sub>train</sub> , TACRED <sub>test</sub> )	65.9	59.4	74.2
	(Re-TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	77.6	77.1	78.1
C-GCN	(TACRED <sub>train</sub> , TACRED <sub>test</sub> )	72.6	71.1	74.3
	(TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	74.8	79.6	70.6
	(Re-TACRED <sub>train</sub> , TACRED <sub>test</sub> )	69.5	64.1	75.8
	(Re-TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	79.6	81.2	78.2
SpanBERT	(TACRED <sub>train</sub> , TACRED <sub>test</sub> )	75.0	74.7	75.3
	(TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	78.9	84.9	73.7
	(Re-TACRED <sub>train</sub> , TACRED <sub>test</sub> )	72.2	66.3	79.3
	(Re-TACRED <sub>train</sub> , Re-TACRED <sub>test</sub> )	84.9	85.1	84.7

Table 7: Results for multiple RE models (leftmost column) on different train-and-evaluation combinations. Each combination is represented by a pair of the form (“train split”, “test split”). For instance, (TACRED<sub>train</sub>, Re-TACRED<sub>test</sub>) indicates that a method is trained on the TACRED train partition and evaluated on the Re-TACRED test split. The remaining columns show metric results.

ing in substantially lower scores. For instance, SpanBERT trained on Re-TACRED<sub>train</sub> exhibits 49.4% fewer correct positively labeled instances in TACRED<sub>test</sub> compared to Re-TACRED<sub>test</sub>. This highlights the effects of our label changes described in Section 4.1: many positively labeled sentences in Re-TACRED are either negatively labeled or assigned another positive relation in TACRED. Fourth, models trained and evaluated on Re-TACRED perform significantly better than any other combination. Thus, while methods trained on TACRED<sub>train</sub> achieve performance boosts when testing on Re-TACRED<sub>test</sub> (compared to evaluating on TACRED<sub>test</sub>), training on Re-TACRED<sub>train</sub> is critical to achieving the strongest performance on Re-TACRED<sub>test</sub>.

## D Hyperparameters

We train all our TACRED-based models using the reported hyperparameters by their respective contributors. All hyperparameter details for our Re-TACRED-based methods can be found below. Additionally, all texttt required to reproduce our results and our new dataset can be found in our repository at <https://github.com/gstoica27/Re-TACRED>. We train our PA-LSTM and C-GCN models on a single Nvidia Titan X GPU, and utilized a single Nvidia Tesla V100 GPU to train SpanBERT.

**Re-TACRED PA-LSTM.** We perform an extensive grid-search over LSTM hidden dimension sizes from {100, 150, 200, 250, 300}, LSTM depth of {1, 2, 3}, word dropout from {0.0, 0.01, 0.04, 0.1, 0.25, .5}, and position-encoding dimension size among {15, 20, 25, 30, 50, 75, 100}. However, we observe the best performance with the hyperparameters reported by Zhang et al. (2017). In addition, we employ the equivalent training strategy as is reported in Zhang et al. (2017) (detailed under Appendix B of their publication).

**Re-TACRED C-GCN.** Similar to our PA-LSTM experiments, we find that keeping the majority of hyperparameters equivalent to those reported by Zhang, Qi, and Manning (2018) yield the best results. The sole parameter we alter is in-

creasing the residual neural network hidden dimension from 200 to 300. In addition, we use the same training procedure as Zhang, Qi, and Manning (2018) (described in Appendix A of their publication).

**Re-TACRED SpanBERT.** For SpanBERT, we perform a grid-search over learning rate sizes in {1e-6, 2e-6, 2e-5} and warm-up proportions in {.1, .2}. However, we observe the best performance using the reported parameters by Joshi et al. (2020). We refer readers to Joshi et al. (2020) (detailed in Section 4.2 and Appendix B in their publication) for further details on training strategy.

## E Amazon Mechanical Turk

Our annotation process can be broken down by super-cluster, where each cluster represents as distinct annotation task. Overall, we had 8 such tasks (number of super-clusters), and each consisted of 2-4 labeling rounds. The first round gathered 2 distinct annotations for every sentence in the respective super-cluster. Any disagreements were then given to a third annotator in the second round. Then, if necessary, the third and fourth label rounds asked an additional worker to annotate remaining disagreements. Sentences to be annotated in label rounds were grouped into Human Intelligence Tasks (HIT). Each HIT consisted of 5 sentences, of which one was gold (i.e., its correct label was known). We priced HITs competitively at \$.15 per HIT. We utilized annotations from 243 total workers, and the total time taken to sequentially annotate all our label rounds across all annotation tasks was  $\approx 784$  hours. While this number is large, it is important to note that many labeling rounds were completed in parallel, significantly decreasing the overall time.

## F Relation Alterations

As presented in Section 3.3, we observed substantial label inconsistencies among sentences describing identity pronominal relationships between entities. These sentences were frequently either classified as either PERSON:OTHER\_FAMILY or NO\_RELATION due to the ambiguity of the TAC KBP guidelines. In this section we further motivate the creation of the PERSON:IDENTITY relation by describing how the original TAC KBP label documentation is insufficient. We do this by presenting the TAC KBP definitions of each affected relation, and explaining their shortcomings.

### F.1 Definitions

All label definitions are given in Table 6.

### F.2 Encoding Identity Shortcomings

The TAC KBP relations above cover a wide array of interpersonal relationships between two entities. However, classifying identity sentences is notably difficult because neither definition explicitly accounts for the relation. While PERSON:ALTERNATE\_NAMES describes two entities that refer to the same person, these entities must be *different names*. Pronominal reference is not covered in the definition. In contrast, PERSON:OTHER\_FAMILY captures general familial relationships. Does this include pronominal relations? Based

on the original TACRED label assignments, the answer to this question appeared subjective: it depended on the crowdworkers' interpretations. If an annotator interpreted pronominal relations as familial, PERSON:OTHER\_FAMILY was chosen, the sentence would be classified as NO\_RELATION.

In an effort to address this issue, we first create the new PERSON:IDENTITY relation (described in Table 6), which explicitly covers pronominal relationships between sentence entities. Second, because PERSON:IDENTITY is a generalization of PERSON:ALTERNATE\_NAMES, we absorb PERSON:ALTERNATE\_NAMES in PERSON:IDENTITY. We then bar PERSON:OTHER\_FAMILY from accepting pronominal relationships while leaving the rest unchanged.