

SDTM Mapping Based on TF-IDF and Neural Network Probabilistic Models

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NJ CDISC Users Group Meeting

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Brief Introduction

- Sam Tomioka
- Director, Clinical Data Programming – Data Science
- Sunovion Pharmaceuticals

- Current ML Projects
 - SDTM Mapping
 - Protocol Optimization
 - Digital Endpoints (Seizure)
- Past ML Projects
 - Adverse Events
 - Dose Titration
 - Digital Endpoints (Stroke, Depression)
 - SDTM Mapping

AGENDA



Problem to Solve



SDTM Mapping with “Machine Learning”



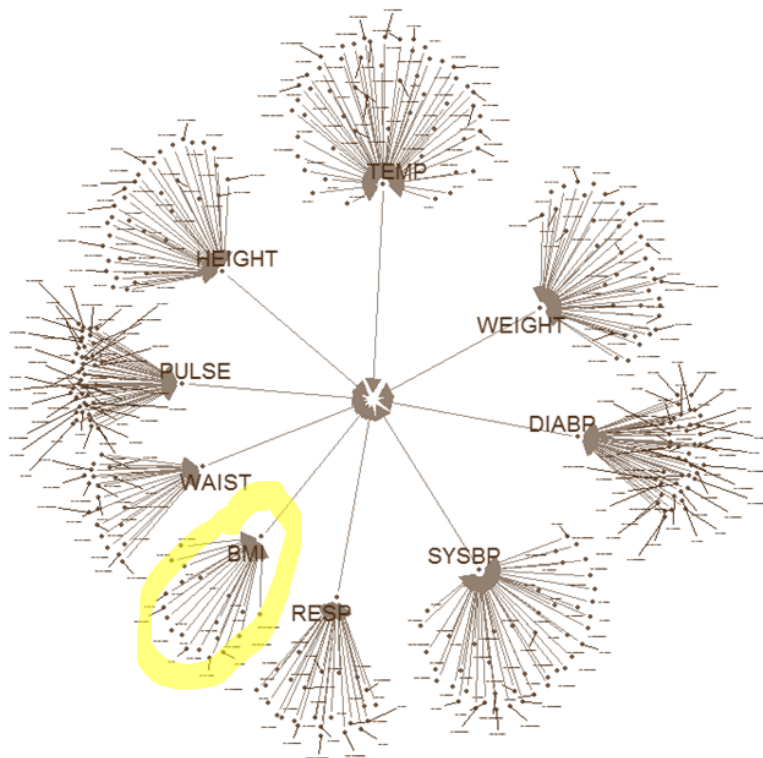
Tools Used



Thought

ENDLESS MAPPING...

SDTM.VS.VSORRES mapping for
12 Sunovion studies delivered by one CRO

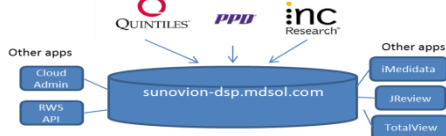


20 sources for BMI

```
"VS.BMI"  
"VS.BMI_RAW"  
"VS.BMI_Z"  
"VS.BMI_Z_RAW"  
"VS.BMIS"  
"VS.BMIS_RAW"  
"VS1.BMI"  
"VS1.BMI_RAW"  
"VS1.BMI_Z"  
"VS1.BMI_Z_RAW"  
"VS1.VS1BMI"  
"VS2.BMI"  
"VS2.BMI_RAW"  
"VS2.D_BMI"  
"VS2.D_BMI_RAW"  
"VS2.VS2BMI"  
"VSMSTR.BMI"  
"VSMSTR.BMI_RAW"  
"VSMSTR.D_BMI"  
"VSMSTR.D_BMI_RAW"
```

Embrace Metadata Standards

RaveX Implementation Project



Go live FY 2018 2Q

MDR Based SDTM Automation Project



Started FY 2018 4Q

SDTM Automation Project



SDTM automation macros
Domain templates

Go Live FY 2018 1Q



STUDYID	DOMAIN	CDISC ID	CDISC ID	REF ID
1	316C1584	DA	01301055	00020001
2	316C1584	DA	01301055	00020002
3	316C1584	DA	01301055	00020003
4	316C1584	DA	01301055	00020004
5	316C1584	DA	01301055	00020005
6	316C1584	DA	01301055	00020006
7	316C1584	DA	01301055	00020007
8	316C1584	DA	01301055	00020008
9	316C1584	DA	01301055	00020009
10	316C1584	DA	01301055	00020010
11	316C1584	DA	01301055	00020011
12	316C1584	DA	01301055	00020012
13	316C1584	DA	01301055	00020013

SDTM

Standard CRF Working Group

- ☐ Sunovion Standard CRF Final v1.0_Central_EG
- ☐ Sunovion Standard CRF Final v1.0_Central_LB
- ☐ Sunovion Standard CRF Final v1.0_DA
- ☐ Sunovion Standard CRF FINAL v1.0_EX
- ☐ Sunovion Standard CRF FINAL v1.0_EX-DA
- ☐ Sunovion Standard CRF FINAL v1.0_PV
- ☐ Sunovion Standard CRF FINAL v1.0_RAND
- ☐ Sunovion Standard CRF FINAL v1.0_SU
- ☐ Sunovion Standard CRF FINAL v1.0_TC
- ☐ Sunovion Standard CRF FINAL v2.0_DS1

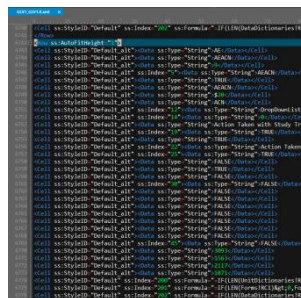
paper

metadata

CDASH



Global Library Volume Implementation Project



metadata in ODM XML

SDTM

CT



Started FY2018 1Q

WHAT NEXT?

Can I use **natural language** model and **machine learning** algorithms to map raw data variables to SDTM variables?

AGENDA



Problem to Solve



SDTM Mapping with “Machine Learning”



Tools Used

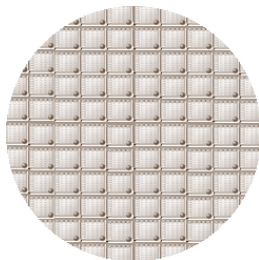


Thought

ML based SDTM mapping for fast, accurate, consistent SDTM generation

Input

Raw data



CDASHIG, SDTM IG



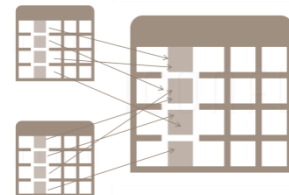
NLP & ML

Wordcloud for AE raw metadata in raw

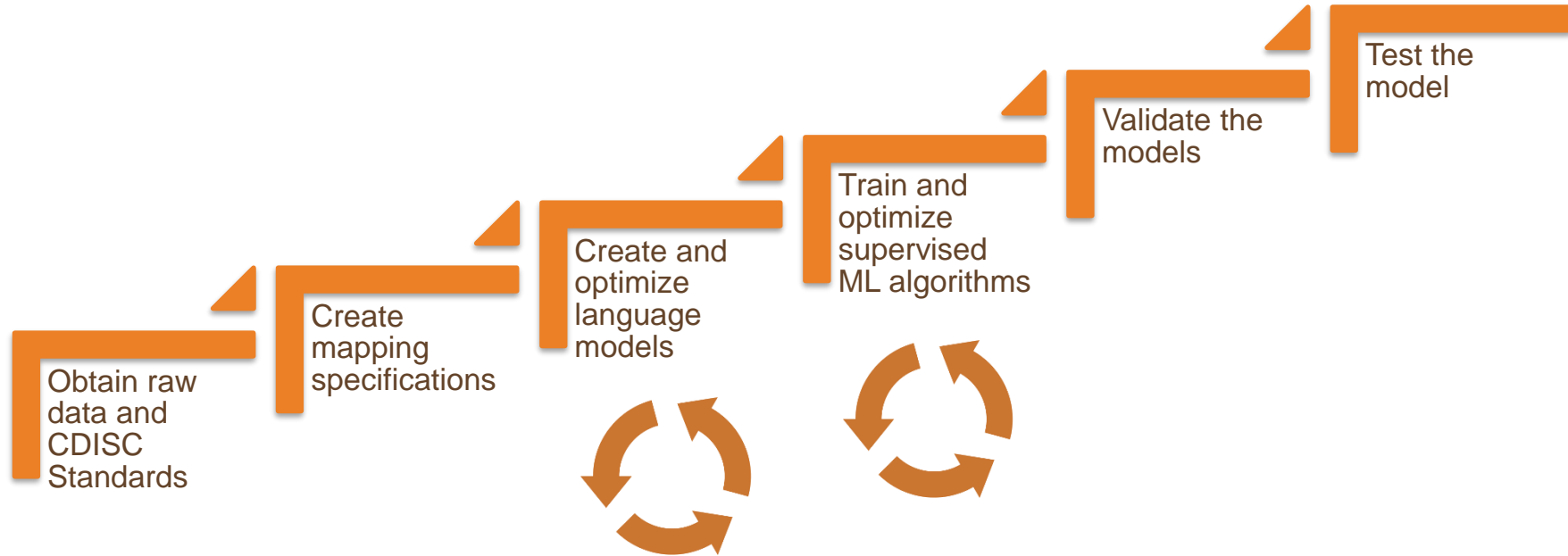


Output

Mapping Specification



Steps



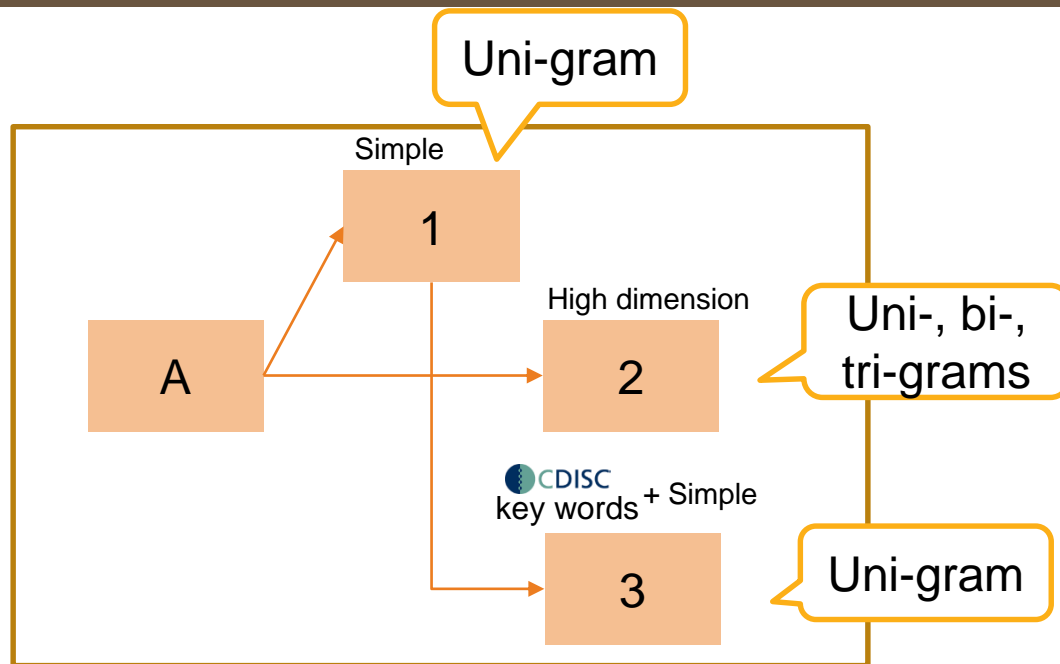
Create mapping specifications (with Human Intelligence)

Raw Variable	SDTM Variable
PT	AEDECOD
SOC	AEBODSYS
PTNAME	AEDECOD
SOCNAME	AEBODSYS
...	...

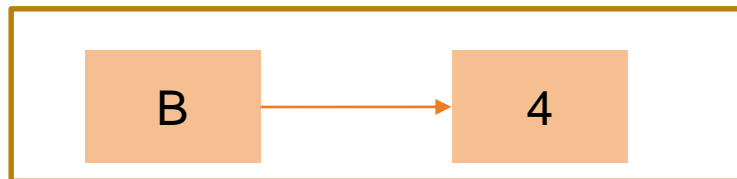
*illustration purpose only

Natural Language Models

TF-IDF



NNLM



Natural Language Model A

TF-IDF algorithm: Weighing terms

- Words occur nearby frequently are important than words that only appear once or twice

$$\text{Frequency (TF)} \quad \text{tf}_{t,d} = \begin{cases} 1 + \log_{10} \text{count}(t,d) & \text{if } \text{count}(t,d) > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Words that are too frequent are not important

$$\text{Inverse Document Frequency (DF)} \quad \text{idf}_t = \log_{10} \left(\frac{N}{\text{df}_t} \right)$$

- Weight $w_{t,d} = \text{tf}_{t,d} \times \text{idf}_t$

Logistic regression,
accuracy=0.64058

AETERM definition in CDASH IG

The reported or pre-specified name of the adverse event.

0.6331503

0.6105753

0.6247964

0.6611213



Document term matrix of 17 studies data and IG



Natural Language Model B

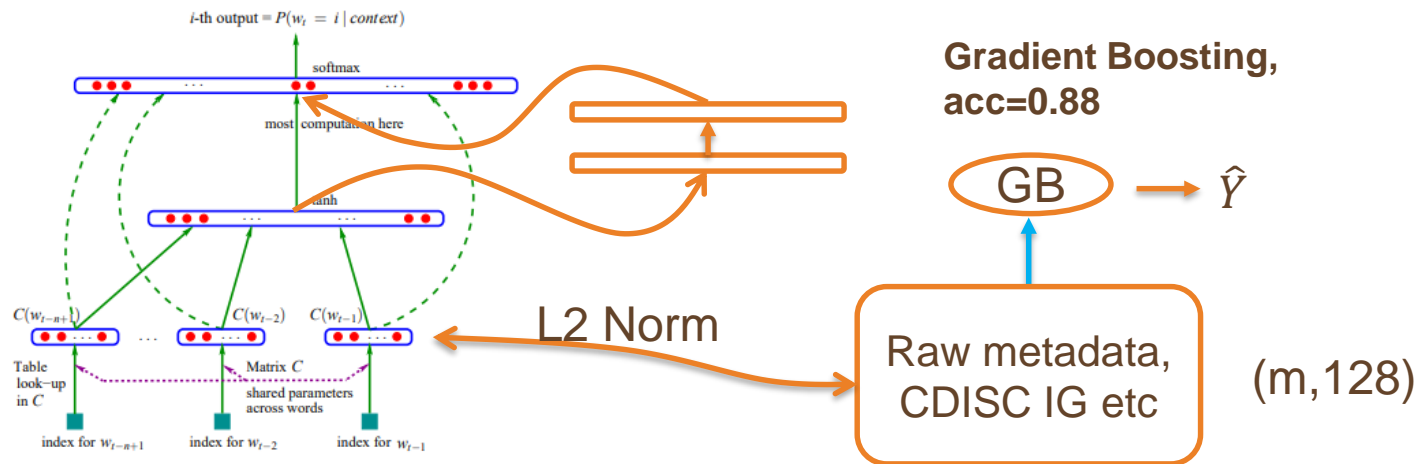


Figure 1: Neural architecture: $f(i, w_{t-1}, \dots, w_{t-n+1}) = g(i, C(w_{t-1}), \dots, C(w_{t-n+1}))$ where g is the neural network and $C(i)$ is the i -th word feature vector.

200,000,000,000 English Google News corpus

Natural Language Models

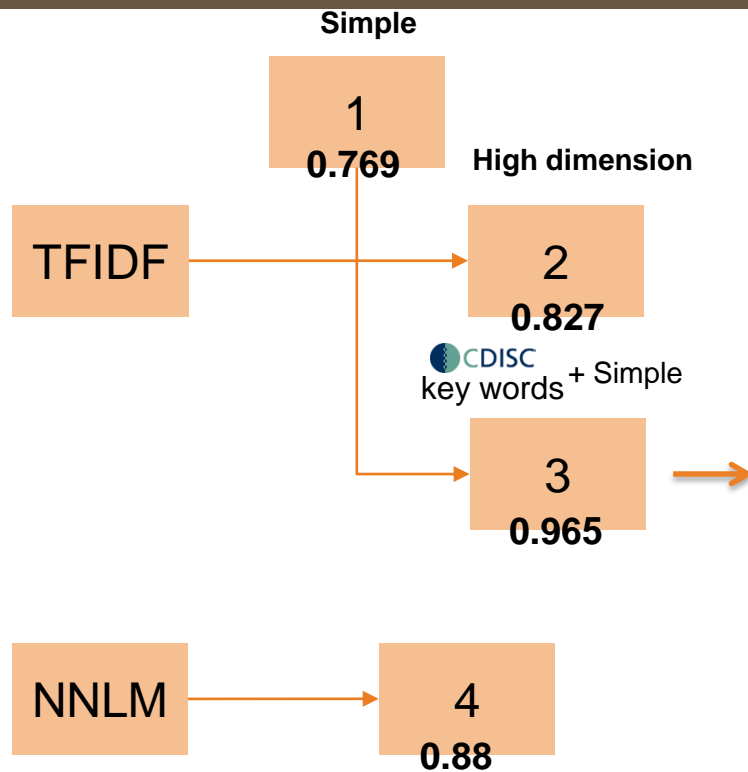
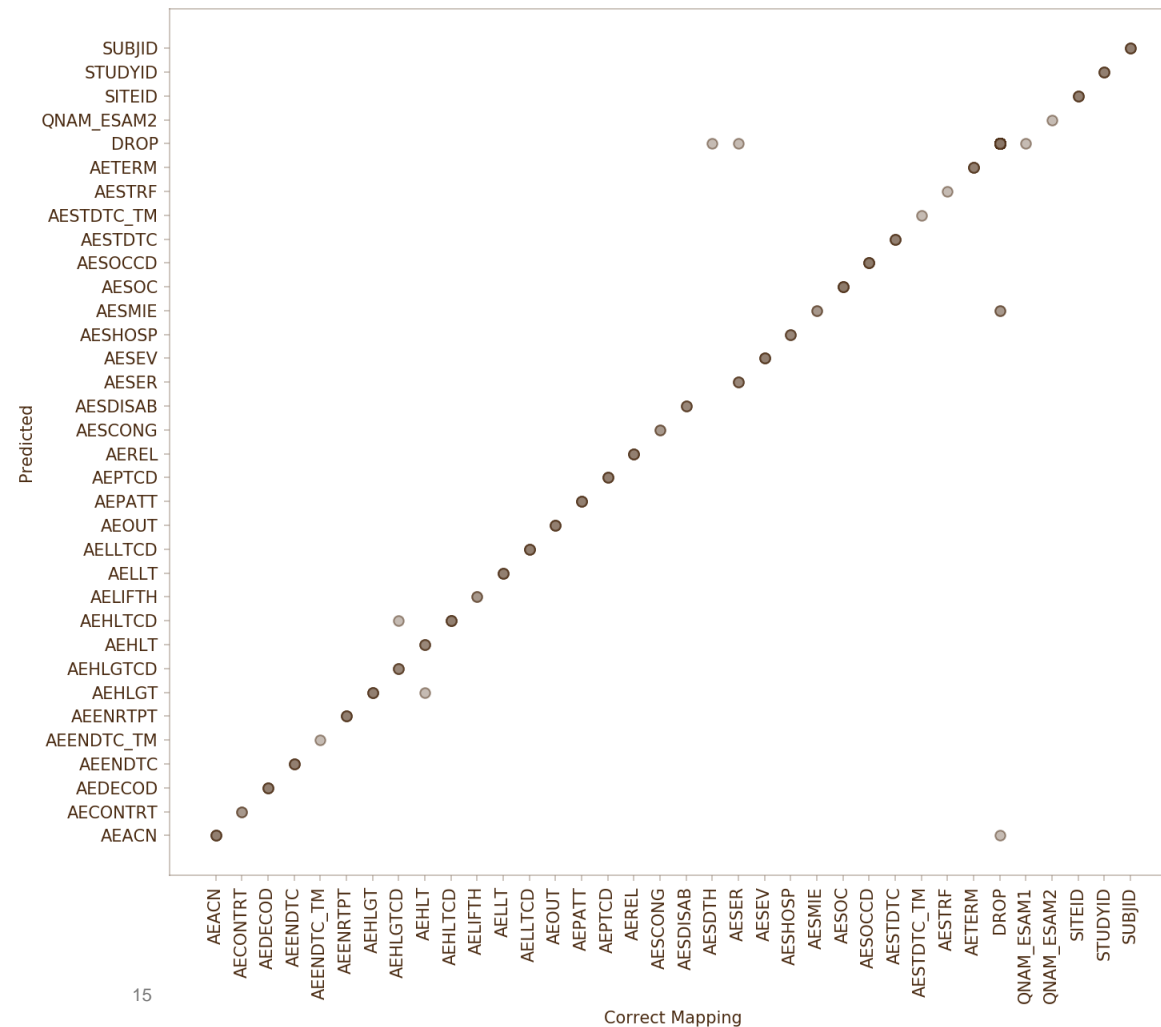


Figure 6. Results of SDTM mapping (Accuracy with 95% CI and Kappa)

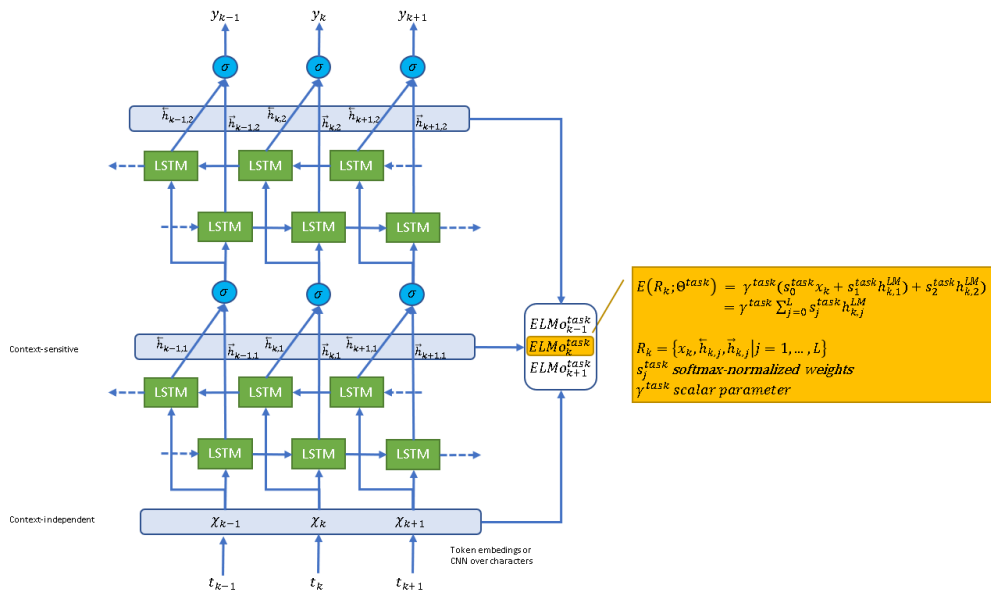
Final Ensemble Model



Mapping Accuracy
on data from 3 new
studies using Final
Ensemble Model

0.97


More robust approach



$$E(R_k; \Theta^{task}) = \gamma^{task} (s_0^{task} x_k + s_1^{task} h_{k,1}^{LM} + s_2^{task} h_{k,2}^{LM})$$

$$= \gamma^{task} \sum_{j=0}^L s_j^{task} h_{k,j}^{LM}$$

$R_k = \{x_k, \tilde{h}_{k,j}, \tilde{h}_{k,j} | j = 1, \dots, L\}$
 s_j^{task} softmax-normalized weights
 γ^{task} scalar parameter



sdtm-mapper 0.3.8

`pip install sdtm-mapper`

AGENDA



Problem to Solve



SDTM Mapping with “Machine Learning”












Tools Used



Thought

Tools used for POC

Programming	IDE	ML Framework	Purpose
		NA	Metadata extraction from sas7bdat
	 	caret	NLP ML Visualizations
		 	Transfer learning ML Visualizations

AGENDA



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SDTM Mapping with “Machine Learning”



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Thought



Summary

- This proof of concept demonstrated that **machine learning** along with a **natural language model** can produce a pretty accurate SDTM mapping specification document.
- As in any ML models, as you feed more mapping specs, the model will learn them and become more robust.

Thank You



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