Disambiguating spatial prepositions: the case of geospatial sense detection

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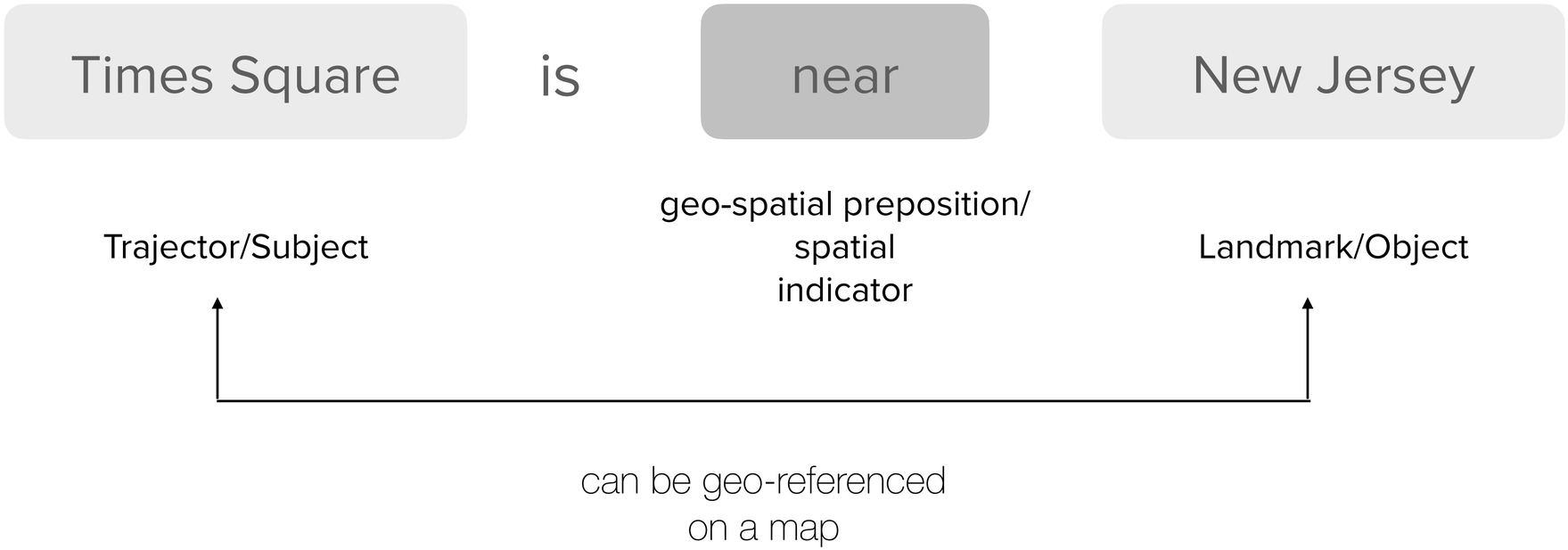
Problem Statement

Disambiguate *geo-spatialness* of a preposition

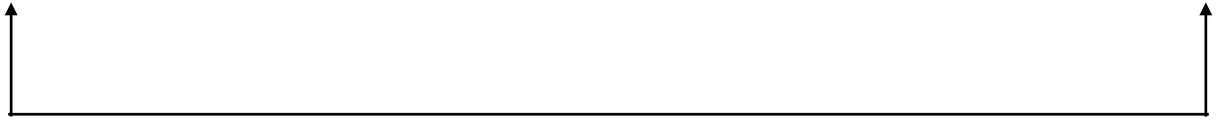


Problem statement

Disambiguate *geo-spatialness* of a preposition

The book is on the table

Trajector/Subject — spatial preposition — Landmark/Object



cannot be geo-referenced on a map

I can count on him

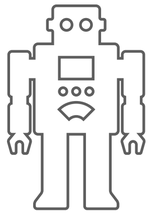
non-spatial preposition

Applications

Direction Understanding

Exit this room and turn right. Go down the hallway past the elevators. The lobby is straight ahead.

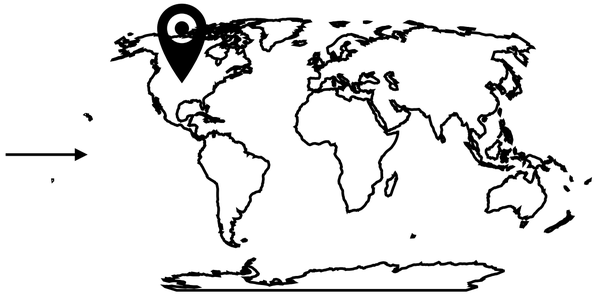
Understood!



Reference: Kollar et al

Automated Geo-referencing

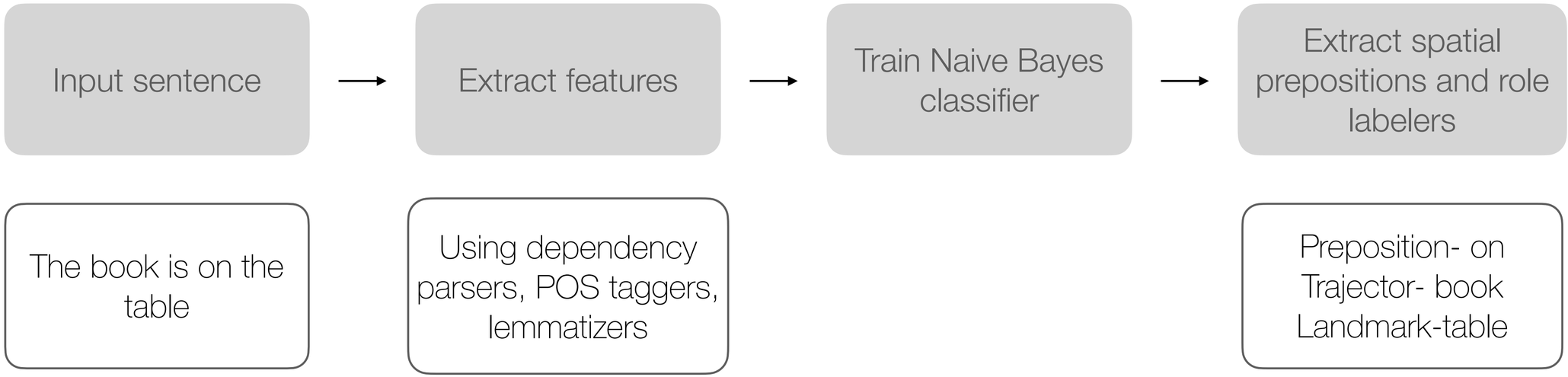
‘Near’ New York



Previous Work

Kordjamshidi et al

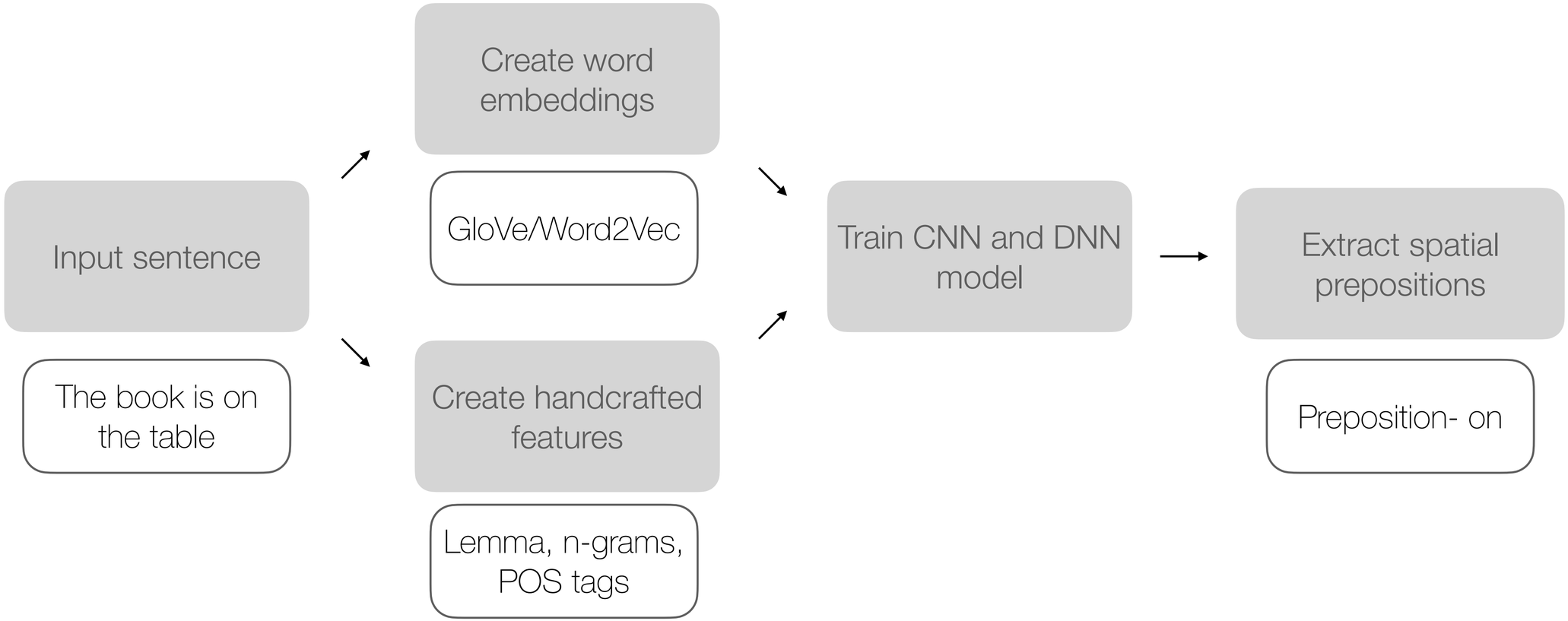
Introduces the notion of spatial role labelling to extract spatial relations in text



Previous Work

Hassani et al

Distinguishes between generic and non spatial sense of prepositions in text.



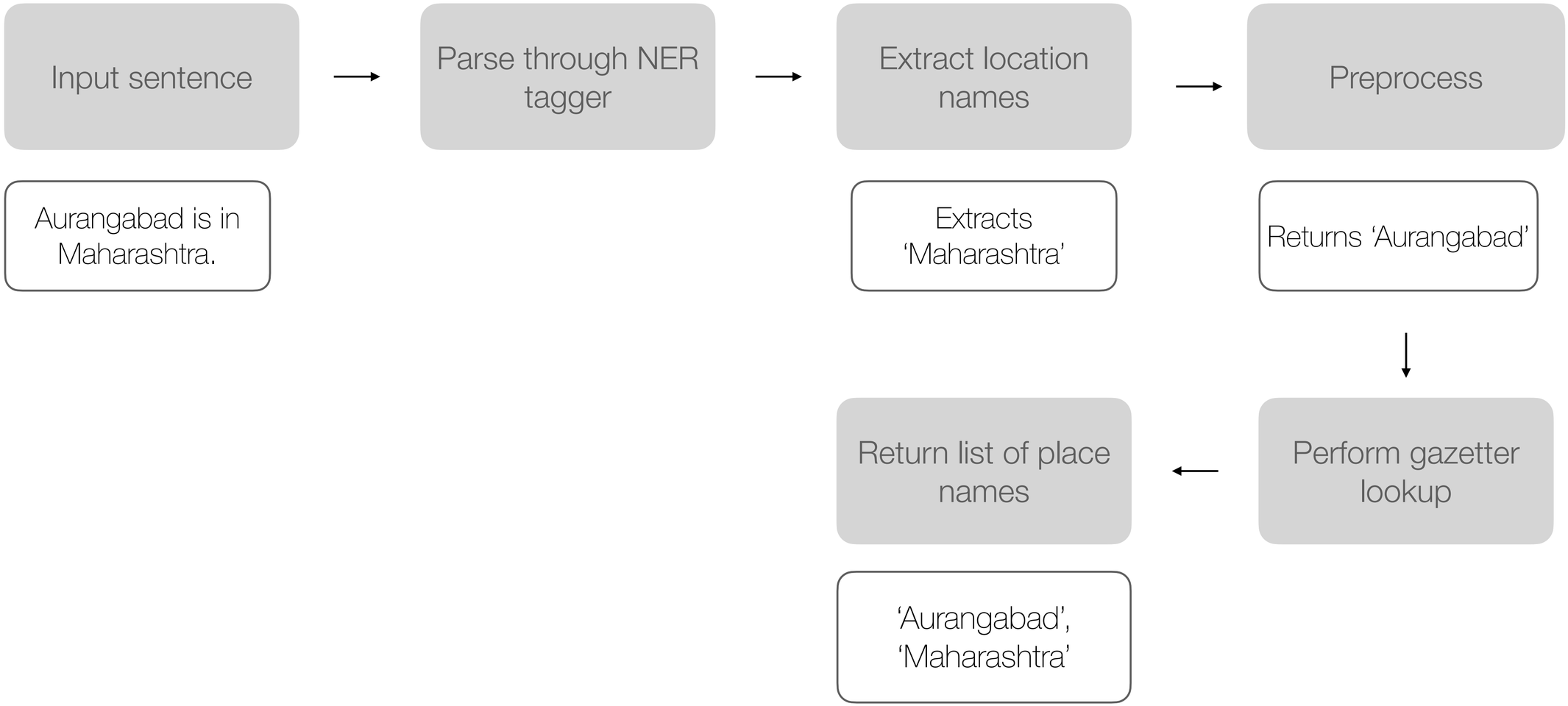
Dataset

We hand annotated over 18000 sentences derived from the Nottingham Corpus of Geospatial Language.

Preposition	Sense
Peoples Republic **of** China	Non-spatial
After 50m you will reach a road	Geo-spatial
She is sitting **at** the back of a room	Spatial

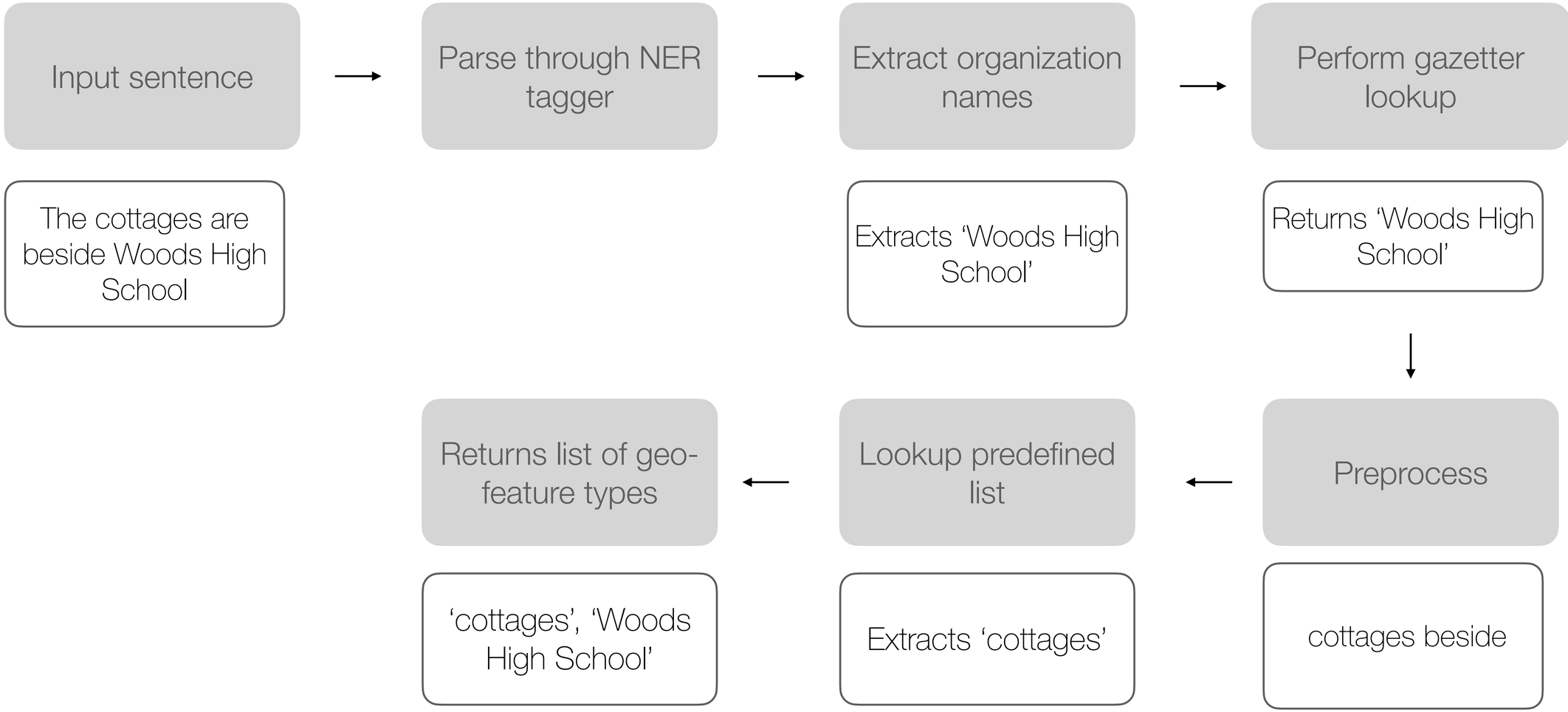
Approach

Geo-parser (Place names)



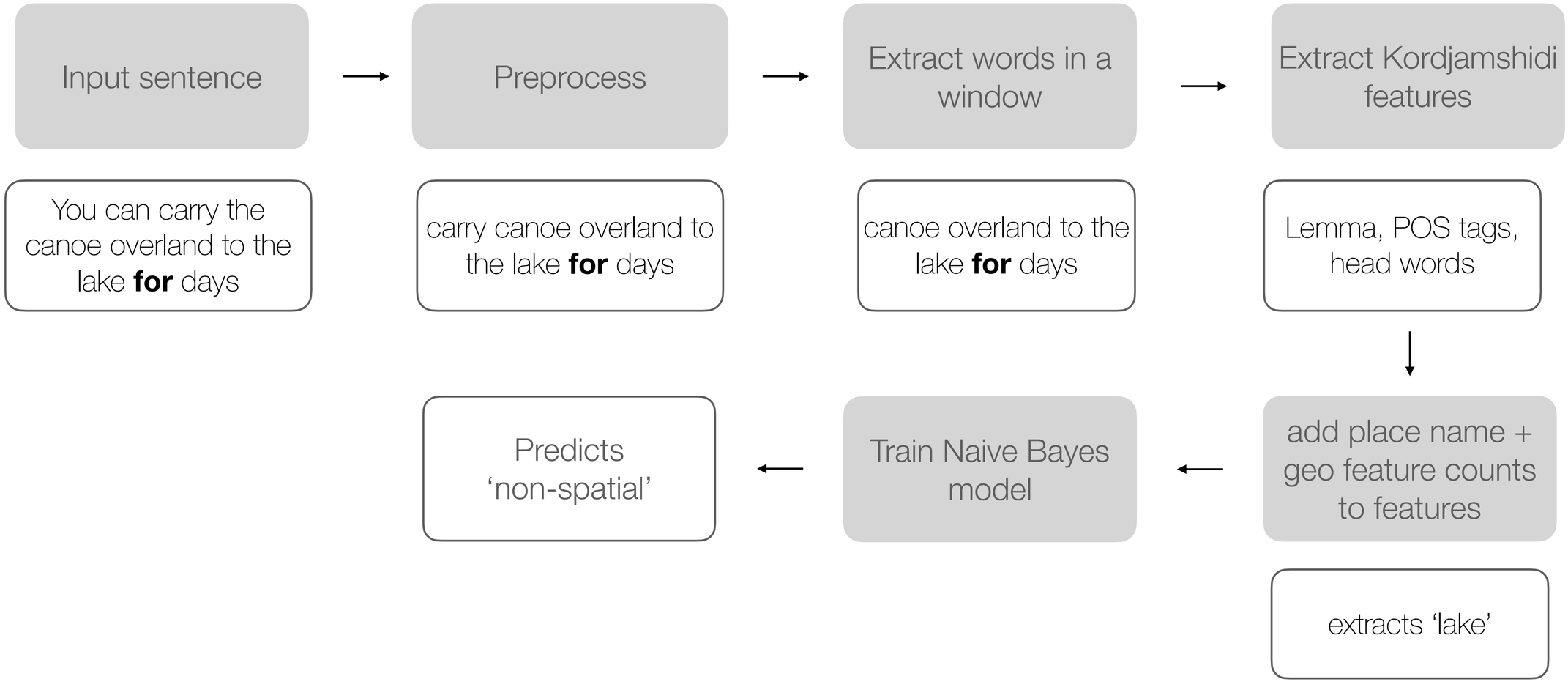
Approach

Geo-parser (Geo-feature types)



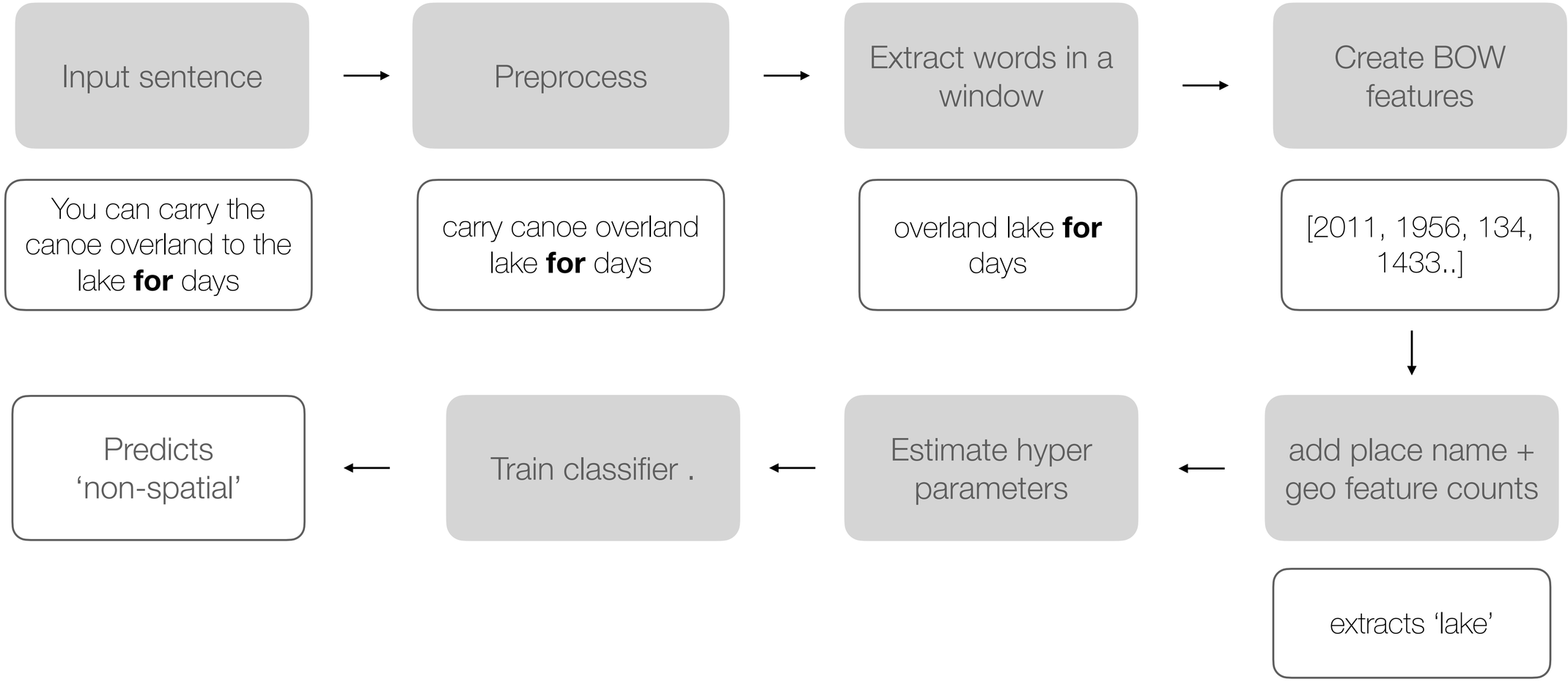
Approach

Baselines



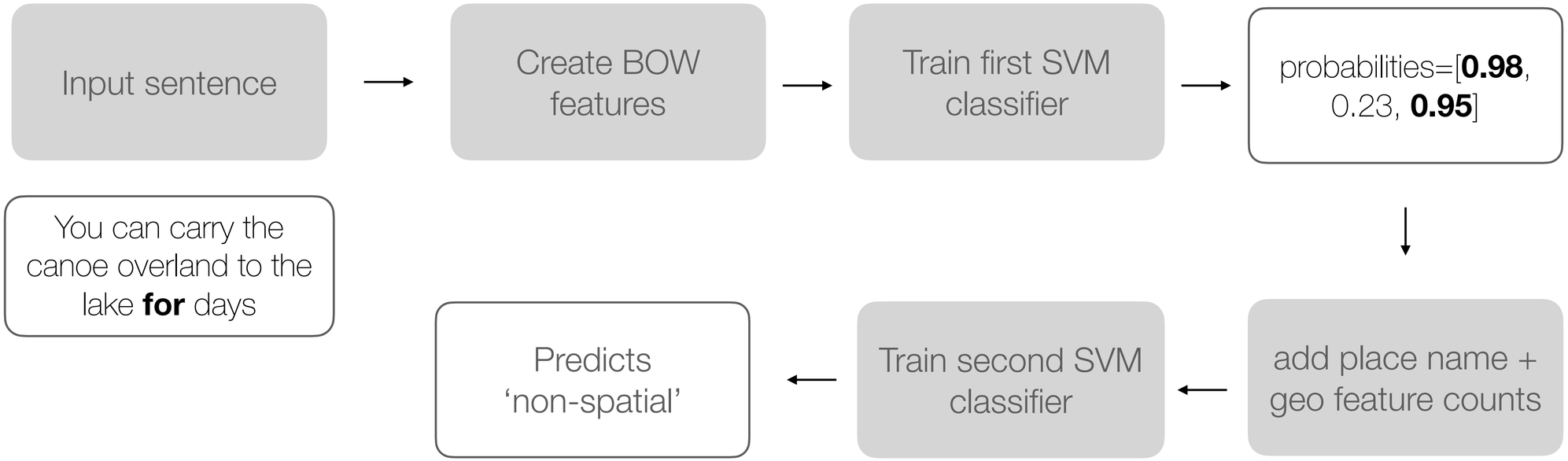
Approach

Baselines



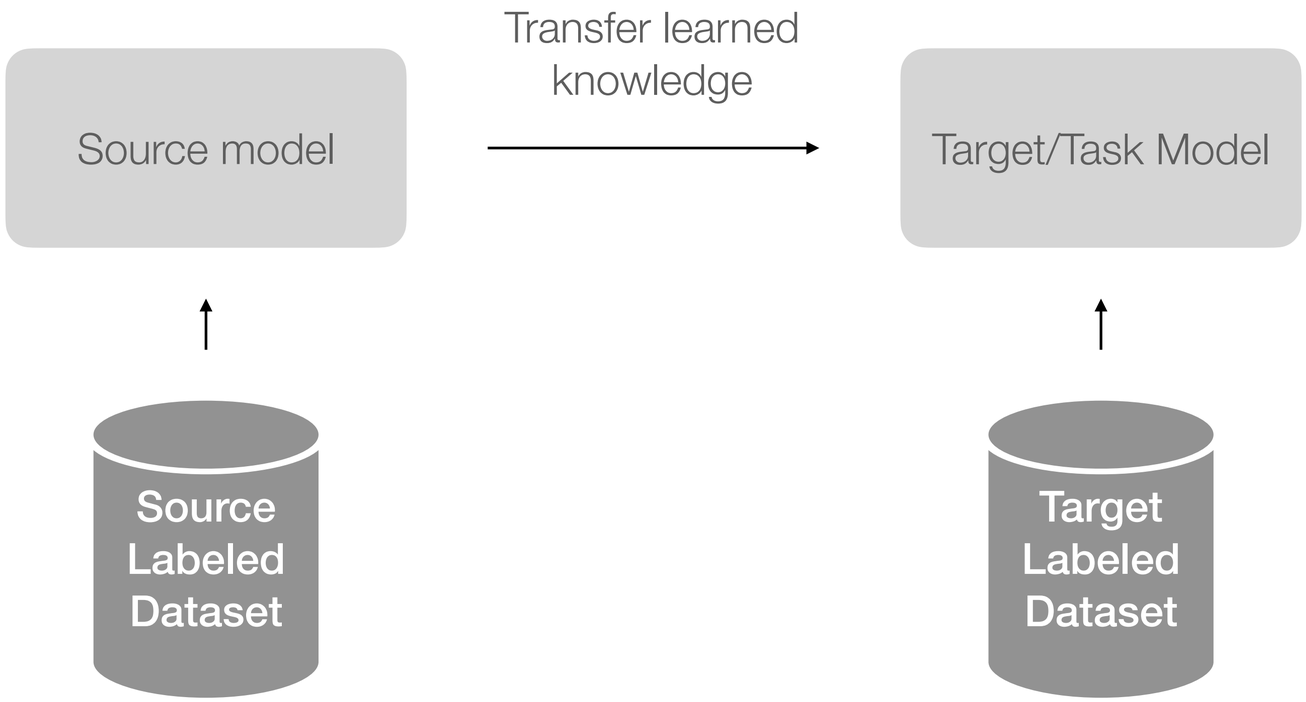
Approach

Meta-classifiers



Approach

Transfer learning

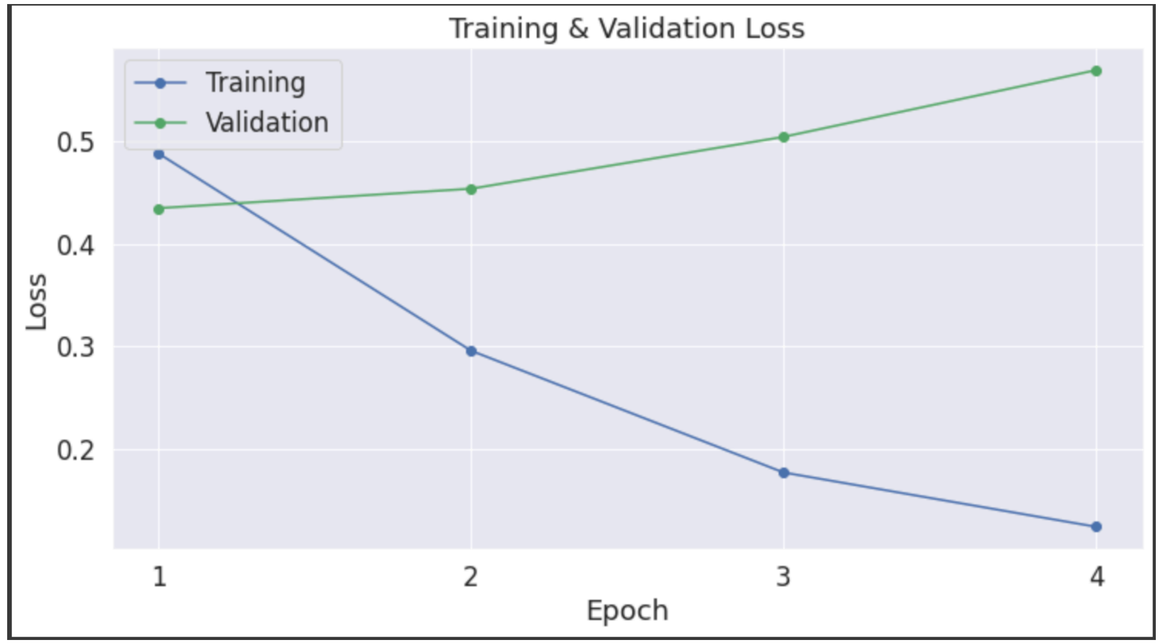


Source: Transfer learning tutorial

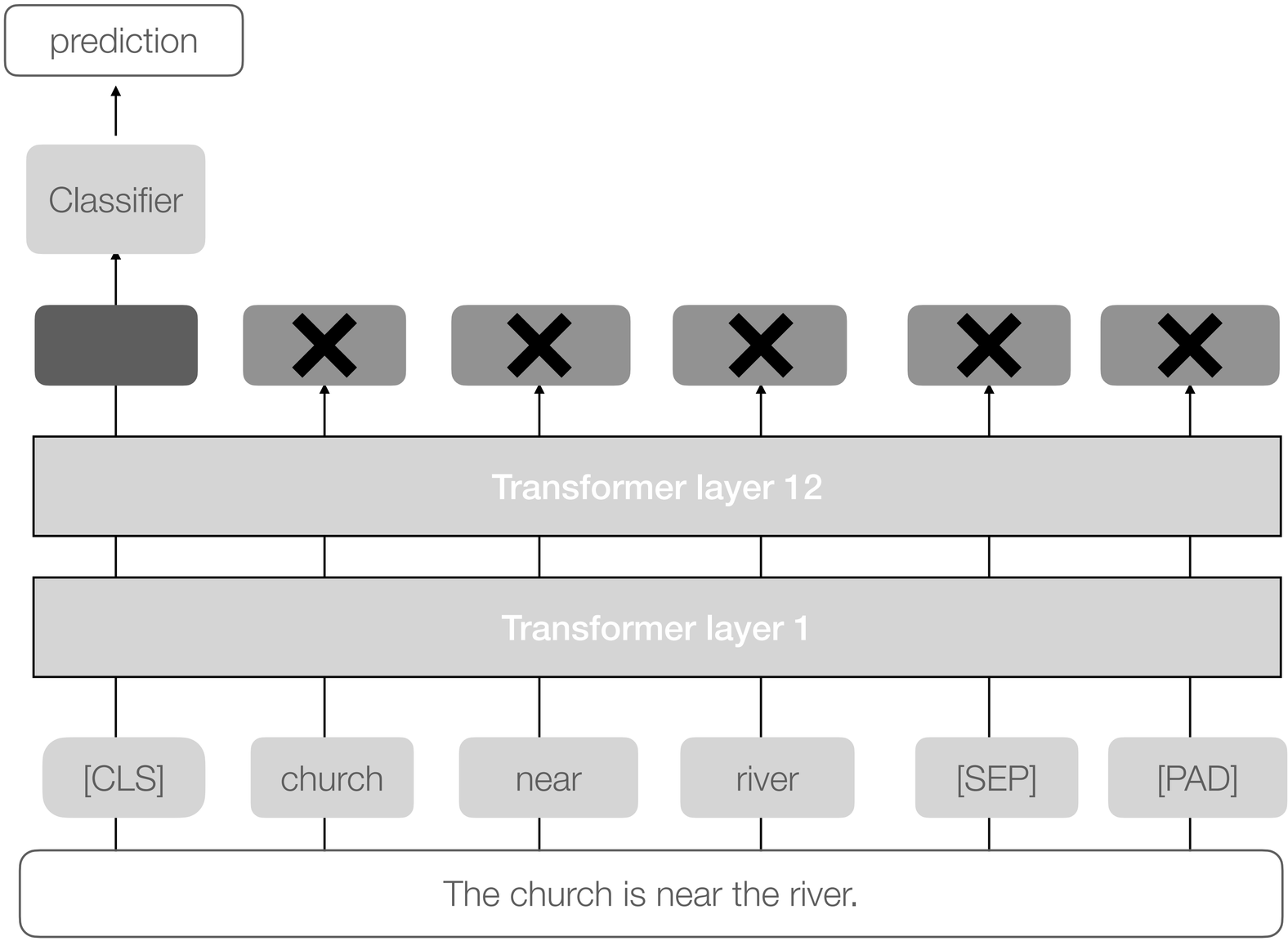
Approach

Transfer learning (Implementation details)

- BERT pre trained model (from Hugging face library (Pytorch)
- Random batch sampling
- learning scheduler (learning rate= 2e-5 , epochs=4)
- BERT tokenizer (cased version)
- BERT’s Adam optimizer



Architecture



Reference: BERT Fine tuning

Results

Task: Geospatial vs (spatial + non spatial) sense

Classifier	**Naive Bayes**	**Naive Bayes**	**Random Forest**	**SVM's**	**SVM-SVM metaclassifier**		**BERT**
Features	Kord features	BOW representation			o/p probabilties	o/p predictions	
Precision	0.746	0.773	0.94	0.87	0.946	0.90	0.938
Recall	0.902	0.874	0.64	0.84	0.770	0.851	0.939
F1-scores	0.816	0.82	0.77	**0.86**	0.849	**0.875**	**0.939**

Results

Task: (Geospatial +spatial) vs non spatial sense

	Kordjamshidi et al	**Hassani et al**	**Ours (using BERT)**
F1-scores	0.88	0.9398	**0.951**