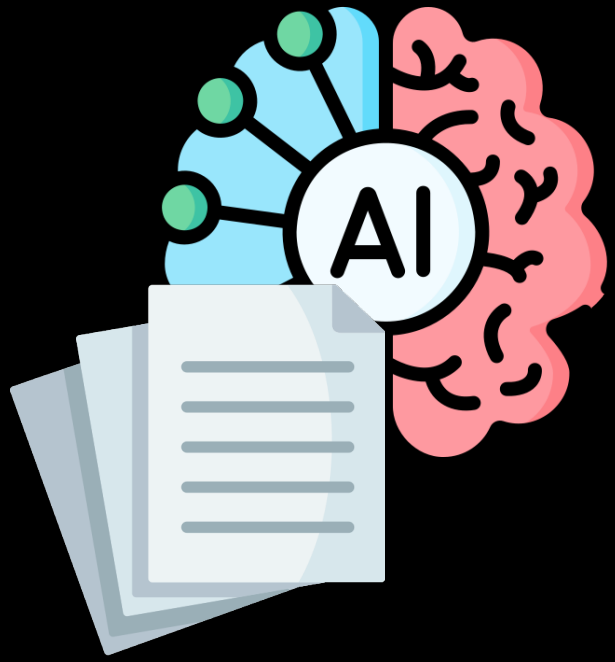
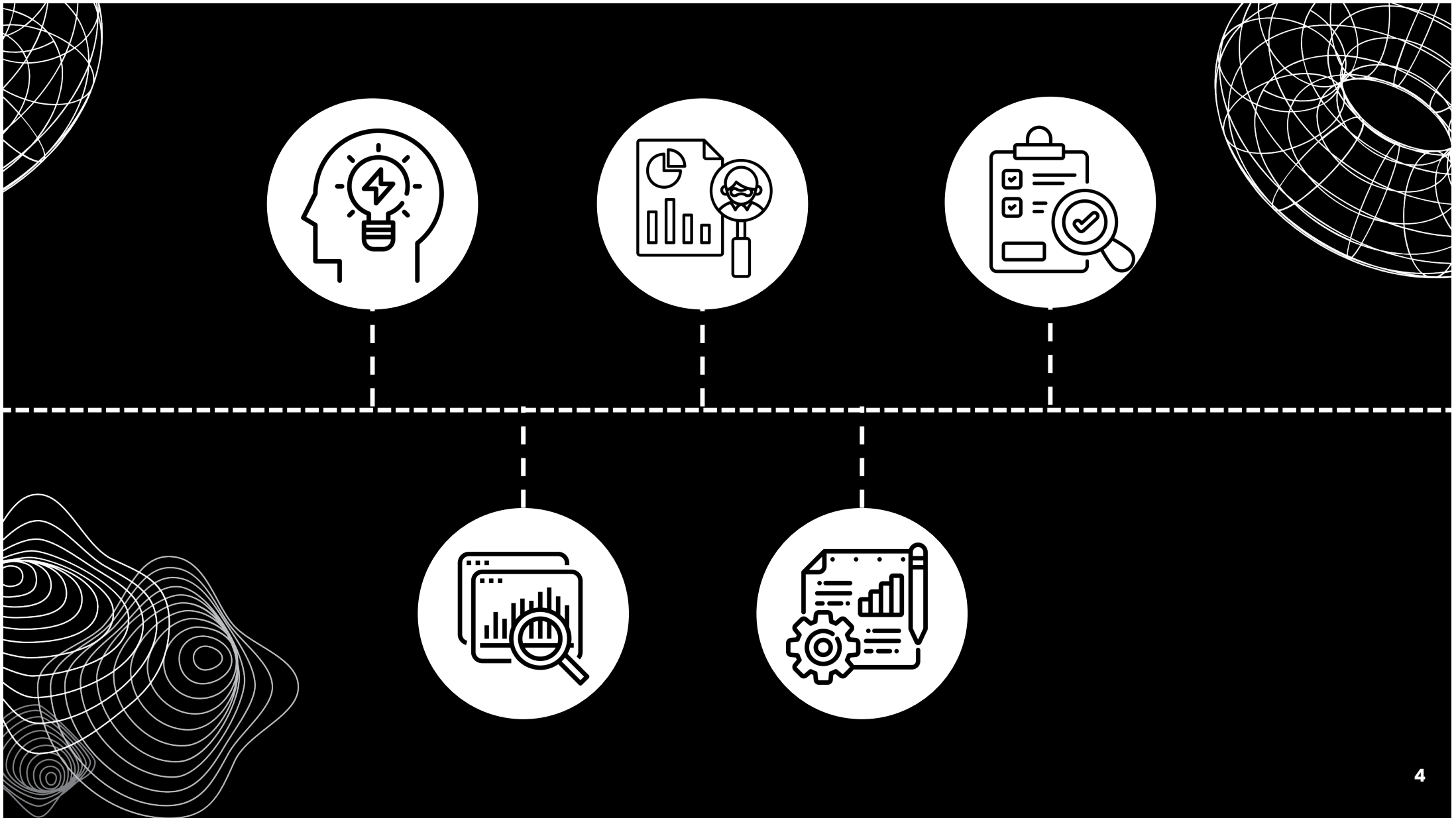
Personenbezogene Daten in LLms

Maximilian Werzinger


AI

- Namen
- E-Mail-Adressen
- Telefonnummern
- Kundennummern



Was sind personenbezogene Daten?

„Personenbezogene Daten sind alle Infos, die sich auf eine identifizierte oder identifizierbare Person beziehen.“ [Q1]

Person ist direkt erkennbar
→ *Max Mustermann, Musterstraße 1, 12345 Musterstadt.*

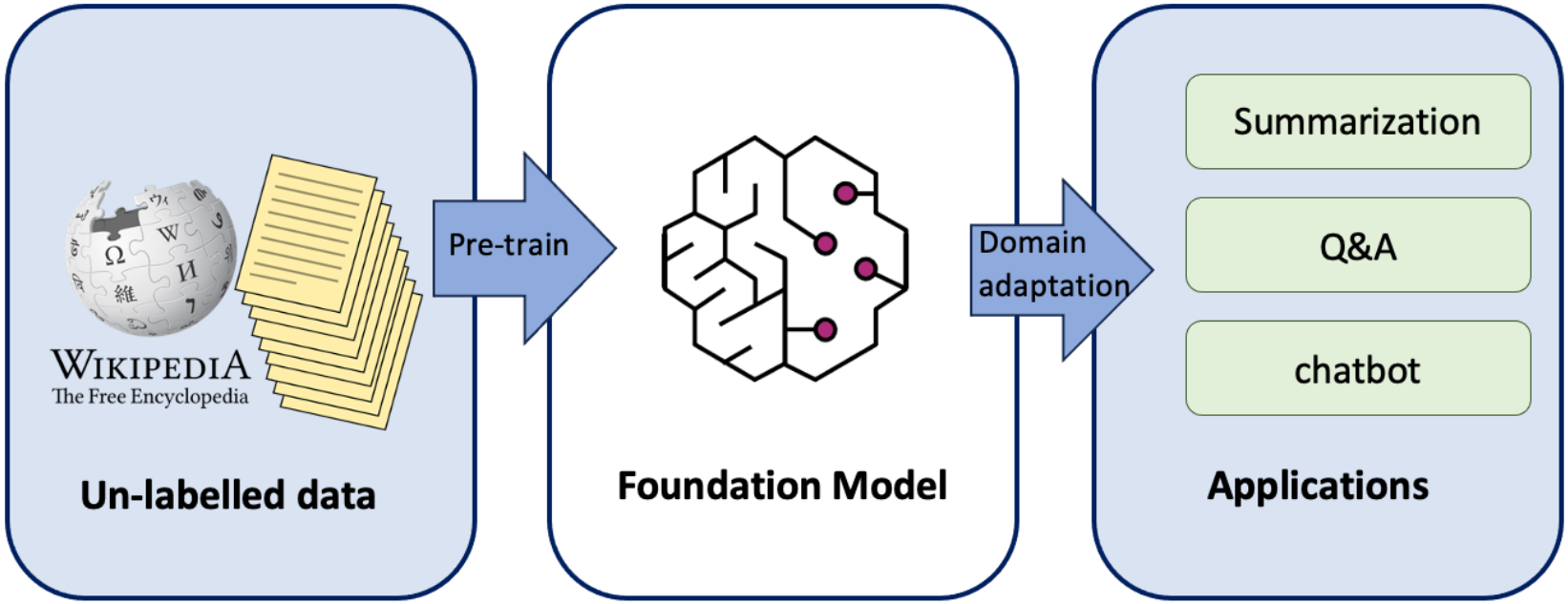
Person wird erst durch Kombination von Infos erkennbar
→ z.B. „Data Scientist in Firma X in München, Jahrgang 1999“.

Was sind personenbezogene Daten?

- Name, Anschrift
- E-Mail-Adresse, Telefonnummer
- Ausweis-, Kundenummer, Kontonummer

- Gesundheitsdaten
- Biometrische/genetische Daten
- Politische Meinung, Religion/Weltanschauung
- Gewerkschaftszugehörigkeit, sexuelle Orientierung

- IP-Adresse, Cookie-ID, Geräte-ID, Browser-Fingerprint
- Standortdaten (GPS, Wohnort + Postleitzahl)
- Kombinationen wie *Jobtitel + Firma + Stadt*


WIKIPEDIA
The Free Encyclopedia
Un-labelled data
Pre-train
Foundation Model
Domain adaptation
Summarization
Q&A
chatbot
Applications

[Q1]

Wie gelangen PII in LLM-Trainingsdaten?

LLMs werden auf riesigen Textmengen aus dem Web, Büchern, Foren, Code usw. trainiert.

Web-Scraping erfasst dabei auch personenbezogene Daten:

- öffentliche Profile, Blogs, Foren, Social Media
- GitHub-Commits, Issue-Tracker
- Datenleaks, Pastebin & Co.
- Lebensläufe, Berichte, Gerichtsurteile

Im Unternehmen:

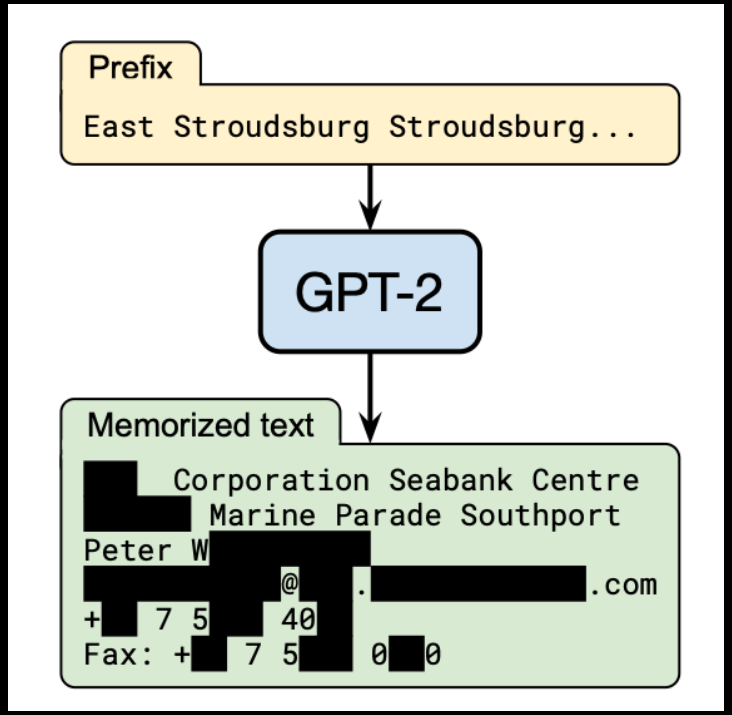
- Logs
- Tickets
- Internet Dokumente


usenix
THE ADVANCED
COMPUTING SYSTEMS
ASSOCIATION
Extracting Training Data from Large Language Models
Nicholas Carlini, Google; Florian Tramèr, Stanford University; Eric Wallace,
UC Berkeley; Matthew Jagielski, Northeastern University; Ariel Herbert-Voss,
OpenAI and Harvard University; Katherine Lee and Adam Roberts, Google;
Tom Brown, OpenAI; Dawn Song, UC Berkeley; Úlfar Erlingsson, Apple;
Alina Oprea, Northeastern University; Colin Raffel, Google

[Q2]

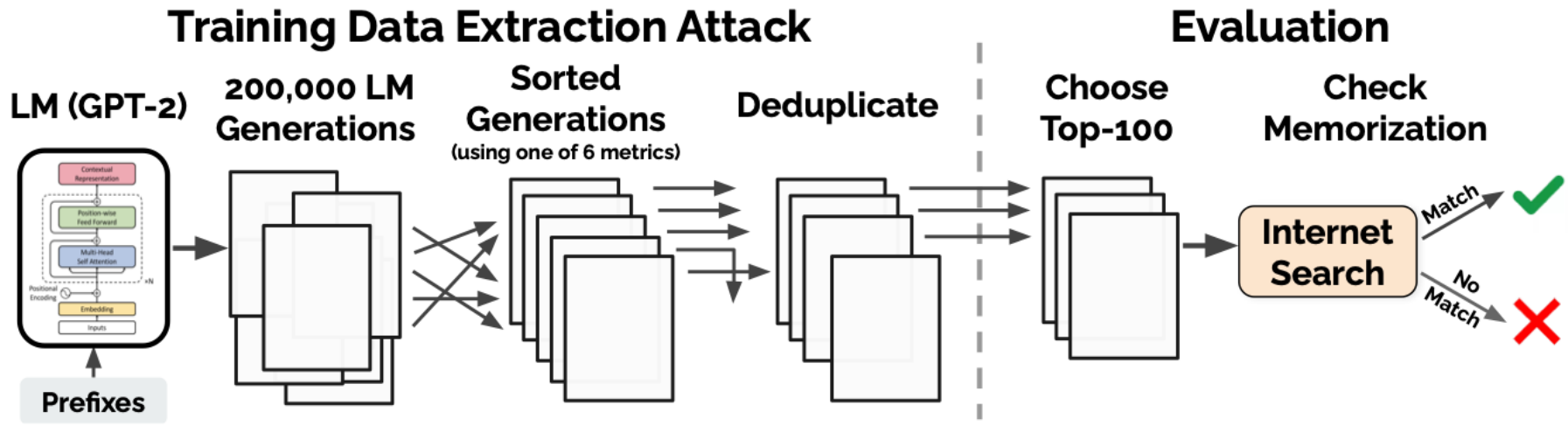
Fallstudie: Extracting Trainign Data From Large Language Models

- GPT-2 (1,5Milli. Parameter) auf Web-Scrapes trainiert
- Forschende extrahieren hunderte wortwörtliche Trainingssätze
- Darunter reale PII: Namen, Telefonnummern, E-Mails, Adressen
- Teilweise stammen die Sequenzen aus nur einem einzigen Dokument im Training



Beispiel einer PII-Extraktion aus GPT-2 [Q2]

Fallstudie: Extracting Trainign Data From Large Language Models



[Q2]

Angriffsarten auf LLMs – Angriffe auf PII

[Q3]

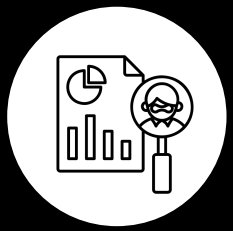
1. Training-Data-Extraction
   - Gezielte Rekonstruktion von Trainingsdaten

2. Prompt Hacking / Jailbreaks
   - Sicherheitsfilter umgehen, um sensible Antworten zu erzwingen

3. Membership Inference & Profiling
   - Herausfinden, ob ein bestimmtes Beispiel im Training war

- PII sind in Trainings- und Eingabedaten weit verbreitet
- LLms können einzelne Beispiele memorisieren
- Angriffe können diese Informationen wieder sichtbar machen

PII sollten vor der Verarbeitung erkannt und geschützt werden



Organisatorischen Schutzmaßnahmen

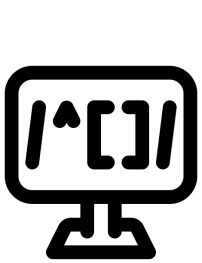
Technischen Schutzmaßnahmen

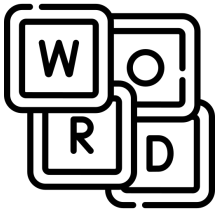
Rechtlichen Schutmaßnahmen

Microsoft Presidio

- Open-Source-SDK von Microsoft zur Erkennung & Anonymisierung sensibler Daten.
- Unterstützt Text, Bilder und strukturierte Daten.
- Zwei Kernkomponenten:
  - Analyzer-Engine → findet PII
  - Anonymizer-Engine → maskiert/ersetzt gefundene PII

Analyzer

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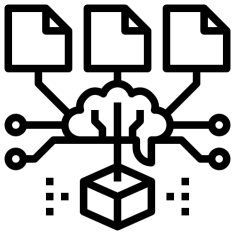

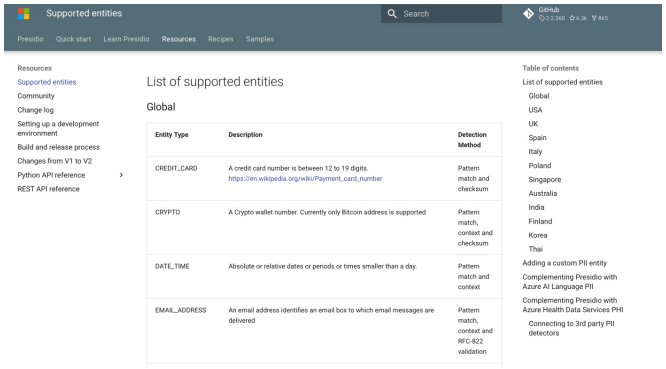
Supported entities
Search
GitHub
Presidio
Quick start
Learn Presidio
Resources
Recipes
Samples
Resources
Supported entities
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Change log
Setting up a development environment
Build and release process
Changes from V1 to V2
Python API reference
REST API reference
List of supported entities
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Entity Type
Description
Detection Method
CREDIT_CARD
A credit card number is between 12 to 19 digits.
https://en.wikipedia.org/wiki/Payment_card_number
Pattern match and checksum
CRYPTO
A Crypto wallet number. Currently only Bitcoin address is supported
Pattern match, context and checksum
DATE_TIME
Absolute or relative dates or periods or times smaller than a day.
Pattern match and context
EMAIL_ADDRESS
An email address identifies an email box to which email messages are delivered
Pattern match, context and RFC-822 validation
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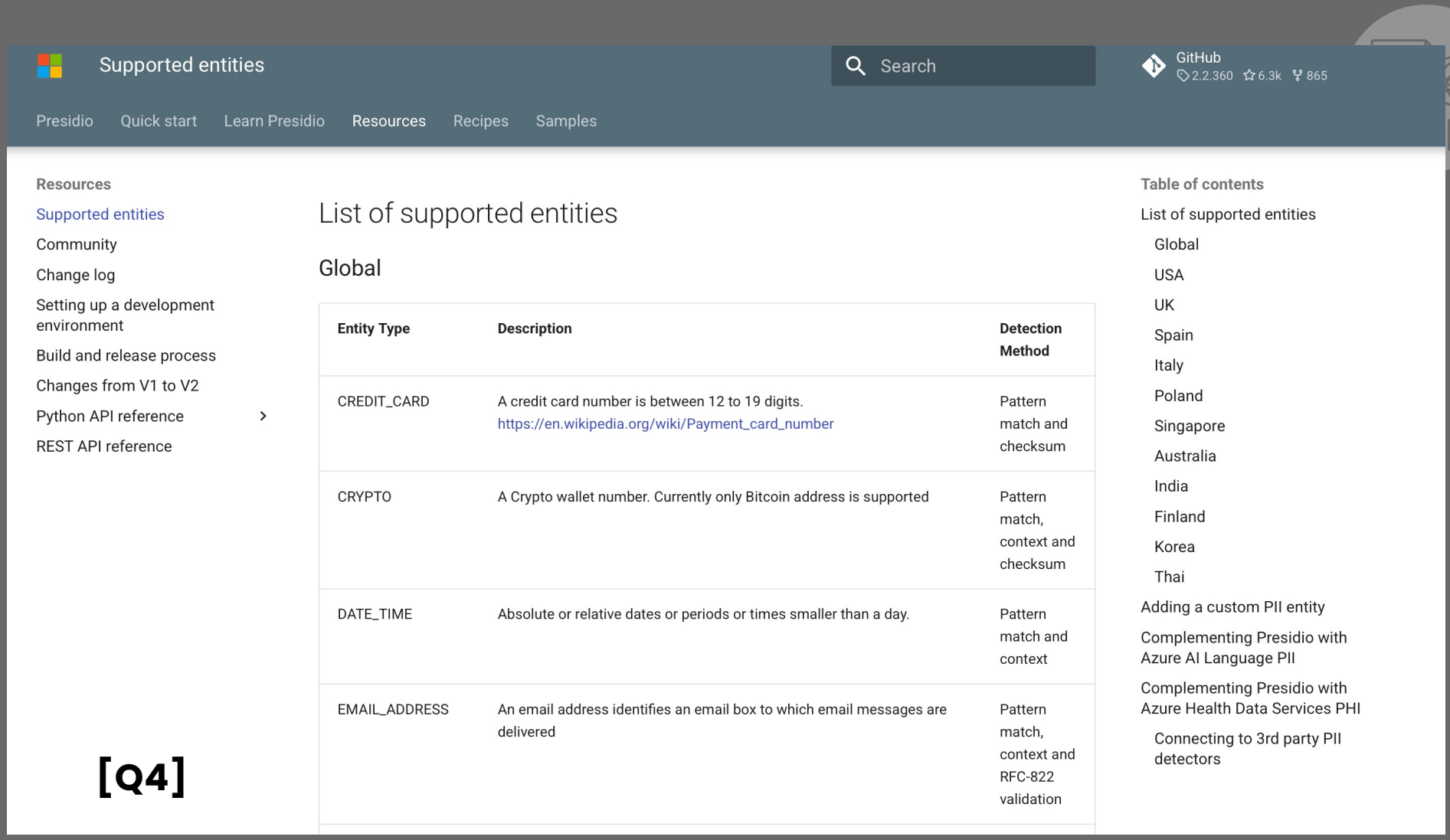
USA
UK
Spain
Italy
Poland
Singapore
Australia
India
Finland
Korea
Thai
Adding a custom PII entity
Complementing Presidio with Azure AI Language PII
Complementing Presidio with Azure Health Data Services PHI
Connecting to 3rd party PII detectors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6.3k
865
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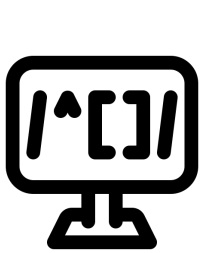
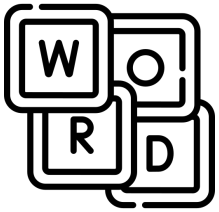
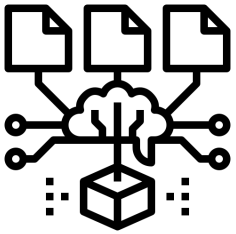
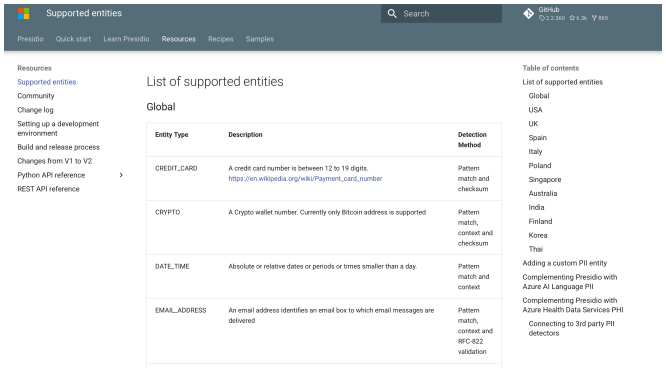
[Q4]

Analyzer









PII-Typ

Start/End-Index

Score

Anonymizer

- **Redact**
  - Max Mustermann → ▉ oder gar nichts
- **Replace**
  - Max Mustermann → [PERSON]
- **Mask**
  - max.mustermann@example.com→ m*********@example.com
- **Hash/Encrypt**
  - ID 12345678 → bca896f7a640039367c209c2441a18b0

Presidio Detection Flow

[Q5]

Regex
pattern recognition

NER(ML)*
leveraging natural language to detect entities

Checksum
validate patterns (if applicable)

Context Words
increase the detection confidence

Anonymization
multiple anonymization techniques

*NER – Named Entity Recognition

Projekt – Ziele, Artefakt & Praxis-Levels

- Redaktion-Script für personenbezogene Daten vor LLM-Verarbeitung
- Vor/Nach-Vergleich der LLM-Antwort
- Messung von:
  - Antwortqualität
  - Datenschutz

Regel-/NER-basierte Erkennung & Maskierung

Analyse von Falsch-Positiven/-Negativen auf 50 Beispielen

Selektive Demaskierung (post-hoc) mit Audit-Log

Redaktion-Script

```
EMAIL = re.compile(r"[a-zA-Z0-9_.+-]+@[a-zA-Z0-9-]+\.[a-zA-Z0-9-.]+")
ID = re.compile(r"(ID[-:]?\s?\d{3,}|TK-\d{3,}|\d{4}-LLM)")
NAME = re.compile(r"\b[A-Z][a-z]+\s[A-Z][a-z]+\b")
```

```
def mask_pii(text: str) -> Tuple[str, Dict[str, int]]:
    counts = Counter()
    def repl_email(m):
        counts['email'] += 1
        return '[EMAIL]'
    def repl_id(m):
        counts['id'] += 1
        return '[ID]'
    def repl_name(m):
        counts['name'] += 1
        return '[NAME]'
    text = EMAIL.sub(repl_email, text)
    text = ID.sub(repl_id, text)
    text = NAME.sub(repl_name, text)
    return text, counts
```

Redaktion-Script

```
Original : Anna Schmidt (anna.schmidt@example.com) bestellte Laptop ID-99123.
Maskiert : [NAME] ([EMAIL]) bestellte Laptop [ID].
Gefunden : {'email': 1, 'id': 1, 'name': 1}

Original : Kontakt: Max Bauer, max.bauer@firma.de, Ticket ID: TK-4455.
Maskiert : Kontakt: [NAME], [EMAIL], Ticket ID: [ID].
Gefunden : {'email': 1, 'id': 1, 'name': 1}

Original : Supportanfrage von Li Wei: li.wei@uni.edu zum Kurscode ID-2024-LLM.
Maskiert : Supportanfrage von [NAME]: [EMAIL] zum Kurscode [ID]-LLM.
Gefunden : {'email': 1, 'id': 1, 'name': 1}
```

Redaktion-Script - Antwortqualität der LLMs (roh vs. maskiert)

Modell	Frage	Similarity roh vs. Maskiert
Qwen2.5-3b	Bestellung Kundin?	0.085
Qwen2.5-3b	Ticketnummer & Einreicher?	0.113
Llama3.2-3b	Bestellung Kundin?	0.718
Llama3.2-3b	Ticketnummer & Einreicher?	0.139

Redaktion-Script - Antwortqualität der LLMs (roh vs. maskiert)

„Welche Bestellung hat die Kundin aufgegeben?“

[Q6]

„Die Kundin hat Laptop ID-99123 bestellt.“ Ohne Maskierung

„Die Kundin hat Laptop [ID] aufgegeben.“ Mit Maskierung

Bronze – Regel-/NER-Erkennung

```python
@dataclass
class Entity:
    label: str
    start: int
    end: int
    value: str

EMAIL = re.compile(r"[a-zA-Z0-9_.+-]+@[a-zA-Z0-9-]+\.[a-zA-Z0-9-.]+")
ID = re.compile(r"(ID[-:]?\s?\d{3,}|TK-\d{3,}|ORD-\d{3,}|\d{4}-LLM)")
NAME = re.compile(r"\b[A-Z][a-z]+\s[A-Z][a-z]+\b")
DATE = re.compile(r"(\d{2}\.\d{2}\.\d{4}|\d{4}-\d{2}-\d{2})")
```

Bronze – Regel-/NER-Erkennung

```
--- Beispiel 3 ---
Original : Kursanmeldung: Li Wei schreibt an li.wei@uni.edu bezueglich Kurscode ID-2024-LLM am 01.04.2024.
Maskiert : Kursanmeldung: [PERSON] schreibt an [EMAIL] bezueglich Kurscode [ID]-LLM am [DATE].
Gefunden : [('PERSON', 'Li Wei'), ('EMAIL', 'li.wei@uni.edu'), ('ID', 'ID-2024'), ('DATE', '01.04.2024')]
```

```python
PATTERN_REGEX = [
    (re.compile(r"\bACME\sGmbH\b", re.IGNORECASE), "ORG"),
    (re.compile(r"\buni\b", re.IGNORECASE), "ORG"),
    (re.compile(r"\bAnna\sSchmidt\b", re.IGNORECASE), "PERSON"),
    (re.compile(r"\bMax\sBauer\b", re.IGNORECASE), "PERSON"),
    (re.compile(r"\bLi\sWei\b", re.IGNORECASE), "PERSON"),
    (re.compile(r"\bMaria\sLopez\b", re.IGNORECASE), "PERSON"),
    (re.compile(r"(id|tk|ord)[-]\d+", re.IGNORECASE), "ID"),
]
```

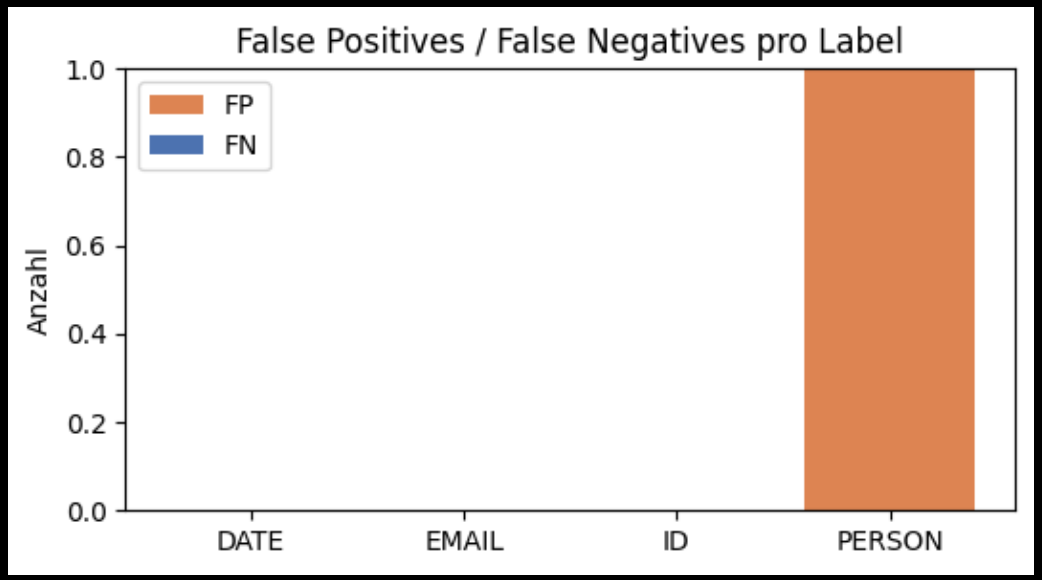
Silber – Falsch-Positiv/-Negativ

„Ticket ORD-7788 gemeldet von Anna Schmidt…“

„Allgemeine Anfrage ohne Kundendaten.“

```
TP: {'PERSON': 33, 'ID': 30, 'EMAIL': 25, 'DATE': 12}
FP: {'PERSON': 1}
FN: {}
Precision: 0.990 | Recall: 1.000 | F1: 0.995
```

Silber – Falsch-Positiv/-Negativ




```
TEXT: Allgemeine Anfrage ohne Kundendaten.
Truth: set()
Pred: {'PERSON'}
FP: ['PERSON']
```

Gold– Selektive Demaskierung & Audit Log

```
Original: Support: Max Bauer, Ticket TK-4455, Kontakt max.bauer@firma.de.
Maskiert: Support: [PERSON:d58a3053a1], Ticket [ID:3abd9d1614], Kontakt [EMAIL:408298183d]
```

```
Maskierter Text: Support: [PERSON:d58a3053a1], Ticket [ID:3abd9d1614], Kontakt [EMAIL:408298183d]
Demaskiert  : Support: Max Bauer, Ticket TK-4455, Kontakt max.bauer@firma.de.
```

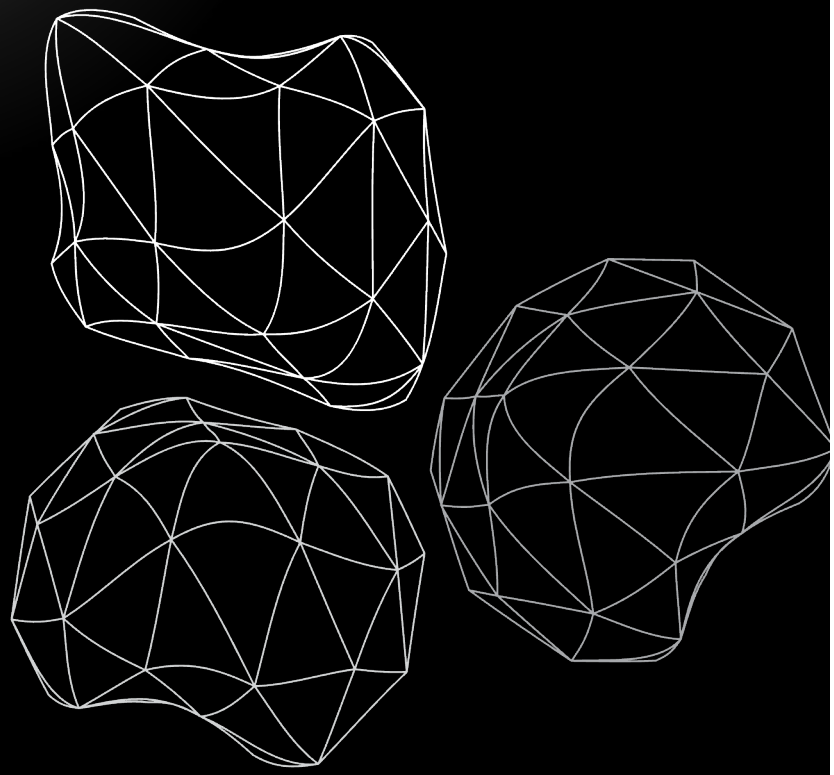
```
Audit-Events:
{'actor': 'analyst', 'reason': 'Support eskalation', 'token_hash': 'd58a3053a1', 'original': 'Max Bauer', 'label': 'PERSON', 'timestamp': '2025-12-11T18:20:58.049982Z'}
{'actor': 'analyst', 'reason': 'Support eskalation', 'token_hash': '3abd9d1614', 'original': 'TK-4455', 'label': 'ID', 'timestamp': '2025-12-11T18:20:58.049999Z'}
{'actor': 'analyst', 'reason': 'Support eskalation', 'token_hash': '408298183d', 'original': 'max.bauer@firma.de.', 'label': 'EMAIL', 'timestamp': '2025-12-11T18:20:58.050005Z'}
{'actor': 'qa', 'reason': 'Qualitaetskontrolle', 'token_hash': 'a21e4283ee', 'original': 'Anna Schmidt', 'label': 'PERSON', 'timestamp': '2025-12-11T18:20:58.080713Z'}
```

Fazit

- **PII ist überall und LLMs vergessen nicht von selbst**
- **Redaktion-Script oder allgemeiner Schutz bevor Daten ins LLM gehen sind ein wirksamer Schutzfilter**
- **Auswirkung auf die Qualität ist meist moderat**

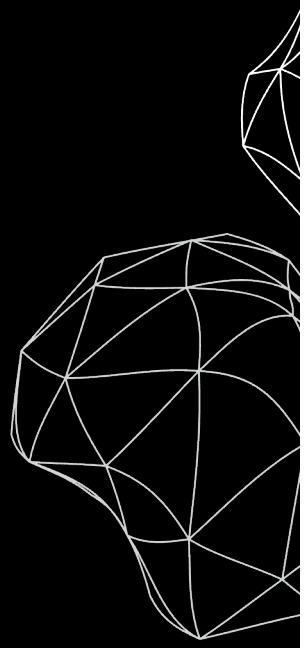
Ausblick

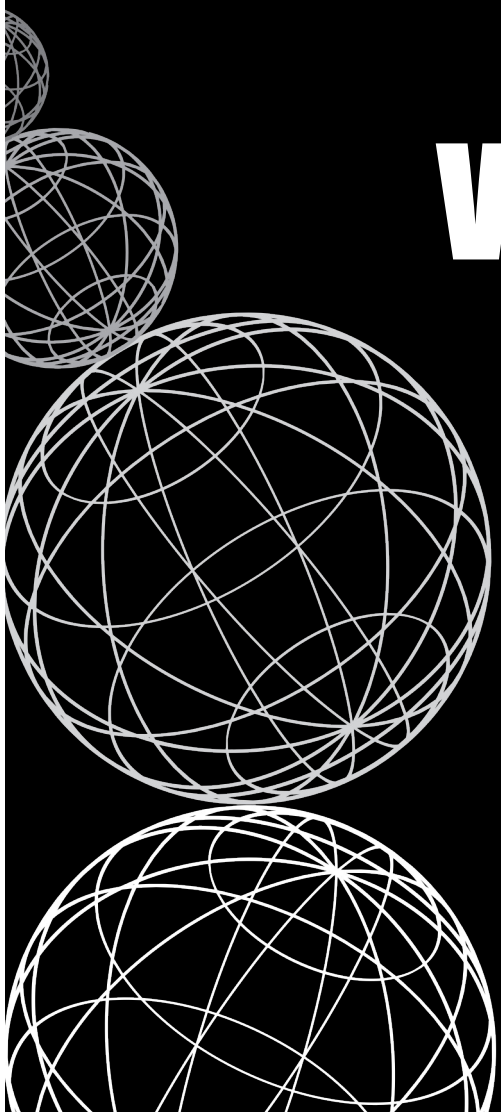
- **Bessere PII-Erkennung**
- **Weitere Qualitätsbewertung**
- **Integration in wirklichen Workflow**



Quellen

- [Q1]: https://ai.gopubby.com/the-training-pipeline-of-large-language-models-afd5fa57df46
- [Q2]: https://arxiv.org/abs/2012.07805
- [Q3]: https://www.unite.ai/de/prompt-hacking-and-misuse-of-llm/
- [Q4]: https://microsoft.github.io/presidio/supported_entities
- [Q5]: https://microsoft.github.io/presidio/
- [Q6]: https://www.youtube.com/watch?v=ITpyjyZDwcs





Vielen Dank für eure Aufmerksamkeit

Fragen ?