

An Automatic Approach for Generating Rich, Linked Geo-Metadata from Historical Map Images

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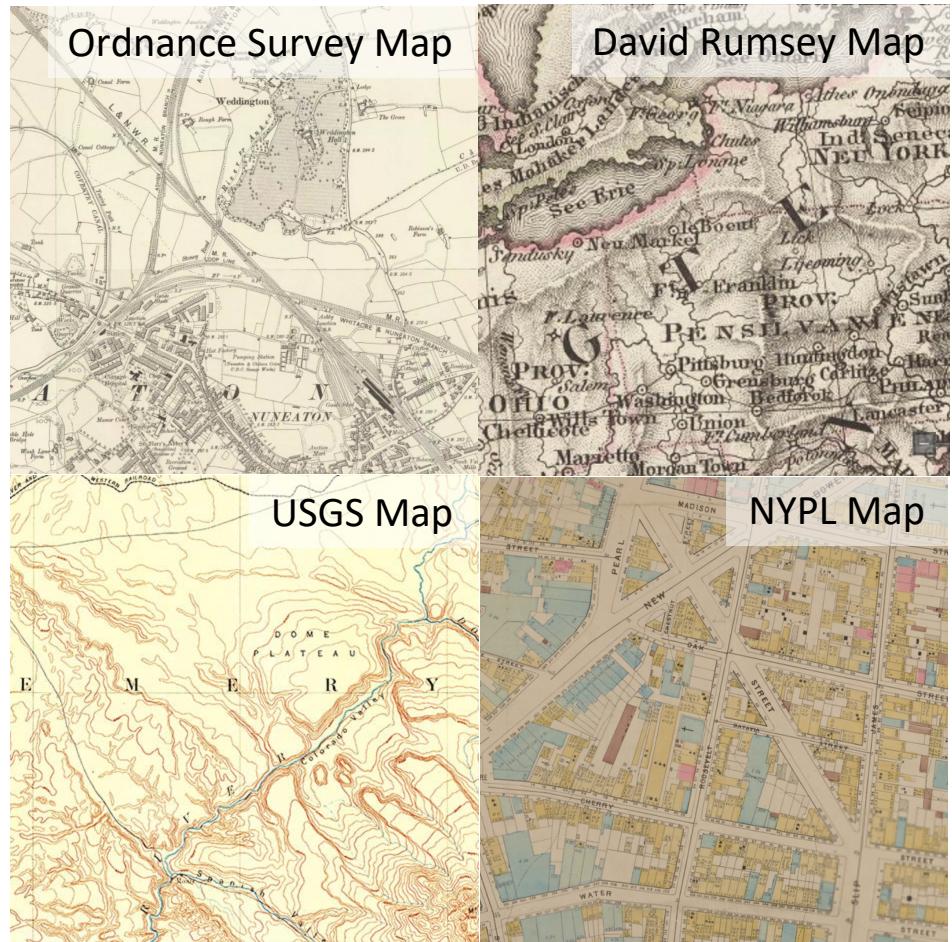
³ University of Colorado, Boulder

Motivation

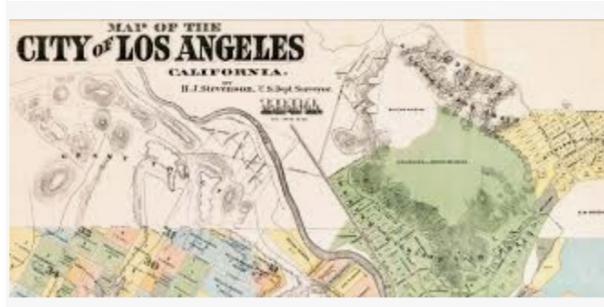
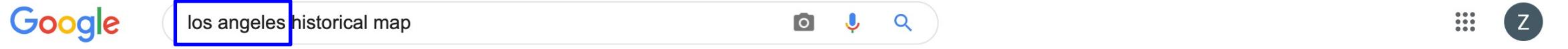
- Many historical maps available in archives
- Good sources for longitudinal studies
 - But most maps still remain **undiscovered and unanalyzed**
- Reason: Missing metadata
 - **Location names** contained in the map
 - **Geolocation** (latitudes and longitudes) of map region
 - **Population, altitude**, and other location information

Question

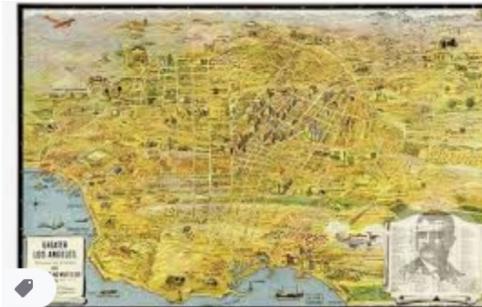
- How to generate the meta-data information from map images?



Why Do We Need Metadata?



Historical Research Maps: Los Angeles
familytreemagazine.com



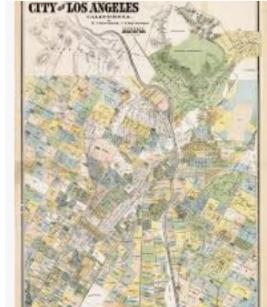
Historic Los Angeles, CA Map 1932 ...
houzz.com · In stock



Historic Map of Los Angeles...
vintageprintgallery.com · In sto...



David Rumsey Historical Map Collection
davidrumsey.com



Los angeles map ...
pinterest.com



History · University Park Camp...
upcmasterplan.usc.edu



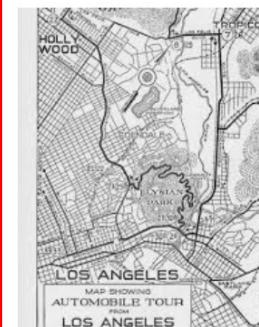
Map of Santa Monica and vicinity as it ...
pinterest.com



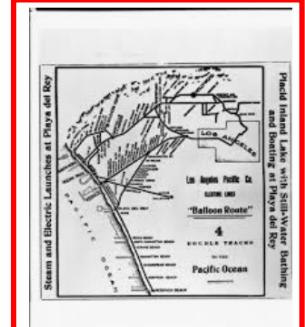
History · University Park Campus M...
upcmasterplan.usc.edu



History · University Park Campus Ma...
upcmasterplan.usc.edu



Map showing automobile...
pinterest.com



Historical society, Los ...
pinterest.com

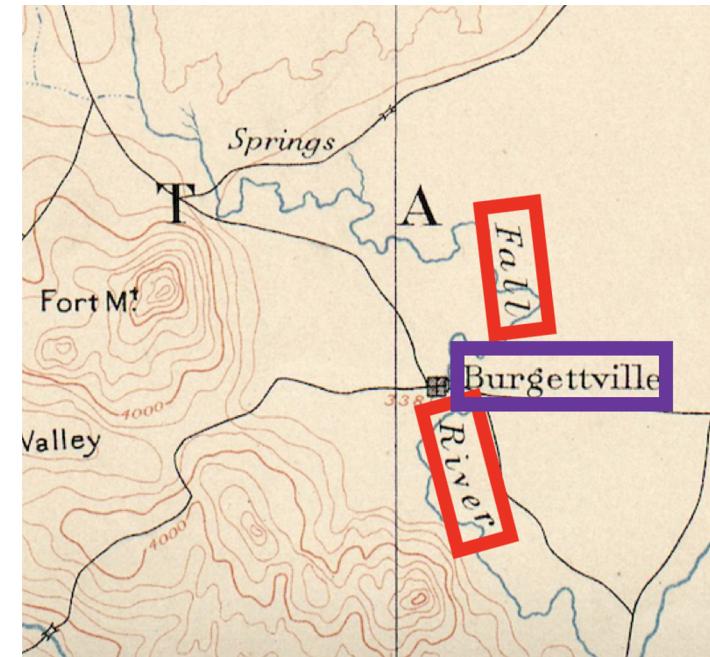
Related Work: Text Label Extraction

- **Text labels** can be extracted with existing text detection and recognition tools
- But it only extracts **separate** words instead of full location phrase [1][2][3]

[1] Zhou, Xinyu, et al. "East: an efficient and accurate scene text detector." *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*. 2017.

[2] Google LLC. [n.d.]. Google Cloud Vision API.
<https://cloud.google.com/vision>

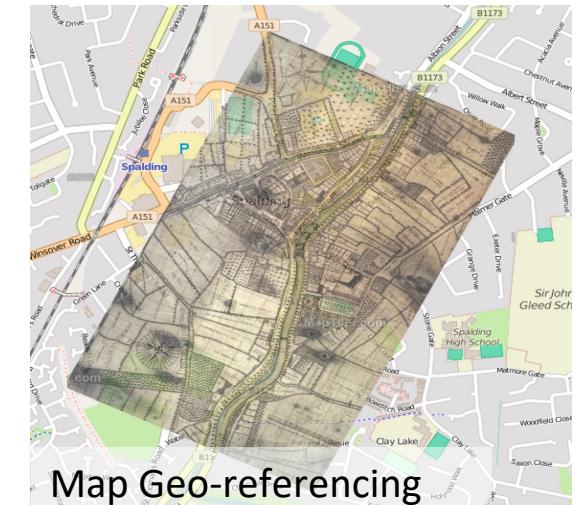
[3] Wang, Wenhui, et al. "Shape robust text detection with progressive scale expansion network." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.



OCR tools can extract "Fall" and "River", but **not** "Fall River". Single words do not give us much information, only the full **location phrase** "Fall River" carries geographical meaning.

Related Work: Geolocation Prediction

- Existing pipeline for metadata extraction involves a lot of manual work (e.g., crowd sourcing for map geolocalization) [1, 2]
- Tavakkol et al. [3] has developed a text based method for automatic geolocalization, and they used single words instead of phrases



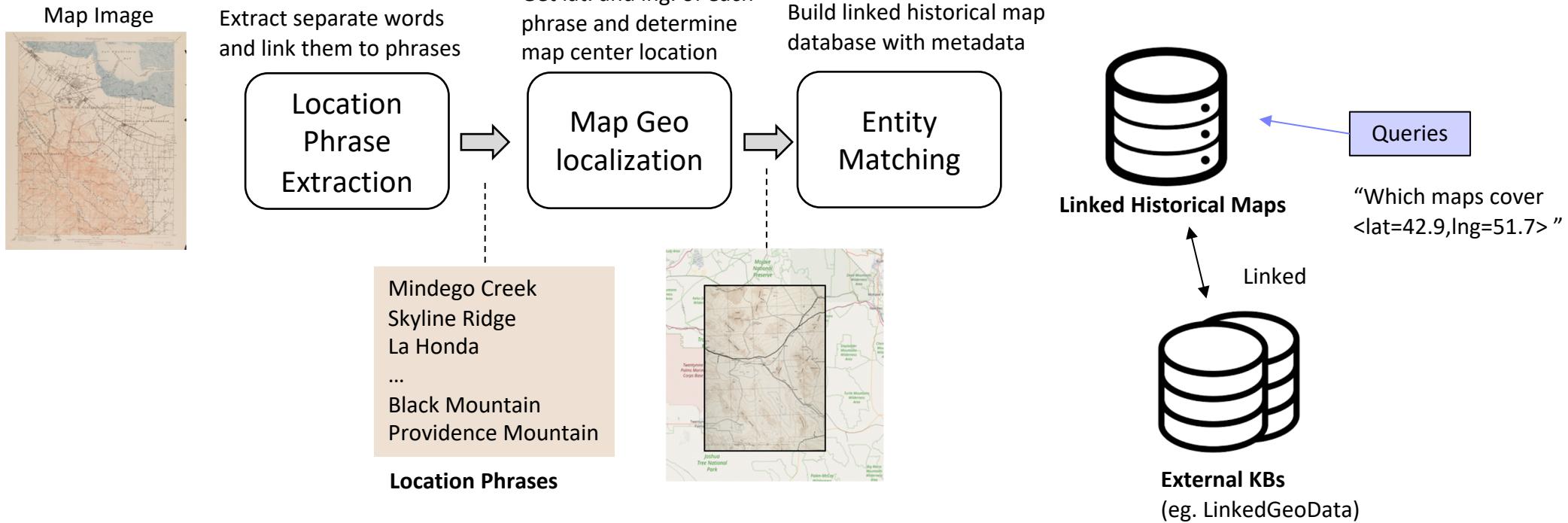
[1] Alex, Beatrice, et al. "Adapting the Edinburgh geoparser for historical georeferencing." *International Journal of Humanities and Arts Computing* 9.1 (2015): 15-35.

[2] Fleet, Christopher, Kimberly C. Kowal, and Petr Pridal. "Georeferencer: Crowdsourced georeferencing for map library collections." *D-Lib magazine* 18.11/12 (2012).

[3] Tavakkol, Sasan, et al. "Kartta labs: Unrendering historical maps." *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*. 2019.



Pipeline for Automatic Map Understanding



A fully automatic pipeline!

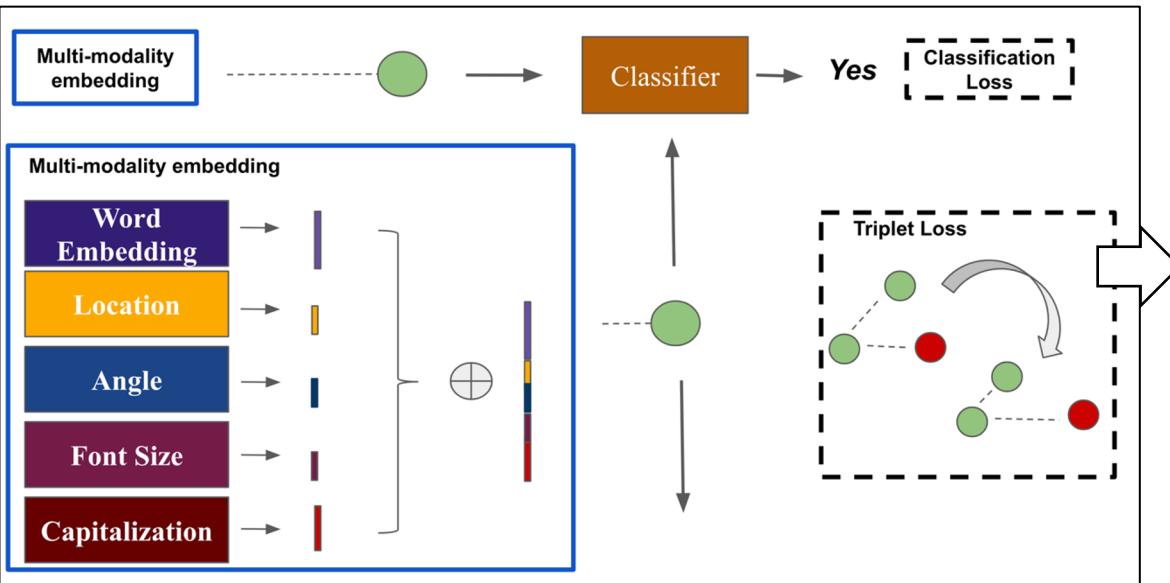
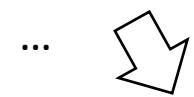
- Location names contained in the map
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Location Phrase Extraction



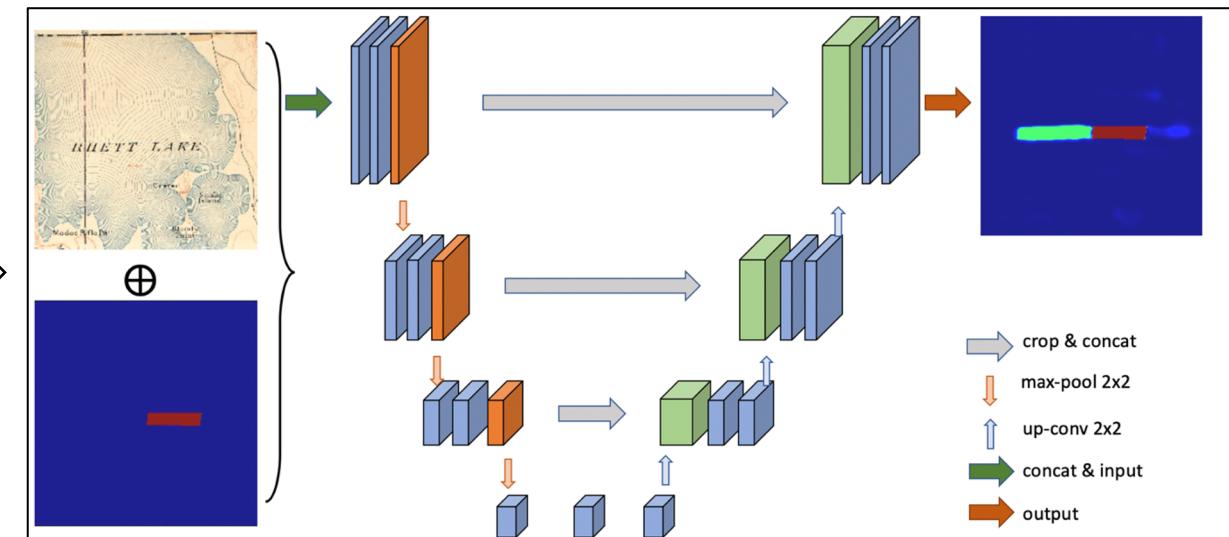
Textual Model: Labels in the same phrase should share similar textual features

High Recall/Low Precision
Help to determine a search neighborhood



Visual Model: Labels in the same phrase could have similar nearby geographic features

Low Recall/High Precision
Help to refine the results



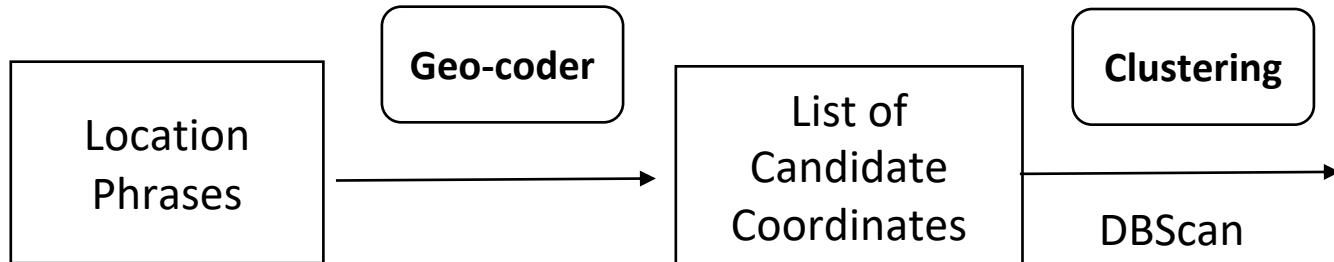
U-Net semantic segmentation

- Location names contained in the map
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Map Geo-localization

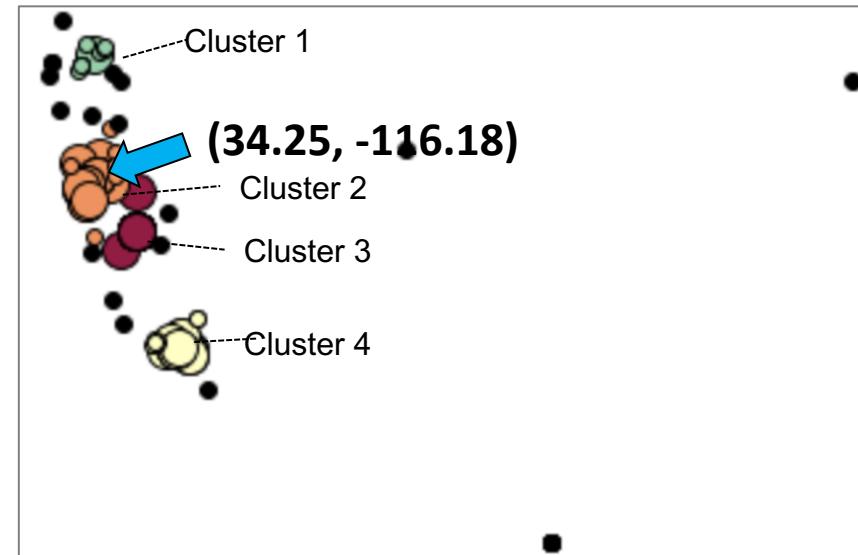


We use Google Geocoding API as the geo-coder: text to lat/long



Mindego Creek
Skyline Ridge
La Honda
...
Black Mountain
Springfield

Mindego Creek
(36.77, -119.48)
(36.54, -119.72)
...
Springfield
(38.72, -120.53)
(29.74, -103.42)
...



The centroid of the largest cluster is the map geolocalization result.

- Location names contained in the map
- Geolocation (latitudes and longitudes) of map region
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Entity Matching

Georeferenced
Location Phrases

Entity
Matching

Match name and location

- Mindego Creek
- Skyline Ridge
- La Honda
- Black Mountain
- ...
- ...
- Providence Mountain

[Node 358793688](#)

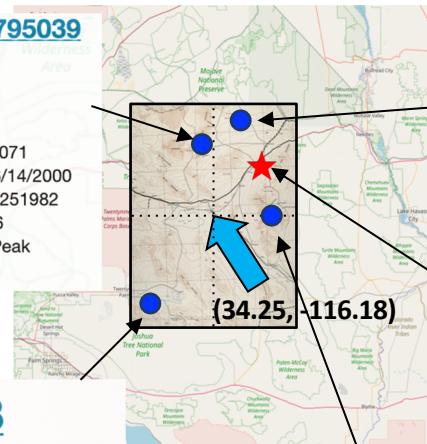
Tags 7

ele=1372
gnis:county_id=071
gnis:created=01/19/1981
gnis:feature_id=250738
gnis:state_id=06
name=Twenty-nine Palms Mountain
natural=peak

[Node 358795039](#)

Tags 7

ele=2057
gnis:county_id=071
gnis:created=06/14/2000
gnis:feature_id=251982
gnis:state_id=06
name=Granite Peak
natural=peak



[Node 358807886](#)

Tags 7

ele=1559
gnis:county_id=071
gnis:created=01/19/1981
gnis:feature_id=1660436
gnis:state_id=06
name=Carbonate Peak
natural=peak

[Node 358816160](#)

Tags 7

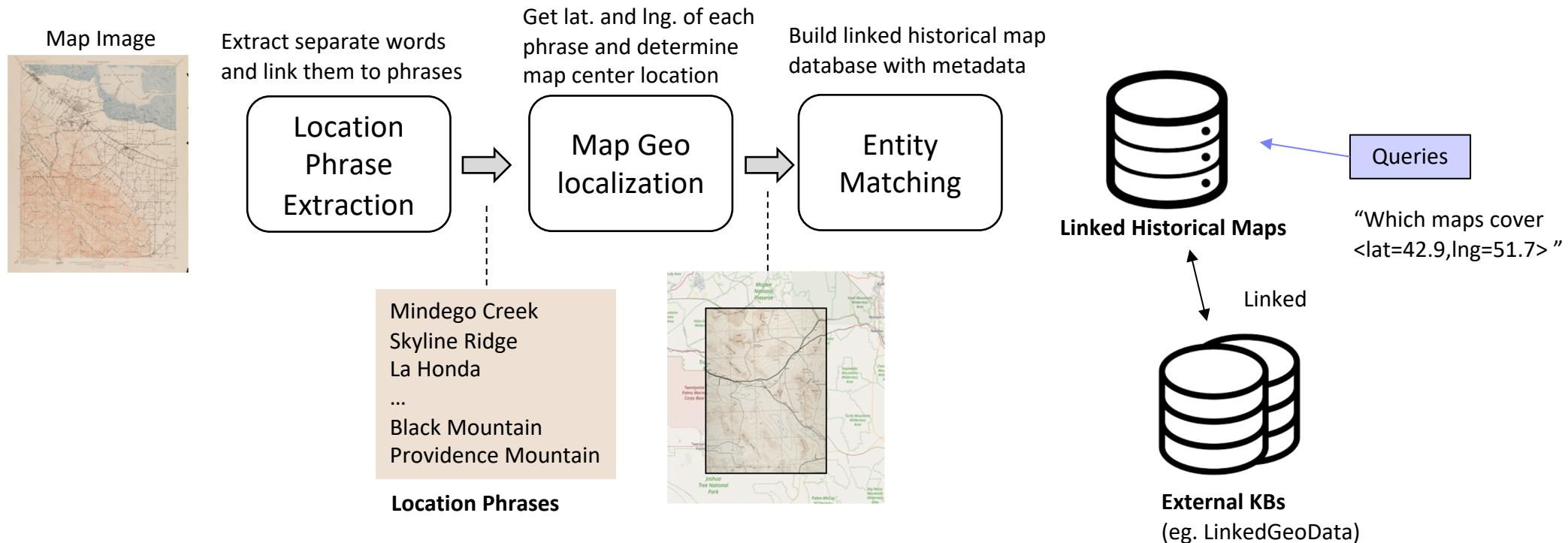
ele=2183
gnis:county_id=071
gnis:created=06/01/1995
gnis:feature_id=1667059
gnis:state_id=06
name=Edgar Peak
natural=peak

arbitrary location
<lat=42.9,lng=51.7>

Which maps overlaps with ★ ?



Pipeline for Automatic Map Understanding

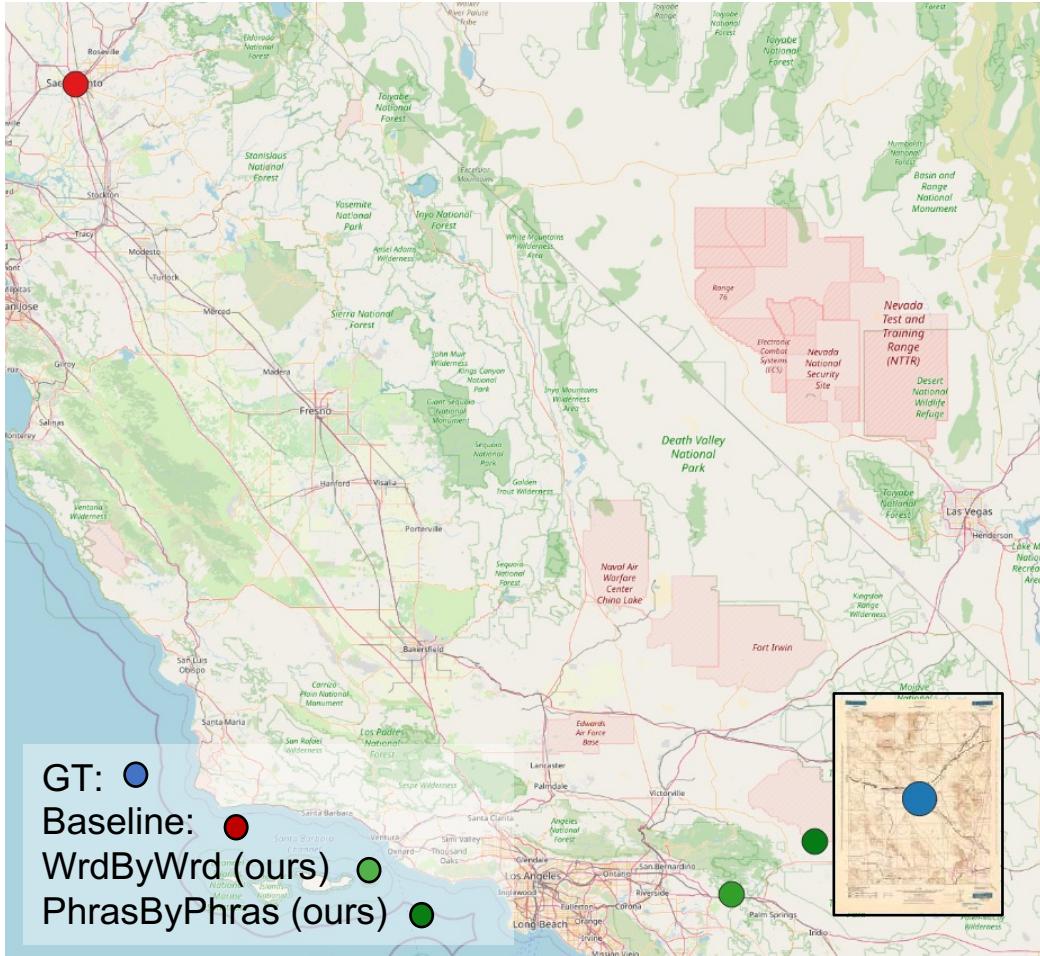


Location Phrase Extraction: https://github.com/kartta-labs/Linker/tree/master/zekun_linker

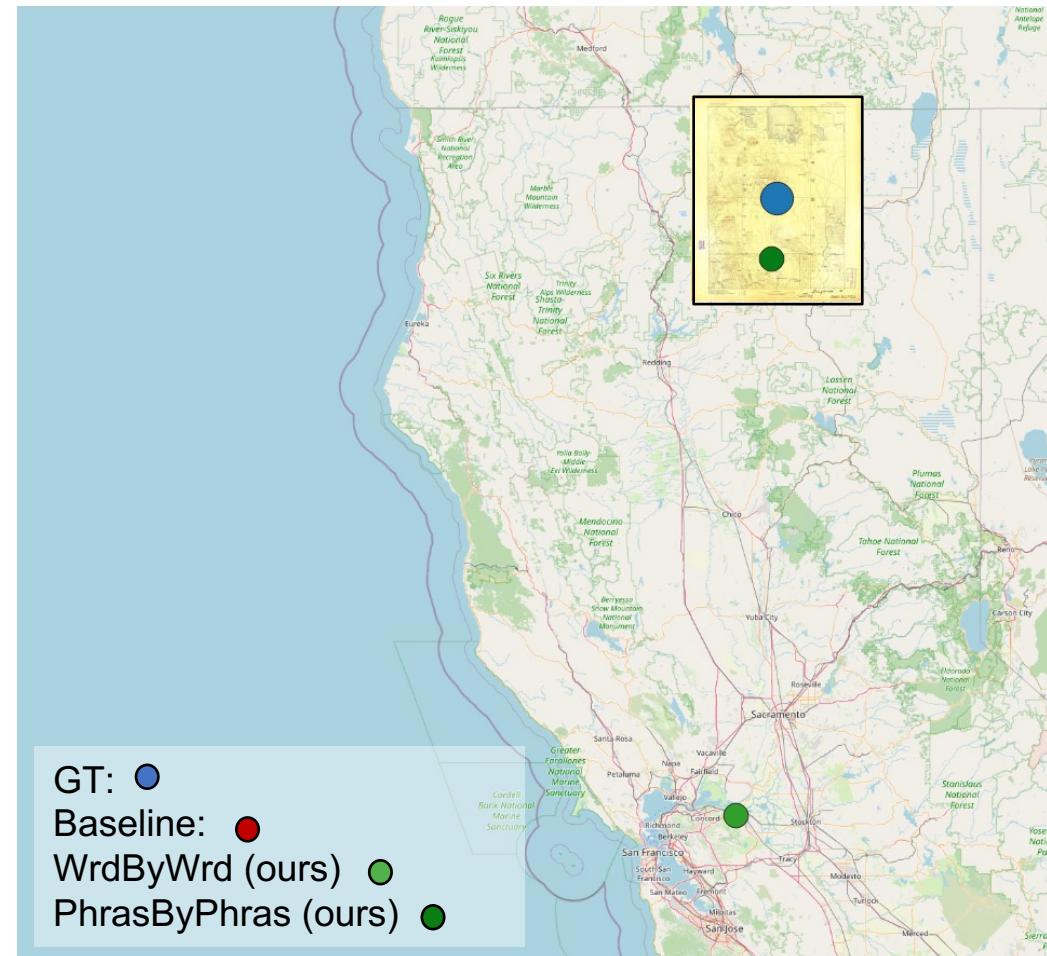
Entity Matching: https://github.com/zekun-li/linked_historical_maps

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Geolocalization Result on USGS Dataset



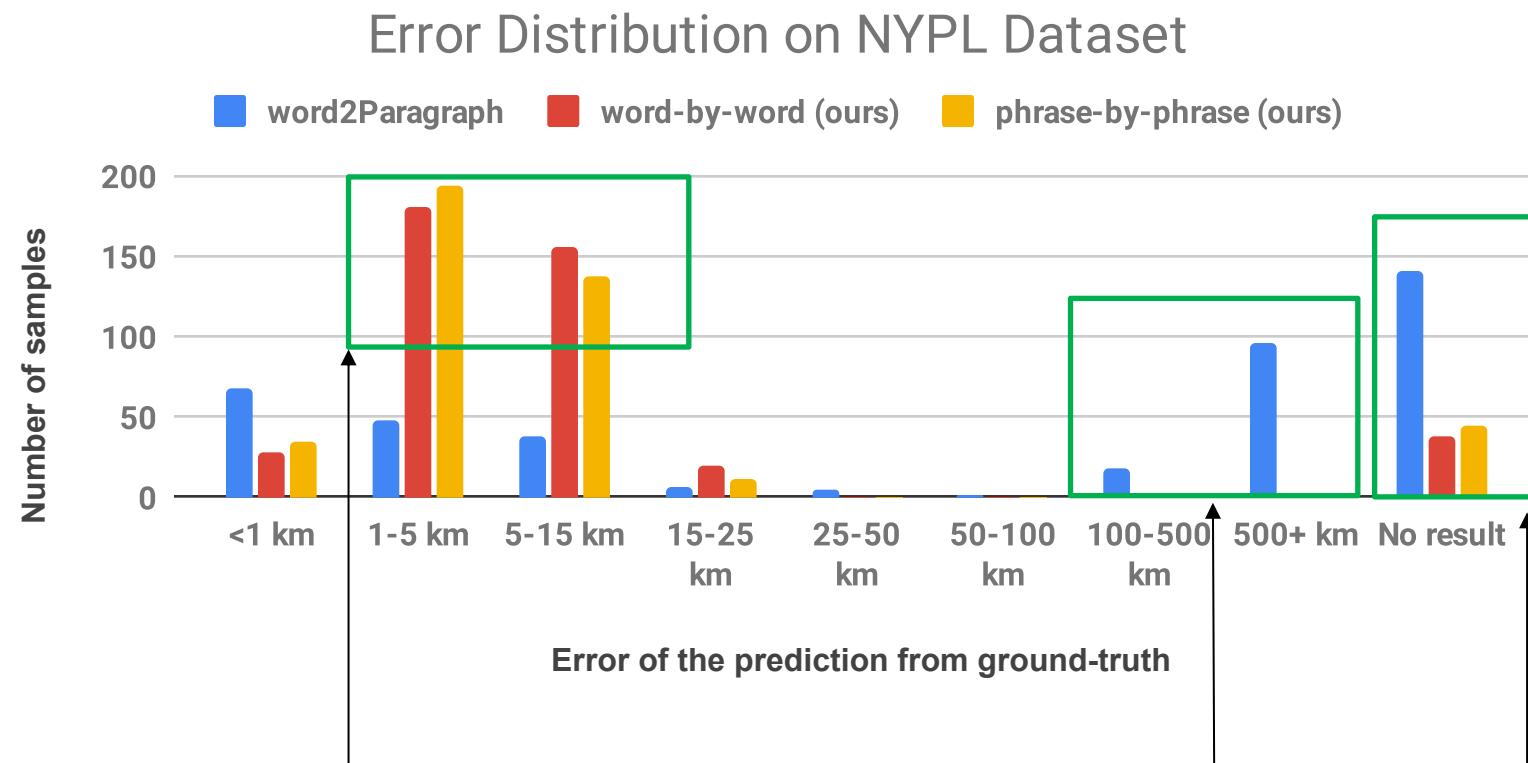
Baseline prediction is very far away from the ground-truth



Baseline method fails to generate <lat, lng> coordinates for this map

Geolocalization Result on NYPL Dataset

- NYPL dataset contains 500 images

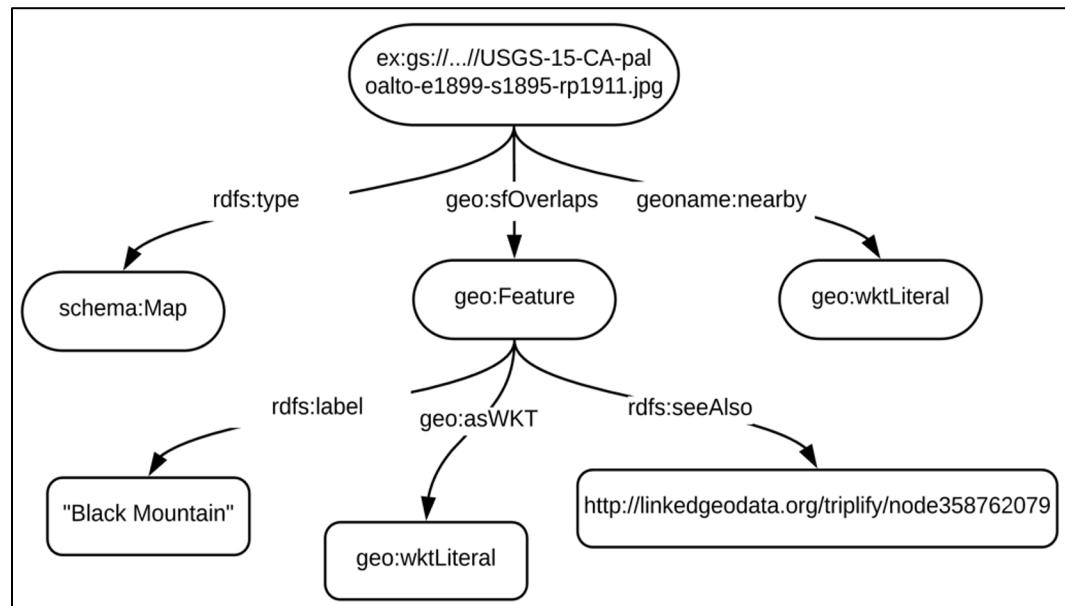


phrase-by-phrase (ours) has **more** samples with **smaller error** compared with word-by-word (ours)

word-by-word (ours) and phrase-by-phrase (ours) has much **fewer** samples with **large error** compared with word2Paragraph baseline

word-by-word (ours) and phrase-by-phrase (ours) has **fewer** samples that fail to geo-localize compared with word2Paragraph baseline

Entity Matching Example



```

PREFIX geo: <http://www.opengis.net/ont/geosparql#>
PREFIX rdfs: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX geoname: <http://linkedgeodata.org/ontology/>

SELECT ?map
WHERE {
  ?map geo:sfOverlaps
  [ rdfs:seeAlso ?lgd_uri ] .
  SERVICE <http://linkedgeodata.org/sparql> {
    ?lgd_uri geoname:elevation ?h .
  }
  FILTER (?h > 1000)
}
GROUP BY ?map
  
```

Sample query: search for maps that contain mountains higher than 1000m

Conclusion and Future Work

- We created a **fully automatic** pipeline to generate a set of meta-data that is linked to large external geospatial knowledge bases
 - Location names contained in the map
 - Geolocation (latitudes and longitudes) of map region
 - Population, altitude, and other location information
- Combining both **visual** and **textual** information significantly improve the location phrase generation result
- Our **geo-localization** pipeline outperforms the baseline model that concatenate words into paragraphs by a large margin
- We will continue working on using the text labels for **semantic typing**.

Discussion

Thank you!

