[DRAFT SLIDES] Anonymization of Sensitive Information in Financial Documents

Using Python, Diffusion Models, and Named Entity Recognition

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Overview

- **Why anonymize financial documents?**
  - Compliance with privacy laws (GDPR, HIPAA, etc.)
  - Protect sensitive client data
  - Facilitate internal analytics without exposing real PII
- **Key Techniques**
  1. Named Entity Recognition (NER) for PII detection
  2. Masking or synthetic replacement for anonymization
  3. Diffusion models for advanced inpainting (images/text)

Data as Fuel

- **Data = "Fossil Fuel"** of Machine Learning
  - Essential for training high-quality models
  - Often locked away due to privacy restrictions
- **Goal**
  - Use real documents **without** exposing actual personal data
  - **Replace** sensitive data with realistic stand-ins
  - Maintain structure and context for valid ML training

Challenges of Using ChatGPT

- **Hallucinations**: Large language models can introduce factual errors
- **Inconsistency**: Repeated queries might yield different anonymizations

Solution:

- Self-hosted open-source tools (SpaCy, NLTK, PyTorch, etc.)
- Consistent, customizable pipelines
- Infilling using specilised diffusion models

High-Level Approach

1. **Identify Sensitive Entities**
    - Names, addresses, account numbers, SSNs, etc.
    - Use Named Entity Recognition (NER)
2. **Anonymize or Replace**
    - Simple: Mask entities with placeholders (`<NAME>`, `<ACCOUNT>`)
    - Advanced: Generate synthetic but realistic replacements
3. **Use Diffusion Models**
    - Inpaint text or images for realistic fill-ins
    - Keep the document’s visual or textual consistency

Named Entity Recognition (NER)

- **Definition**:
  - Automatically identifying and classifying named entities (e.g., PERSON, ORG, LOCATION)
- **Libraries**:
  - **SpaCy**: Fast, easily customizable, good pre-trained pipelines
  - **NLTK**: Classic, robust for general NLP tasks
  - **PyTorch**: Build custom deep learning models for domain-specific needs

SpaCy NER Example

```
import spacy

# Load a pre-trained NER model
nlp = spacy.load("en_core_web_sm")

text = "John Doe has an account number 1234-5678-9101 at ABC Bank."
doc = nlp(text)

for ent in doc.ents:
    print(ent.text, ent.label_)
```

- Outputs named entities like `John Doe (PERSON)`, `ABC Bank (ORG)`, etc.

Simple Anonymization

```
anonymized_text = text
for ent in reversed(doc.ents):
    start, end = ent.start_char, ent.end_char
    placeholder = f"<{ent.label_}>"
    anonymized_text = anonymized_text[:start] + placeholder + anonymized_text[end:]

print(anonymized_text)
# "<PERSON> has an account number <CARDINAL> at <ORG>."
```

- **Pros**: Quick and easy
- **Cons**: Loses natural structure and context (sometimes needed for model training)

Synthetic Replacements

- **Why?**
  - Preserves format/length (e.g., valid credit card pattern)
  - Maintains a semblance of realism for training or software testing
- **Approaches**:
  1. **Rule-Based**: Randomly generate valid-looking strings (e.g., `4000-1234-5678-9999`)
  2. **Generative Models**: Use a trained model to produce realistic text (names, addresses, etc.)

Text vs. Image Documents

- **Text Documents** (Word, PDF with embedded text)
  - Easier to process with direct NER, tokenization, etc.
  - “Inpainting” can mean replacing tokens in context
- **Image/Scanned PDFs**
  - Requires **OCR** (Tesseract, EasyOCR) for text extraction
  - Then apply NER
  - Use **image inpainting** if you need to maintain the look of the scanned doc

Diffusion Models for Inpainting

What are Diffusion Models?

- Generative models that learn to **denoise** data
- Typically used for **image** generation, but concept extends to text inpainting

Workflow:

1. Mask region containing PII
2. Use diffusion or a similar generative approach to fill in with synthetic data
3. Maintain visual/textual consistency so the anonymized doc looks natural

Limitations of Native Application of Diffusion Models for Inpainting

- **Text Style Complexity**:
  - Difficulty capturing and replicating fine-grained text styles (font, color, orientation)
  - Limited ability to handle complex multilingual text, especially non-Latin scripts
- **Background Consistency**:
  - Challenges maintaining natural background appearance when editing text
  - Particularly problematic in intricate or cluttered scenes

DiffUTE: Universal Text Editing Diffusion Model

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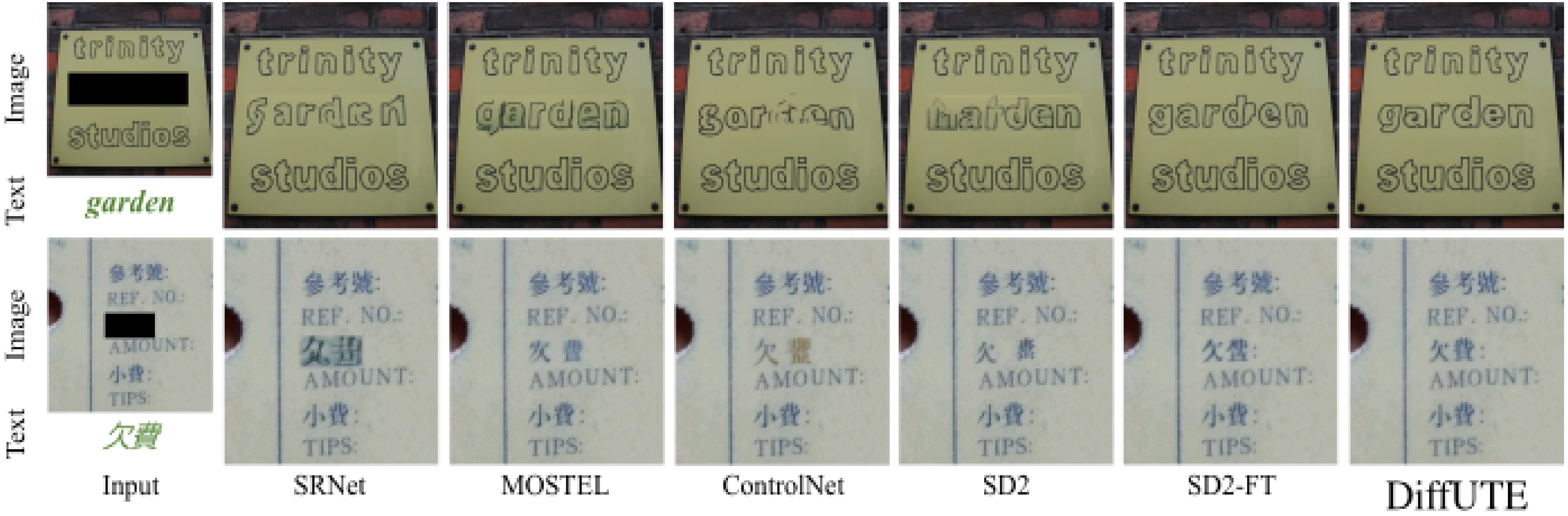
1. **Glyph Control**:
    - Incorporates glyph embeddings to guide the model on character shape and style.
    - Enables accurate and diverse text generation across multiple languages.
2. **Fine-grained Guidance**:

DiffUTE beats other methods with a significant improvement



Practical Considerations

- **Model Accuracy**:
    - Domain-specific training needed for financial documents
    - Regular updates to capture new entity types (e.g., new IBAN formats)
- **Performance**:
    - Large-scale docs? Ensure your pipeline is efficient
    - Generative models can be resource-heavy
- **Compliance & Governance**:
    - Maintain logs of anonymization for auditing
    - Ensure synthetic approach isn’t reversible (avoid re-identification)

Limitations & Edge Cases

- **Misspellings / Obfuscations**:
    - NER might miss “J0hn D0e” or unusual patterns
    - Combine rule-based checks with NER for better coverage
- **Diffute requires training on a dataset**

Conclusion

- **Takeaways**:
  i. **Use NER** to systematically identify sensitive entities
  ii. **Mask or Generate** synthetic replacements to protect privacy
  iii. **Leverage Python's open-source ecosystem** (SpaCy, NLTK, PyTorch) for self-hosted, consistent pipelines
  iv. **Specilised Diffusion Models** can help with realistic inpainting for more complex use cases
- **Q&A**:
  - "Thank you for your attention! Let's discuss your questions."

References & Resources

- **SpaCy**: https://spacy.io
- **NLTK**: https://www.nltk.org
- **PyTorch**: https://pytorch.org
- **Diffusion Models**:
  - Stable Diffusion
  - SD2-FT
  - Diffute

Thank you!

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