

Relation Extraction

Relation Extraction (RE): Determine Relationships between **subjects** and **objects** in text

"Farland joined the FBI in 1942."
per:employee_of

- One of the *largest* and *most-popular* crowd-sourced RE datasets
- Collected from 2009-2014 TAC KBP [2] evaluations
- *Quality*: .54 Fleiss' Kappa from 761 randomly sampled annotations
- 106,264 instances spread among 42 relations

TACREV [3]

- Manually verified 5K most misclassified TACRED evaluation instances from 49 RE models
- Observed >50% *label error* amongst these examples
- Achieved Fleiss' Kappas of .80 on dev & .87 on test
- Revised dataset improved average F1-score by 8.1%
- However, generalization limited by bias

Re-TACRED

- **Comprehensive:** We verify *entire* TACRED dataset
- **Improved Annotation:** We deploy an improved crowd-sourced annotation strategy
- **High Quality:** We achieve .77 Fleiss' Kappa over *entire* dataset
- **Performance:** We improve model F1-score performance on average by 13%

Improved Annotation Strategy

Quality Assurance

All workers must be:

- **Experienced:** Have previously completed at least 500 tasks
- **Reliable:** Have at least 95% task approval rate
- **Specialized:** Have passed custom qualification exams for each super-cluster
- **Careful:** Have correctly answered at least 80% of observed gold-sentences

Wrong Type Handling

- [1] and [3] label sentences by providing workers *all type-compatible* relations with sentence entities
- However, all candidate relations are incorrect when assigned entity type is wrong (occurred in 5% of a random sample of size 1K)

"Thomas More Law Center" → PERSON or ORGANIZATION?

We address this issue in two ways:

1. We extend each label set to include a "wrong_type" relation
2. We preempt "wrong_type" assignments by merging frequently mis-typed entity pairs into "super-clusters"

(PERSON | CITY, STATE/PROVINCE, COUNTRY, LOCATION) → per:locmulti

Relation Refinements

(i) Explicitly Enabling Identity Relations

"Holly showed off her jewelry."
per:identity

(ii) Merging Very Similar Relations

"... Badr is the armed wing of the ISCI."
org:member_of or org:parents?

(iii) Relaxing Challenging Criteria

"Facebook in NYC."
org:city_of_headquarters?

(iv) Enforcing Mutual-Exclusivity

"He is a native of Pittsburgh, PA."
per:city_of_birth or per:city_of_residence?

Results

Dataset	Metric	Models		
		PALSTM*	C-GCN*	SpanBERT*
TACRED	Precision	68.1	68.5	70.1
	Recall	64.5	64.4	69.2
	F1	66.2	66.3	69.7
Re-TACRED	Precision	78.3	79.7	84.6
	Recall	77.6	78.5	83.9
	F1	77.9	79.1	84.2
Change %	Precision	+12.2	+11.2	+14.5
	Recall	+13.1	+14.1	+14.7
	F1	+11.7	+12.8	+14.5

Model	Dataset	Refined Labels			
		(i)	(ii)	(iii)	(iv)
PALSTM*	TACRED	46.7	21.2	55.9	51.9
	Re-TACRED	87.6	48.8	68.8	53.4
	Change %	+30.9	+27.6	+12.9	+1.5
C-GCN*	TACRED	14.6	22.7	56.7	51.5
	Re-TACRED	88.1	51.9	73.7	54.2
	Change %	+73.5	+29.2	+17.0	+2.7
SpanBERT*	TACRED	44.1	51.9	66.8	55.9
	Re-TACRED	91.7	65.1	74.0	69.8
	Change %	+56.6	+13.2	+7.2	+13.9

Model	Train Split	Test Split	Metrics		
			F1	Precision	Recall
PALSTM*	TACRED _{train}	TACRED _{test}	72.3	71.3	73.3
	TACRED _{train}	Re-TACRED _{test}	73.3	76.7	70.2
	Re-TACRED _{train}	TACRED _{test}	68.3	65.9	70.9
	Re-TACRED _{train}	Re-TACRED _{test}	75.9	75.8	76.1
C-GCN*	TACRED _{train}	TACRED _{test}	72.6	71.1	74.3
	TACRED _{train}	Re-TACRED _{test}	73.2	76.0	70.6
	Re-TACRED _{train}	TACRED _{test}	69.2	68.5	69.8
	Re-TACRED _{train}	Re-TACRED _{test}	77.3	78.2	76.5
SpanBERT*	TACRED _{train}	TACRED _{test}	75.0	74.7	75.3
	TACRED _{train}	Re-TACRED _{test}	76.8	81.2	72.8
	Re-TACRED _{train}	TACRED _{test}	74.1	70.9	77.7
	Re-TACRED _{train}	Re-TACRED _{test}	84.1	85.0	83.1