

## GEOSPATIAL DIGITAL HUMANITIES USE CASES

Using machine learning, large language models, and generative AI

Sven Schlarb
DLM Forum Members' Meeting in Brussels 2024, Tuesday, 28th May 2024
State Archives of Belgium, Rue de Ruysbroeck 2, 1000 Brussels

Location names occurring in texts


Peripleo - PELAGIOS Project

## ICTPSP



Peripleo lead developer:
Rainer Simon

## Presented at iPRES 2016

## E-ARK datamining showcase

## Geographical/timeline search



Peripleo - PELAGIOS Project

## ICTPSP



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## Presented at iPRES 2016

## WHAT IS A LANGUAGE MODEL

This evening I am going to the

| cinema $\quad \vee$ |
| :--- |
| cinema |
| theater |
| restaurant |

What is the probability of this token?

Given these preceeding tokens.

## TRAINING DATA IN A NEW DIMENSION



GPT-3 was trained on about 45 terabytes of text data; Common Crawl (60\%), Web (22\%), Books (16\%), Wikipedia (3\%)

## ^ 2.9 billion pages in MS Word

## ~ 10 Million Books

Library of Congress in Washington, D.C., United States: 170 million items

## TRAINING DATA IN A NEW DIMENSION



GPT-4 uses a more diverse and larger database of about 1 petabyte

According to OpenAl the cost was about $\$ 100$ million, and the training took 100 days, utilizing 25000 NVIDIA A100 GPUs.
Source: https://medium.com/@daniellefranca96/gpt4-all-details-leaked-48fa20f9a4a

$19.058^{82 \epsilon}$
Lieferung für 6,10€ $\mathbf{2 3 .} \mathbf{- 2 8}$
Mai. Details
© Liefern nach Österreich
Nur noch 2 auf Lager


GEOAI IS MULTIMODAL


## MULTIMODAL FOUNDATION MODEL



Images and text are encoded into a shared latent space where similar concepts from different modalities are close to each other.


The ONiT-Project

## Der cilften (6tabrio.

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Bildquelle: http://data.onb.ac.at/rep/1032B57A, pp. 91-92


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## The ONiT-Project

Corpus: Western Travelogues to Ottoman empire

- 2500 early modern book prints (1501-1850)
- 30'000 images (woodcuts, engravings, etc.)
- 4 languages (DE, FR, EN, LAT)
- Analysis: Role of nature representations?
- Flora, fauna, landscapes, maps

Bildquelle: http://data.onb.ac.at/rep/1032B57A, pp. 91-92


Begin your search by entering text in the form located at the top left.
To search for similar images, click on the magnifying glass icon $(Q)$ associated with an image.
To view more details of an image, simply click on it.

## WHICH "VIENNA"?

If you've read many of these articles about things to see and do around a Stuckey's, you'll notice that nothing turned a fledgling town into a boom town quite like the railroad. Vienna was no exception. Where families worked to just to survive before the railroad, after the Cairo and Vincennes Railroad was built through Vienna around 1872, the town and its people became more prosperous as they were now able to ship goods farther across the nation.

Vienna is no Berlin when it comes to club culture, but there are a few places where it comes close. If you're looking for a dance-until-dawn, hard-techno experience, Das Werk, on the banks of the Danube Canal, is the place to go (though unlike some exclusive clubs in Berlin, Das Werk's bouncers do not care how you dress). Here, the party doesn't start before 11 p.m., when the crowd becomes hypnotized by the D.J. - or by the light show on the walls around her.

## KNOWLEDGE GRAPH

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX dbo: <http://dbpedia.org/ontology/>
PREFIX dbp: <http://dbpedia.org/property/>
PREFIX dbr: <http://dbpedia.org/resource/>
SELECT ?city
WHERE {
    ?city a dbo:City
        dbo:country dbr:United_States
        rdfs:label ?label
```

https://dbpedia.org/page/Vienna,_Illinois


Vienna, Illinois, United States


Vienna, Austria

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(2)

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## Let's ask a well known LLM ...

The text is likely referring to Vienna, a town in Illinois, United States. This conclusion is drawn from the mention of the Cairo and Vincennes Railroad, which ran through Vienna, Illinois, around 1872, facilitating the shipment of goods across the nation.


Vienna, Illinois, United States

Based on the mention of the Danube Canal and the club culture described, it's highly likely that the text is referring to Vienna, the capital city of Austria.


Vienna, Austria
 the European Union

## TOPONYM/LOCATION DESCRIPTION RECOGNITION

|  | Model | \#Param | Toponym Recognition |  | Location Description Recognition |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Hu2014 | Ju2016 |  |  |  |
|  |  |  | Accuracy $\downarrow$ | Accuracy $\downarrow$ | Precision | $\downarrow$ Recall $\downarrow$ | F-Score $\downarrow$ |
|  | Stanford NER (nar. loc.) [30] | - | 0.787 | 0.010 | 0.828 | 0.399 | 0.539 |
| (A) | Stanford NER (bro. loc.) [30] | - | - | 0.012 | 0.729 | 0.44 | 0.548 |
|  | Retrained Stanford NER [30] | - | - | 0.078 | 0.604 | 0.410 | 0.489 |
|  | Caseless Stanford NER (nar. loc.) [30] | - | - | 0.460 | 0.803 | 0.320 | 0.458 |
|  | Caseless Stanford NER (bro. loc.) [30] | - | - | 0.514 | 0.721 | 0.336 | 0.460 |
|  | spaCy NER (nar. loc.) [44] | - | 0.681 | 0.000 | 0.575 | 0.024 | 0.046 |
|  | spaCy NER (bro. loc.) [44] | - | - | 0.006 | 0.461 | 0.304 | 0366 |
|  | DBpedia Spotlight[99] | - | 0.688 | 0.447 | - | - | - |
| (B) | Edinburgh [7] | - | 0.656 | 0.000 | - | - | - |
|  | CLAVIN [134] | - | 0.650 | 0.000 | - |  | - |
|  | TopoCluster [23] | - | 0.794 | 0.158 | - |  | - |
| (C) | CamCoder [33] | - | 0.637 | 0.004 | - | - | - |
|  | Basic BiLSTM + CRF [77] | - | - | 0.595 | 0.703 | 0.600 | 0.649 |
|  | DM NLP (top. rec.) [139] | - | - | 0.723 | 0.729 | 0.680 | 0.703 |
|  | NeurotPR [135] | - | $0.675^{\dagger}$ | 0.821 | 0.787 | 0.678 | 0.728 |
| (D) | GPT2 [115] | 117M | 0.556 | 0.650 | 0.540 | 0.413 | 0468 |
|  | GPT2-Medium [115] | 345M | 0.806 | 0.802 | 0.529 | 0503 | 0.515 |
|  | GPT2-Large [115] | 774M | 0.813 | 0.779 | 0.598 | 0.458 | 0.518 |
|  | GPT2-XL [115] | 1558M | 0.869 | 0.846 | 0.492 | 0.470 | 0.481 |
|  | GPT-3 [15] | 175B | 0.881 | 0.811* | 0.603 | 0.724 | 0.658 |
|  | InstructGPT [106] | 175B | 0.863 | 0.817* | 0.567 | 0.688 | 0.622 |
|  | ChatGPT (Raw.) [104] | 176B | 0.800 | $0.696^{*}$ | 0.516 | 0.654 | 0.577 |
|  | ChatGPT (Con.) [104] | 176B | 0.806 | $0.656^{*}$ | 0.548 | 0.665 | 0.601 |

[Mai et al.
2023]


Co-funded by the European Union

## PROMPT

## Input Text

In June 2013, heavy flooding affected Central Europe, with significant impacts on cities such as Prague in the Czech Republic and Dresden in Germany. The Elbe River overflowed its banks, reaching a peak flow at $50.1^{\circ} \mathrm{N}, 14.4^{\circ} \mathrm{E}$. Many bridges in Prague were closed, and the fistoric city center of Dresden was submerged under several feet of water. Rescue operations were launched across affected regions, including Austria and Hungary.

## Example Output

| Locations | Central Europe, Prague, <br> Czech Republic, Dresden, <br> Germany, Elbe River, <br> Austria, Hungary |
| :--- | :--- |
| Coordinates | $50.1^{\circ} \mathrm{N}, 14.4^{\circ} \mathrm{E}$ |
| Distances and Directions | several feet of water |
| Geographical Features | Elbe River |
| Human-made Features | bridges, historic city center |
| Events | June 2013 heavy flooding, <br> Elbe River overflow, <br> bridge closures, rescue <br> operations |

## CONTEXTUAL INFORMATION (FEW-SHOT)



## DUTCH-PARIS ESCAPE LINE (WW II)



## Can you give <br> "coordinates":

me the GeoJSON of the Dutch-Paris Escape Line?


Can you create a path in GeoJSON that connects all these cities?
[4.895, 52.370], // Amsterdam, Netherlands
[5.121, 52.090], // Utrecht, Netherlands
[4.300, 52.067], // The Hague (Den Haag), Netherlands [4.477, 51.922], // Rotterdam, Netherlands
[4.352, 50.850], // Brussels, Belgium
[2.352, 48.856], // Paris, France
[4.835, 45.764], // Lyon, France
[1.444, 43.604], // Toulouse, France
[2.895, 42.698], // Perpignan, France
[2.347, 42.573], // Carcassonne, France
[1.610, 42.966], // Foix, France
[1.521, 42.505], // Andorra la Vella, Andorra
[0.045, 43.076], // Lourdes, France
[-0.371, 43.295], // Pau, France
[-1.474, 43.494], // Bayonne, France
[-1.986, 43.321], // San Sebastián (Donostia), Spain
[-1.645, 42.816], // Pamplona (Iruña), Spain
[-0.880, 41.656], // Zaragoza, Spain
[2.176, 41.385], // Barcelona, Spain
[2.824, 41.979], // Girona, Spain
[2.895, 42.698], // Perpignan, France (again)
[3.877, 43.611] // Andorra la Vella, Andorra (again)
]

## QGIS LLM ROUTE EXTRACTION

The provisional appointment date for 72 April 2024 in St Pölten has been set for those born in 2006 in the municipality of Poysdorf. On this occasion, the municipality of Poysdorf is organising a bus trip to St. Pölten and back in cooperation with the company Schiefer Personenbeförderung GmbH. The bus will be provided free of charge by the municipality.

I am born in Retz, studied in Tulln, and now I live in Vienna.

## QGIS LLM ROUTE EXTRACTION

The western Mediterranean route consists of two major sub-routes. One leads across the westernmost part of the Mediterranean or the Strait of Gibraltar from Morocco and Algeria towards the Spanish mainland. Migrants also occasionally land on the Balearic Islands. This sub-route is primarily used by migrants of Algerian and Moroccan nationality. The second sub-route leads from Morocco, Western Sahara and Mauritania to the Canary Islands. It is primarily Moroccan nationals and citizens of various West African countries who land here. Migration from North Africa to Spain (directly, via Ceuta, via Melilla or via the Canary Islands) fell significantly compared to the previous year. A total of around 31,800 people travelled to Europe in this way (previous year 43,200). The proportionate distribution among the subroutes largely corresponds to that of the previous year. Around 15,700 people arrived in the Canary Islands (previous year 23,050) and 14,200 in mainland Spain and the Balearic Islands (previous year 18,930 ). 1,900 people arrived in the two exclaves of Ceuta and Melilla, 650 more than in the previous year. Spanish-Moroccan relations improved significantly over the course of 2022. This is likely to be one of the reasons for the decline in Uber journeys to the Canary Islands and, in particular, the slump in landings in November and December. This route is of secondary importance for migration to Switzerland.

Co-funded by the European Union

## THANKS TO MY COLLEAGUES AT AIT



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## The ONiT-Project

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QGIS LLM EXPERIMENTS movingpandas

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## THANK YOU!

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- [Tsang 2022] Sik-Ho Tsang, „Review - GPT-3: Language Models are Few-Shot Learners", 2022.

