Dataset	Strict			Relaxed		
	Local	Joint	Global	Local	Joint	Global
WikiBios	.54 ±.09	.60 ±.09	.68 ±.09	.61 ±.09	.66±.09	.76±.08
WikiWars	.75 ±.08	.82 ±.07	n/a	.84±.07	.86 ±.06	n/a
News	.58 ±.09	.64 ±.09	.67 ±.09	.69 ±.09	.75 ±.08	.79 ±.08

Table 5: Precision at 95% Wilson interval for different methods.

temponym	Yago	Our model	Time scope	Eval
the Great Recession	`GreatRecession`	`GreatRecession`	[2007, 2009]	Correct
the second term of Merkel		⟨`AngelaMerkel, holdsPosition, ChancellorOfGermany`⟩	[2005, now]	Okay
Obama's graduation		⟨`BarackObama, graduatedFrom, HarvardLawSchool`⟩	[1991, 1991]	Correct
the first Winter Olympics to be hosted by Russia		`2014WinterOlympics`	[2014, 2014]	Correct
Putin's presidency		⟨`VladimirPutin, holdsPosition, PrimeMinisterOfRussia`⟩	[2008, 2012]	Wrong

Table 6: Example of temponyms mapped by our system vs Yago.

global model is not applicable here, as it requires multiple documents on the same or overlapping topics. In contrast, the 22 WikiWars articles are fairly disjoint in their contents and are not mentioned in GDELT news corpus much.

The evaluation is done by marking a mapping with three different scores; Correct, Okay, Wrong. Table 6 shows some examples of Correct, Okay, and Wrong matches. A mapping is considered "Okay" if it has partially correct match. For example, the temponym *the second term of Merkel* is mapped to the correct fact ⟨`AngelaMerkel, holdsPosition, ChancellorOfGermany`⟩ but it is marked as "Okay". The reason is that the second term of Angela Merkel is actually from 2009 to 2013 rather than from 2005 to now.

Precision is calculated in two different ways:

- For *strict* precision, we count the *Okay* mappings as wrong:

$$Precision_{strict} = \frac{\#Correct}{\#Total\ mappings}$$

- For *relaxed* precision, we count the *Okay* mappings as true:

$$Precision_{relaxed} = \frac{\#Correct\ +\ \#Okay}{\#Total\ mappings}$$

Temporal enrichment. To show our methods can substantially add extra temporal information to documents, we compare our methods to well known HeidelTime tagger by running the both methods on WikiWars and WikiBios datasets. We compare the number of normalized TempEx's by HeidelTime tagger to the number of normalized temponyms by our methods.

Knowledge enrichment. The temponym resolution task has two important outcomes in terms of knowledge enrichment: First, temponym resolution enriches the KB by providing additional paraphrases for known events and facts. For example, our methods can add the temponym *"the largest naval battle in history"* as an alias for the event `BattleOfLeyteGulf`, or *"Obama's presidency"* as an alias for the fact `BarackObama, holdsPosition, presidentOfUS`. We add this new knowledge to the KB through "rdfs:label" triples that have a temponym phrase as subject, and an event or a fact identifier as object. We call this task *Knowledge paraphrasing.*

We assess the knowledge paraphrasing, by comparing outcome of our methods to Yago2 knowledge base in terms of paraphrase coverage. Therefore, we randomly chose 100 correctly mapped temponyms and checked how many temponyms are already known to Yago2, either as an event entity or as a fact. We built a text index over all events and facts in Yago2 and their alias names. For the randomly chosen 100 temponyms, we queried this index for each temponym and took the top-10 most relevant results for each query. We manually checked all these returned answers, thus considering also approximate matches for a fair comparison in favor of Yago2.

Second, temponym resolution also enhances the fact extraction tools for knowledge bases by providing them additional temporal and semantic clues. For example, in the sentence "Ronaldo joined Real Madrid during second term of Florentino Pèrez" a fact extraction tool can extract the fact ⟨`f1:CristianoRonaldo, playsFor, RealMadrid`⟩ but no time scope attached. Temponym resolution would normalize the phrase *second term of Florentino Pèrez* to time [2009, now] by mapping it to the fact ⟨`f2:FlorentinoPèrez, isPresidentOf, RealMadrid, [2009, now]`⟩. Thus, a fact extraction tool can temporally link two facts as a new fact ⟨`f3:f1, validDuring, f2`⟩. We call this task *Knowledge linking.*

For the knowledge linking task, we carried out an extrinsic case study. We modified the PATTY's binary fact extraction patterns to ternary patterns so that they can take a temponym as an argument. For example, the PATTY pattern ⟨*subject, verb, object*⟩ is modified to ⟨*subject, verb, object, preposition, temponym*⟩. Thus, a fact extracted from ⟨*subject, verb, object*⟩ triple can be linked to the particular temponym through a particular preposition such as "during, before, after". For this task, we ran PATTY tool on its extraction corpus. We report the number of facts that