

# MULTIVARIATE TIME-SERIES SYNTHETIC DATA GENERATION

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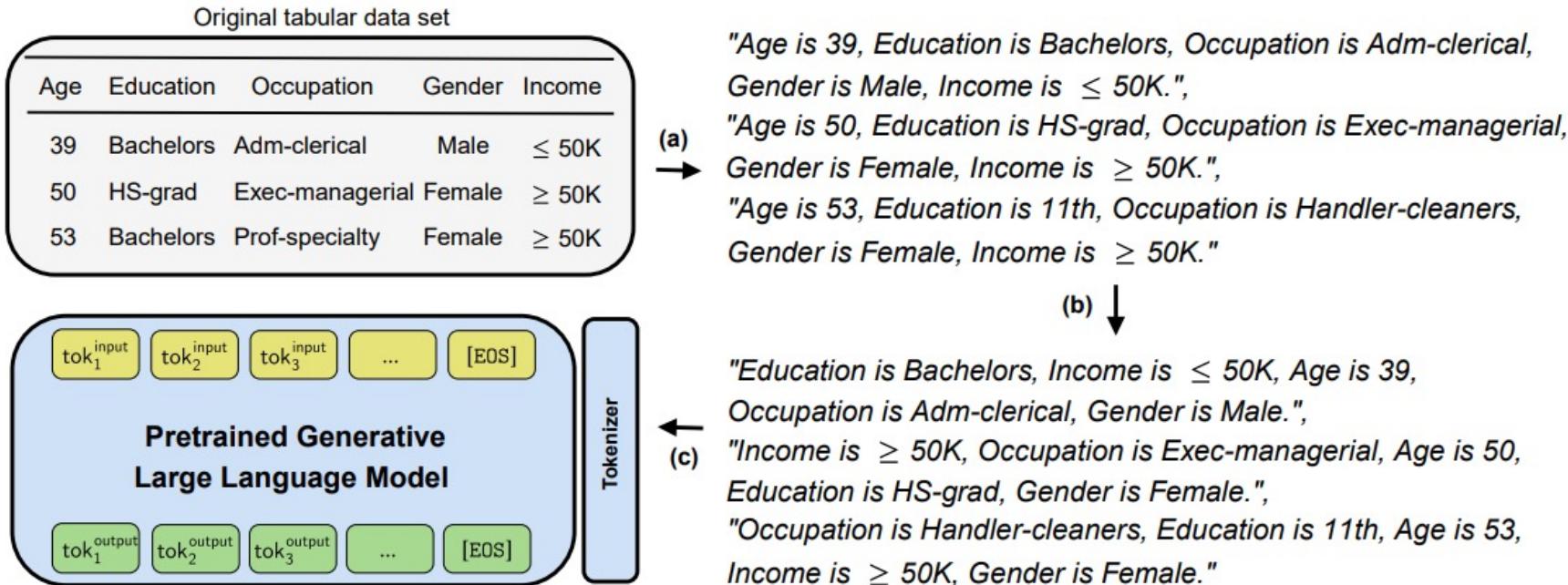
Probabilistic Machine Learning and Deep Learning

2023 – 2024

# **GREAT FRAMEWORK FOR SYNTHESIS**

1. Converting tabular data to string format ' $f_1$  is  $v_1, \dots, f_n$  is  $v_n$ '
2. Shuffling strings ordering to lose positional patterns
3. Fine-tuning pretrained LLM
4. Generating strings with optional preconditioning (prompts)
5. Re-converting the generated strings in tabular data

# GREAT PIPELINE FOR FINE-TUNING



# GENERATING MODEL PIPELINE

- Input: a text  $T$  encoded into a sequence  $t$  of tokens  $w \in W$
- Output: a text  $S$  of strings  $s$  decoded from a text  $T'$  of tokens  $t'$
- The fitting is done by maximizing the probability  $\prod_{t \in T} p(t)$

$$p(t) = p(w_1, \dots, w_j) = \prod_{k=1}^j p(w_k | w_1, \dots, w_{k-1})$$

# SAMPLING

- Output distribution:  $z = q(w_1, \dots, w_{k-1})$
- Each next token  $w$  is sampled by weighted choice sampling with a temperature parameter  $T > 0$ :

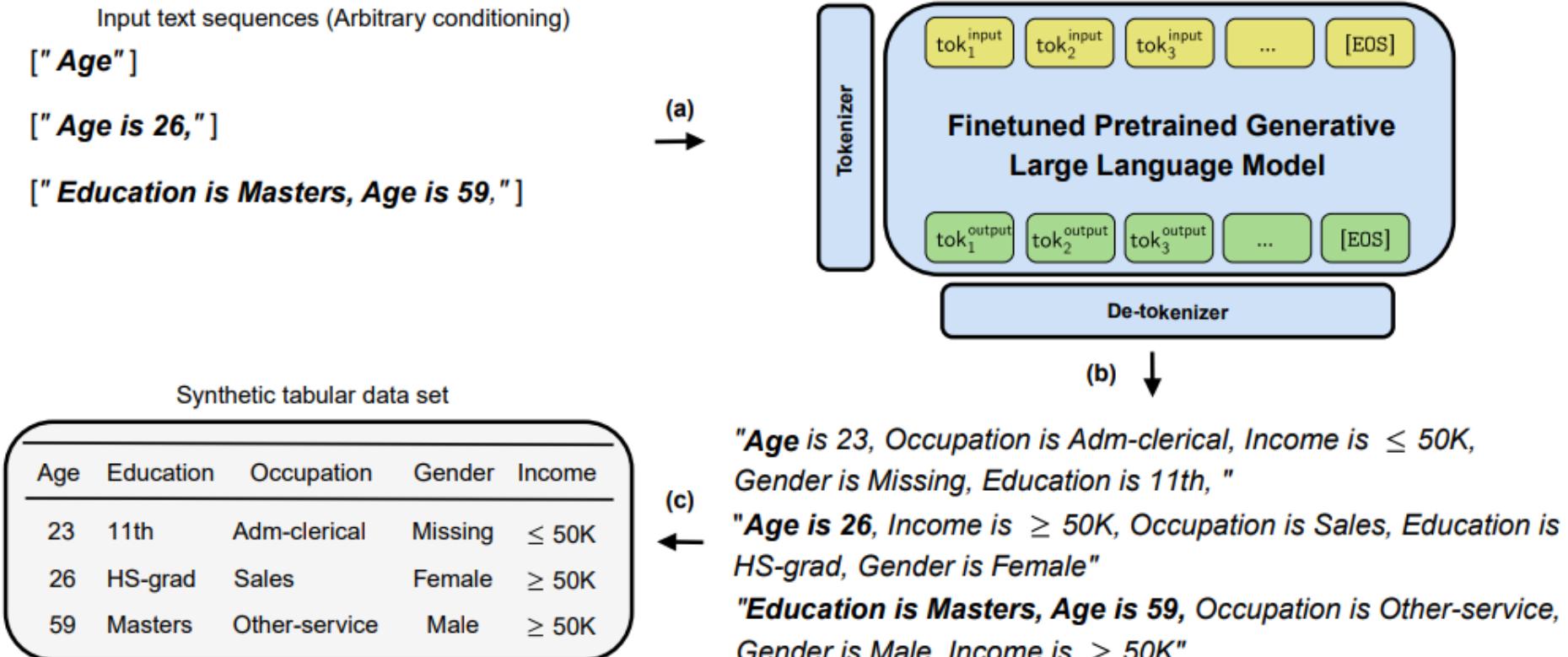
$$p(w_k | w_1, \dots, w_{k-1}) = \frac{\exp\left(\frac{z_{w_k}}{T}\right)}{\sum_{w' \in W} \exp\left(\frac{z_{w'}}{T}\right)}$$

# SAMPLING

- Prompts are given to the model to sample with preconditioning:
  - Multiple name-value pairs  $V_{i_1} = v_{i_1}, \dots, V_{i_k} = v_{i_k}$
  - Sampling is made from the distribution of the remaining features:

$$p(V_{\setminus \{i_1, \dots, i_k\}} | V_{i_1} = v_{i_1}, \dots, V_{i_k} = v_{i_k})$$

# GREAT PIPELINE FOR SAMPLING



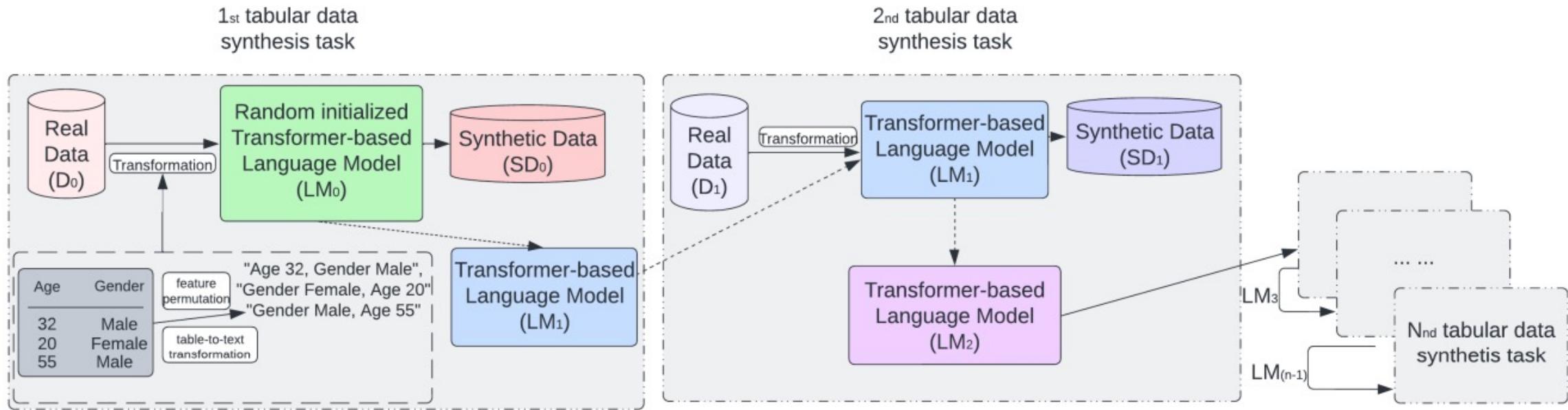
# **GREAT**

- String: ' $f_1$  is  $v_1$ , ...,  $f_n$  is  $v_n$ '
- Expensive tokenization
- Pretrained LLM

# **TABULA**

- String: ' $f_1 v_1$ , ...,  $f_n v_n$ '
- Cheaper tokenization
- LLM from scratch

# TABULA WORKFLOW



# TABULA ON MULTIVARIATE TIME-SERIES DATA

- Main quests:
  - Understanding time dependancy between sequences of observations
  - Avoiding overfitting due to the timestamp

	date	demand	RRP	min_temperature	max_temperature	solar_exposure	school_day
0	2015-01-01	99635.03	25.63	13.3	26.9	23.6	N
1	2015-01-02	129606.01	33.14	15.4	38.8	26.8	N
2	2015-01-03	142300.54	34.56	20.0	38.2	26.5	N
3	2015-01-04	104330.72	25.01	16.3	21.4	25.2	N
4	2015-01-05	118132.20	26.72	15.0	22.0	30.7	N

# STRATEGY: MODIFY TABULA FRAMEWORK

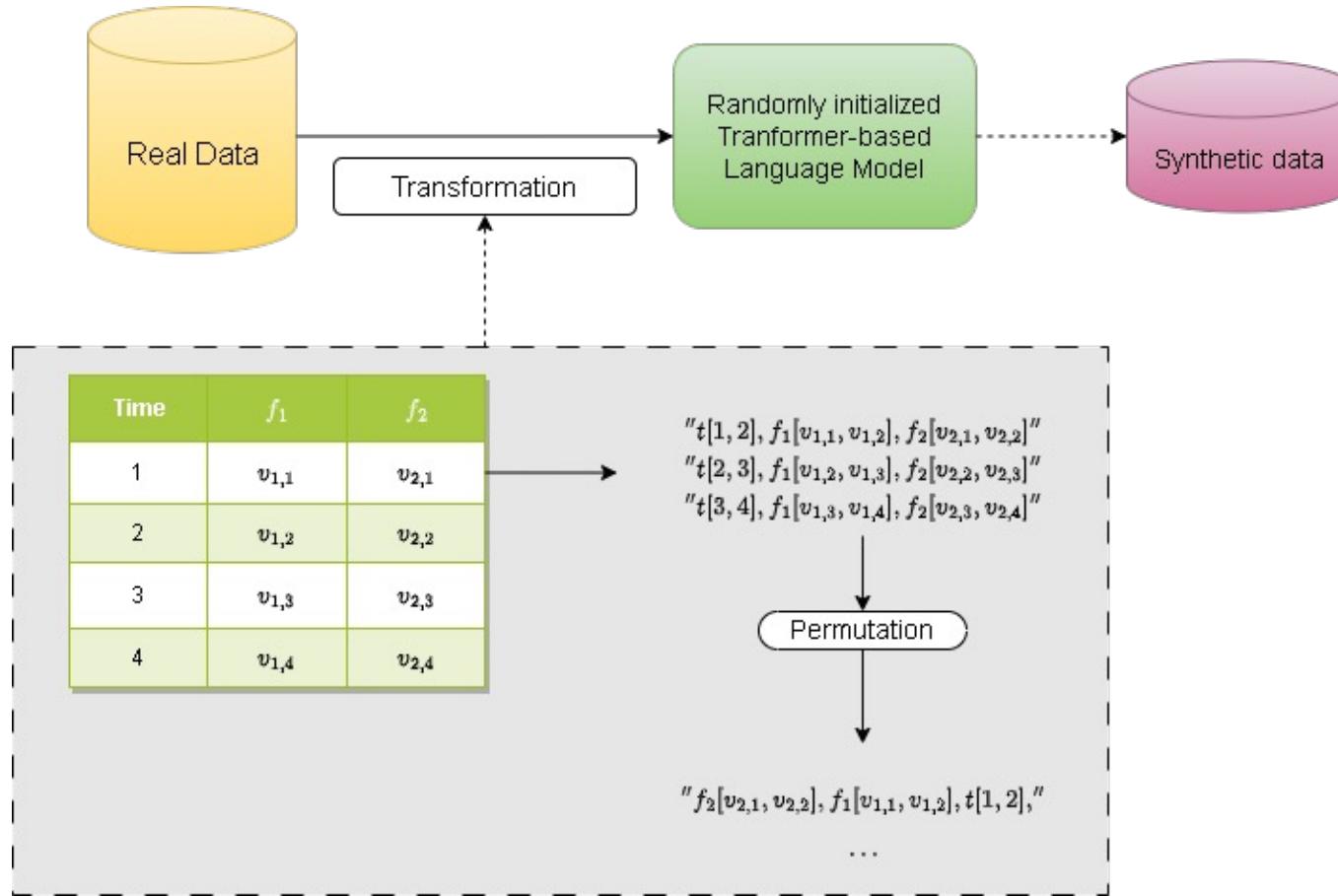
- Data preprocessing:
  - *Breaking timestamp into separate features*
  - *Introducing a temporal window to include values of more rows in a single string*

$$v = [v_{i+1}, v_{i+2}, \dots, v_{i+k}], k = \text{length of the window}$$

- Windows are selected through a stride (or offset)
- New encoded strings:

$$'f_1 [v_{1,1} \ v_{1,2} \ \dots \ v_{1,k}], \dots, f_n [v_{n,1} \ \dots \ v_{n,k}]'$$

# PIPELINE



# EXPERIMENTAL SET-UP

- Three datasets from Kaggle:
  - Energy consumption
  - London weather
  - Web visits
- Machine: GPU node V100 PCIe 32GiB on ORFEO cluster
- Modules: Tabula and Tabula modified with window/stride
- Comparison within the two frameworks

# EXPERIMENTAL SET-UP

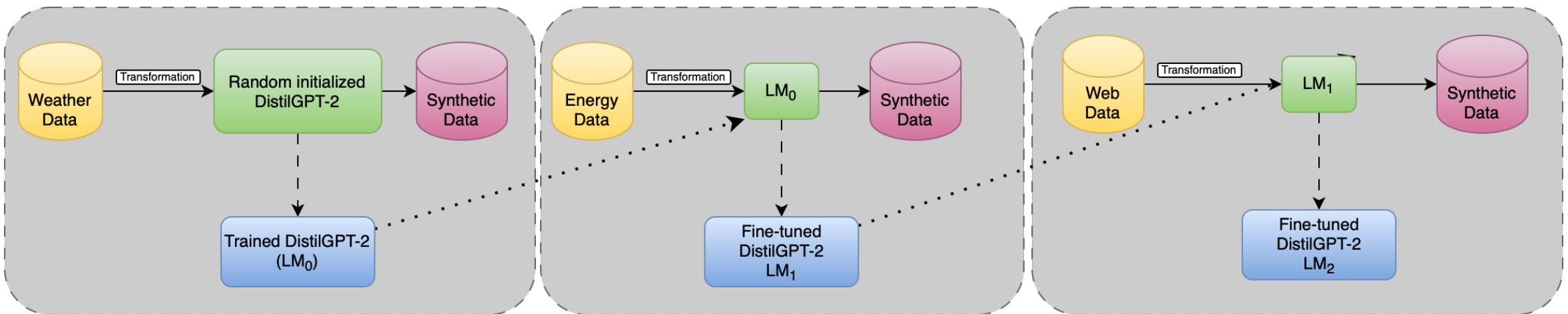
**MODEL** random initialized DistilGPT-2

**ACTIVATION** GeLU

**LOSS** cross-entropy

**OPTIMIZER** AdamW [ $\text{lr} = 5 \cdot 10^{-5}$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ,  $\epsilon = 1 \cdot 10^{-8}$ , decay = 0]

# PIPELINE

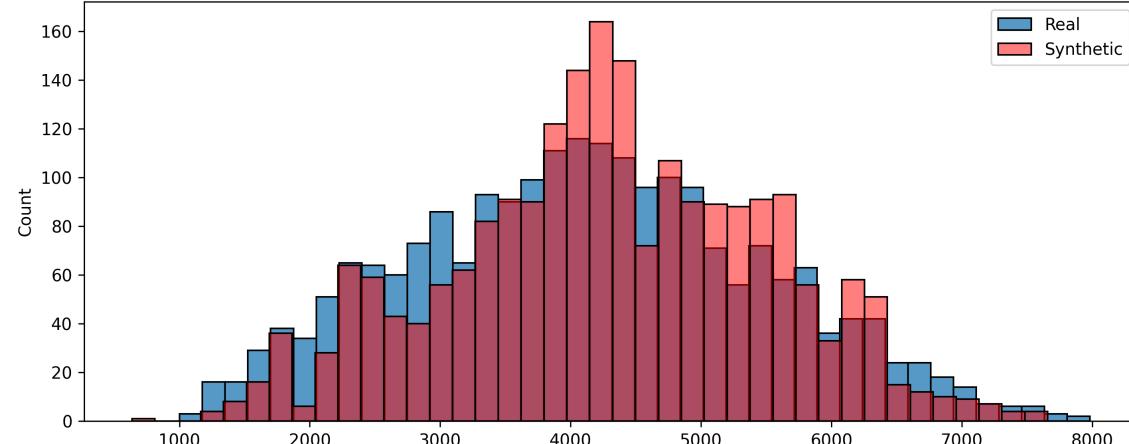


# EVALUATION

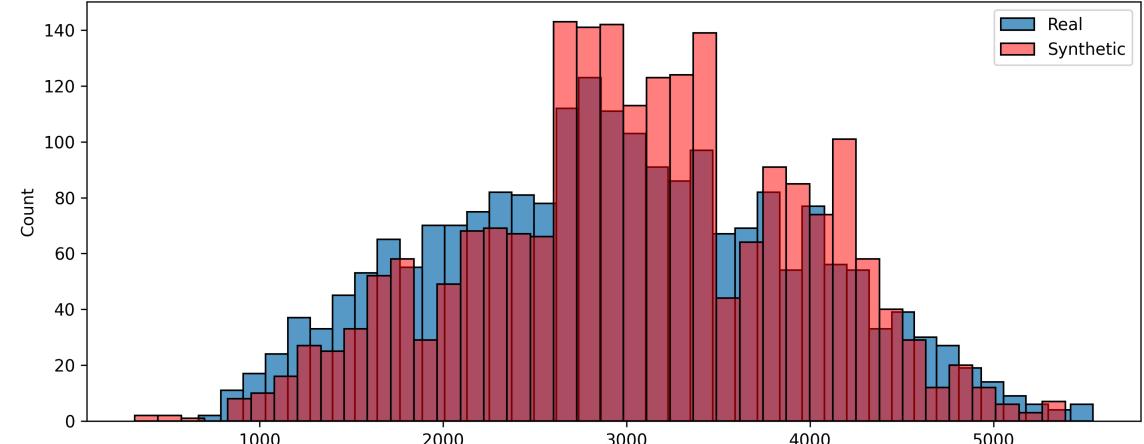
- Exploratory data analysis
  - *KL divergence on marginal distributions*
- Discriminator measure
- Distance to the closest record (DCR)
- Machine learning efficiency (MLE)

# ANALYZING “DAILY WEB VISITS” DATASET RESULTS

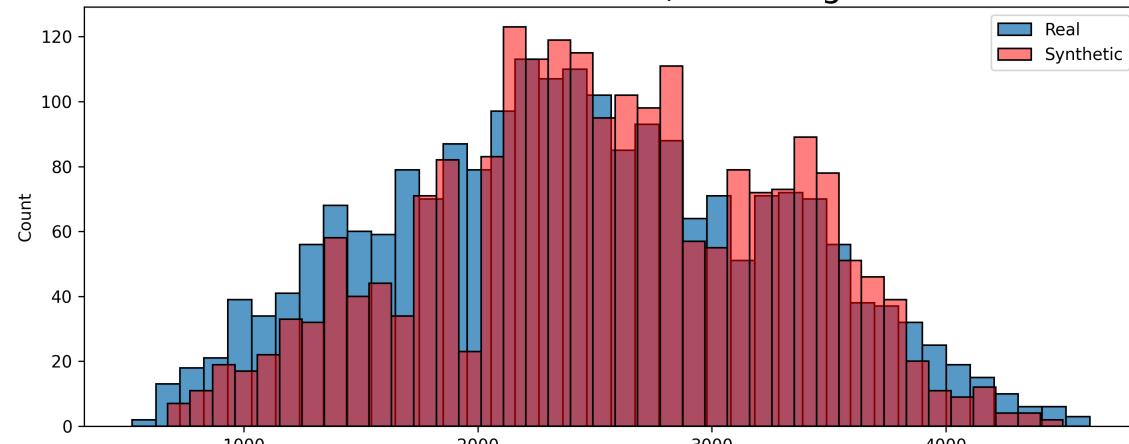
Page.Loads distribution, KL divergence: 0.29



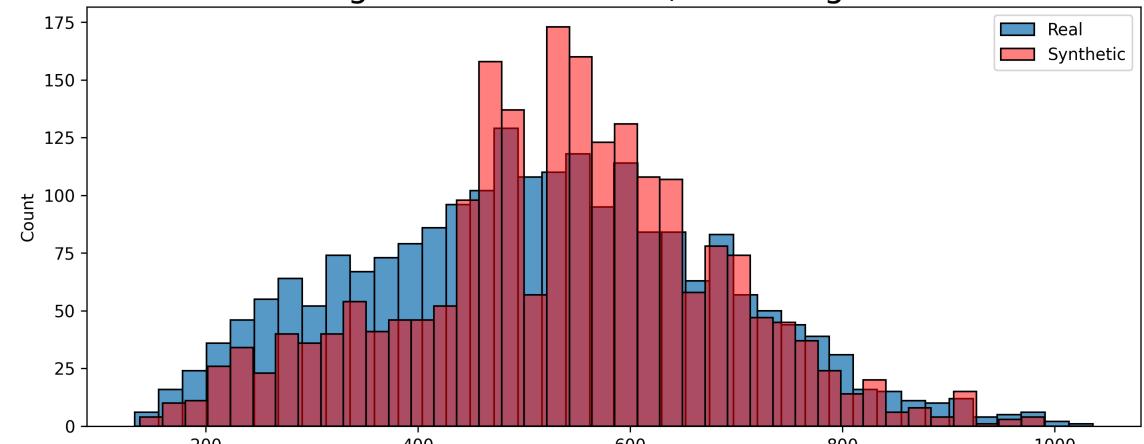
Unique.Visits distribution, KL divergence: 0.29



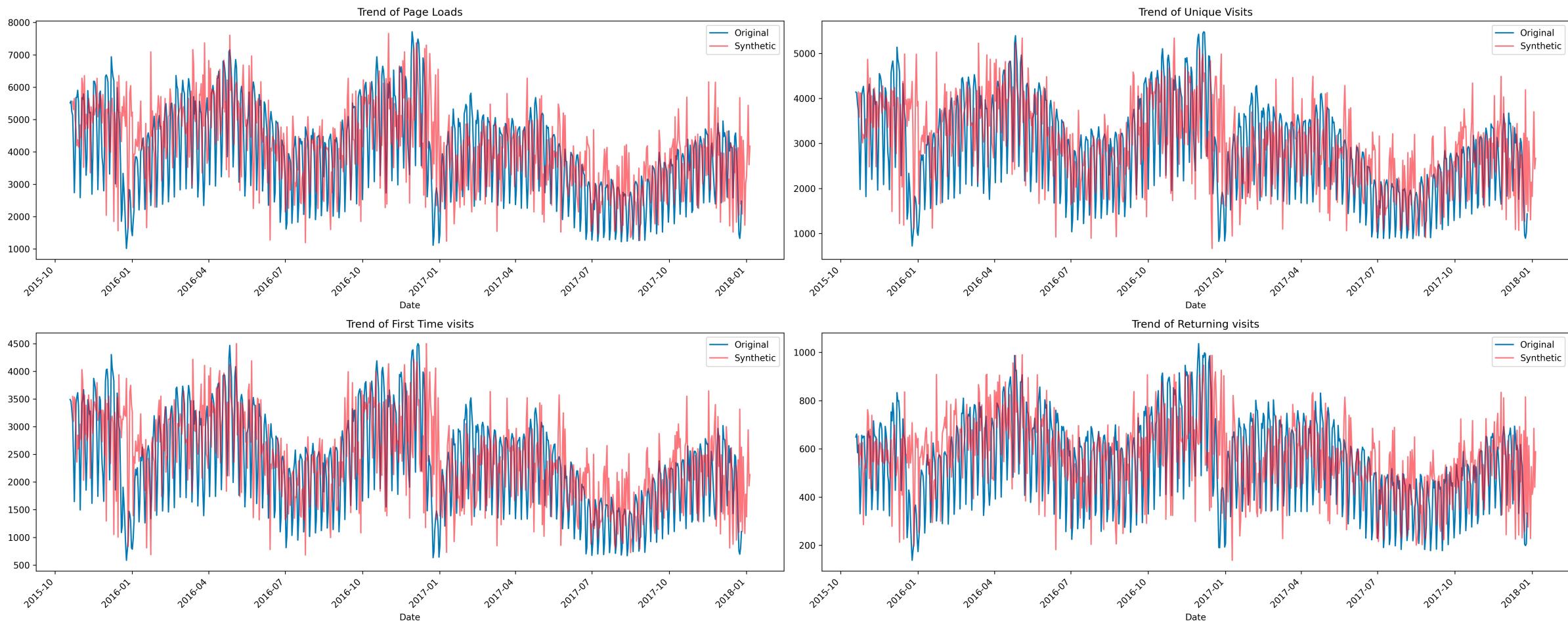
First.Time.Visits distribution, KL divergence: 0.08



Returning.Visits distribution, KL divergence: 0.10

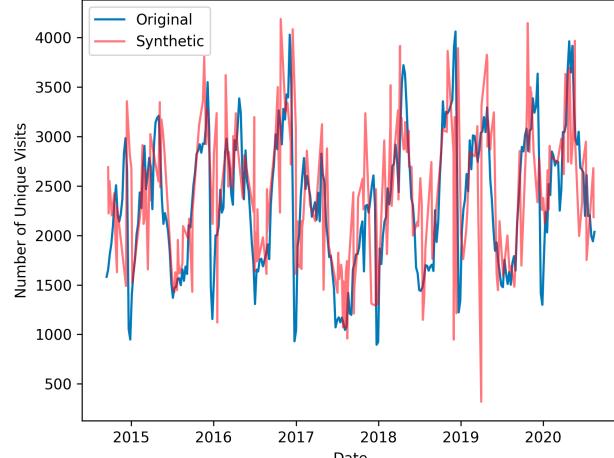
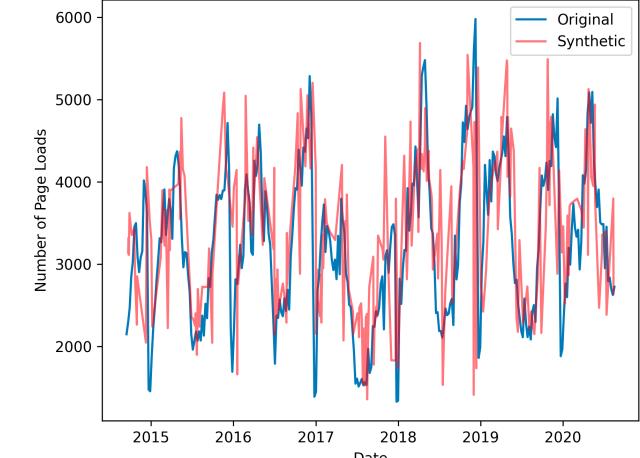


# TRENDS DURING YEARS

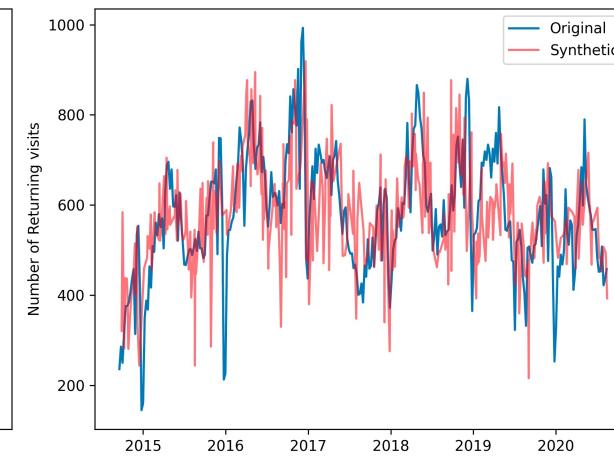
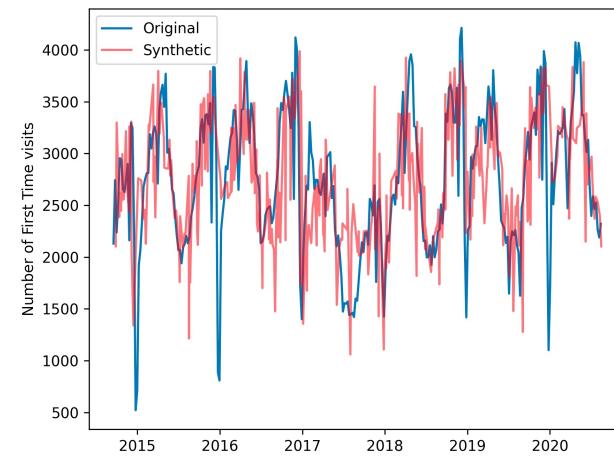
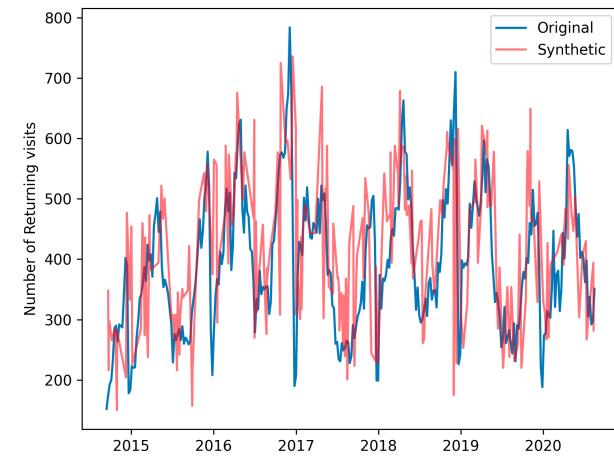
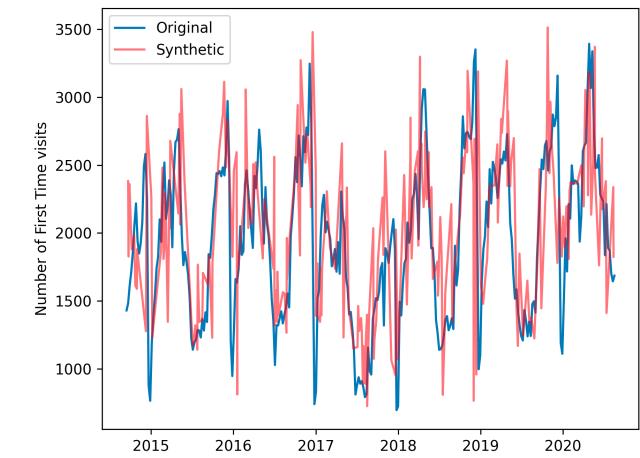
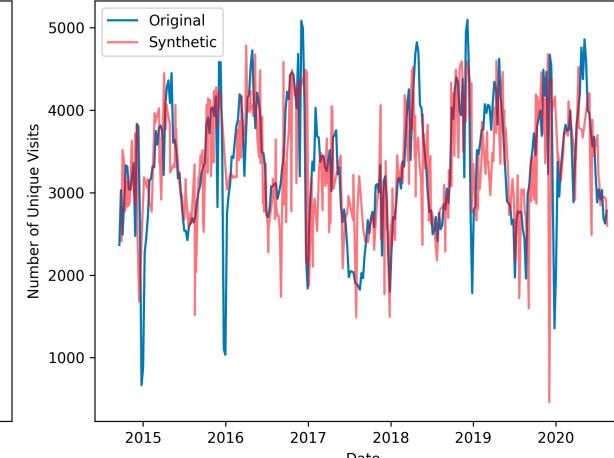
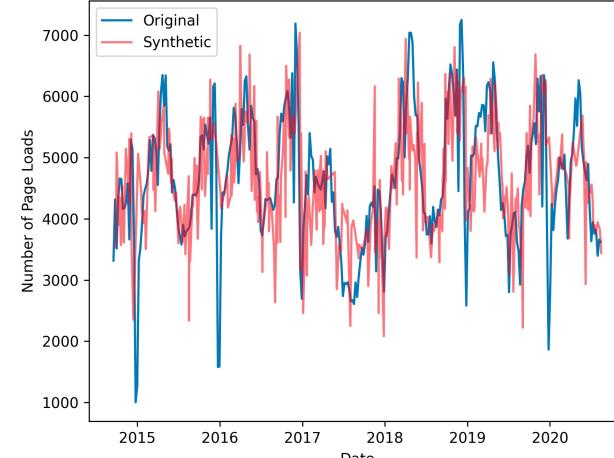


# DAILY TRENDS

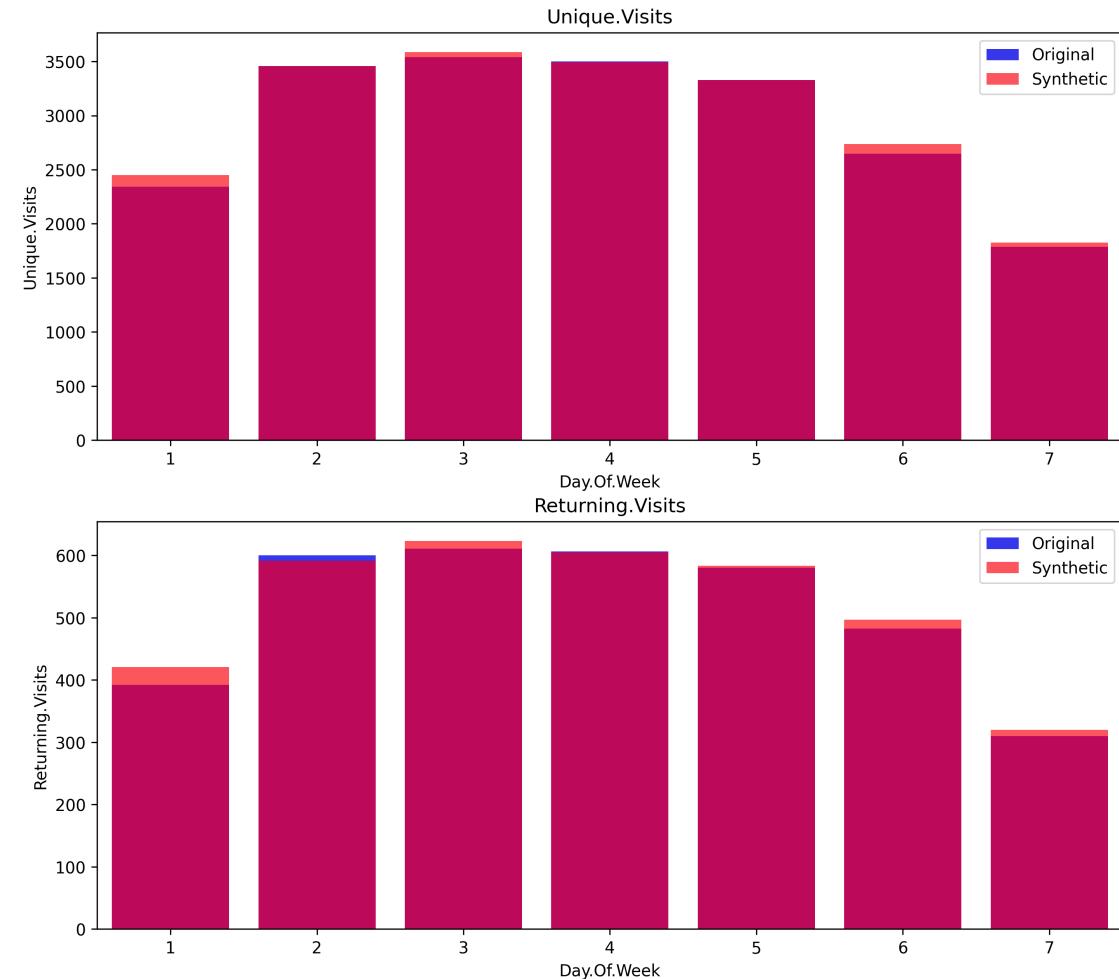
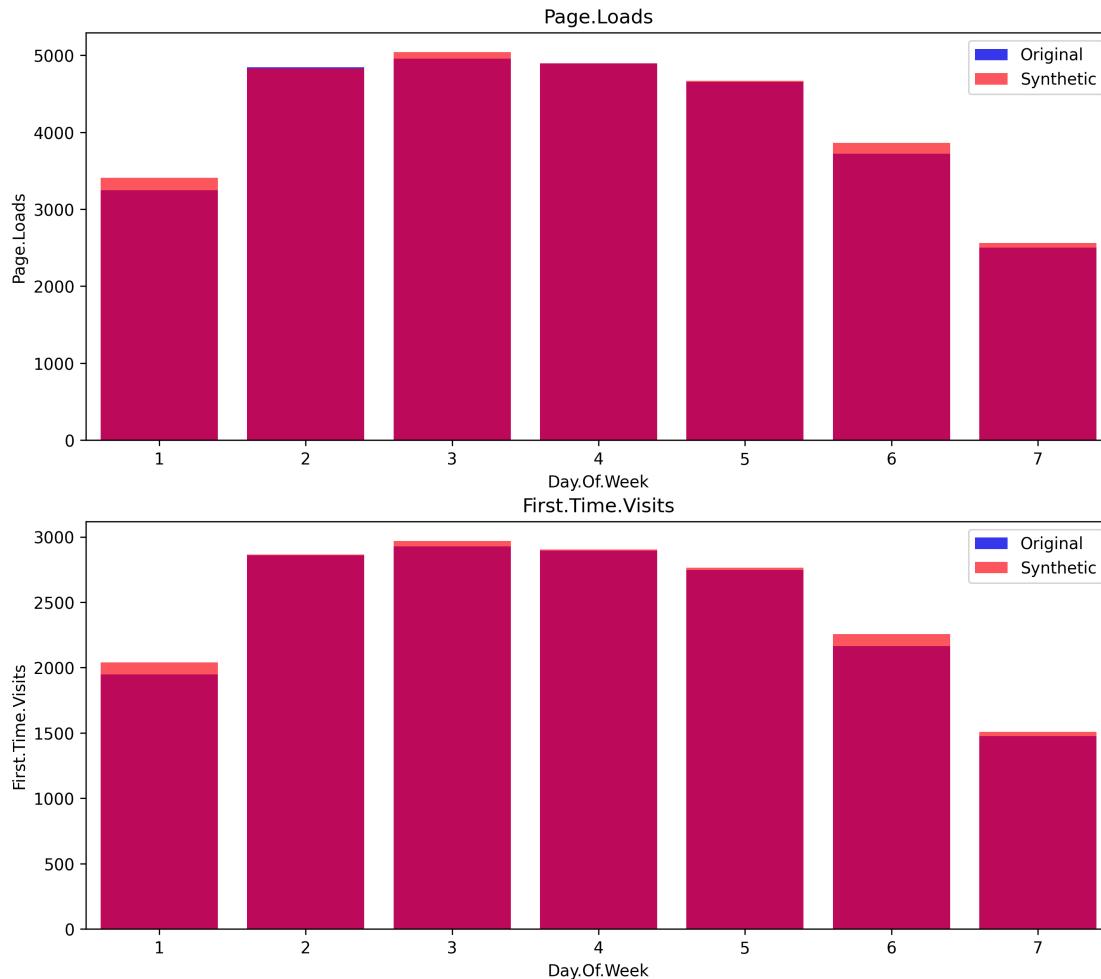
Monday Trend



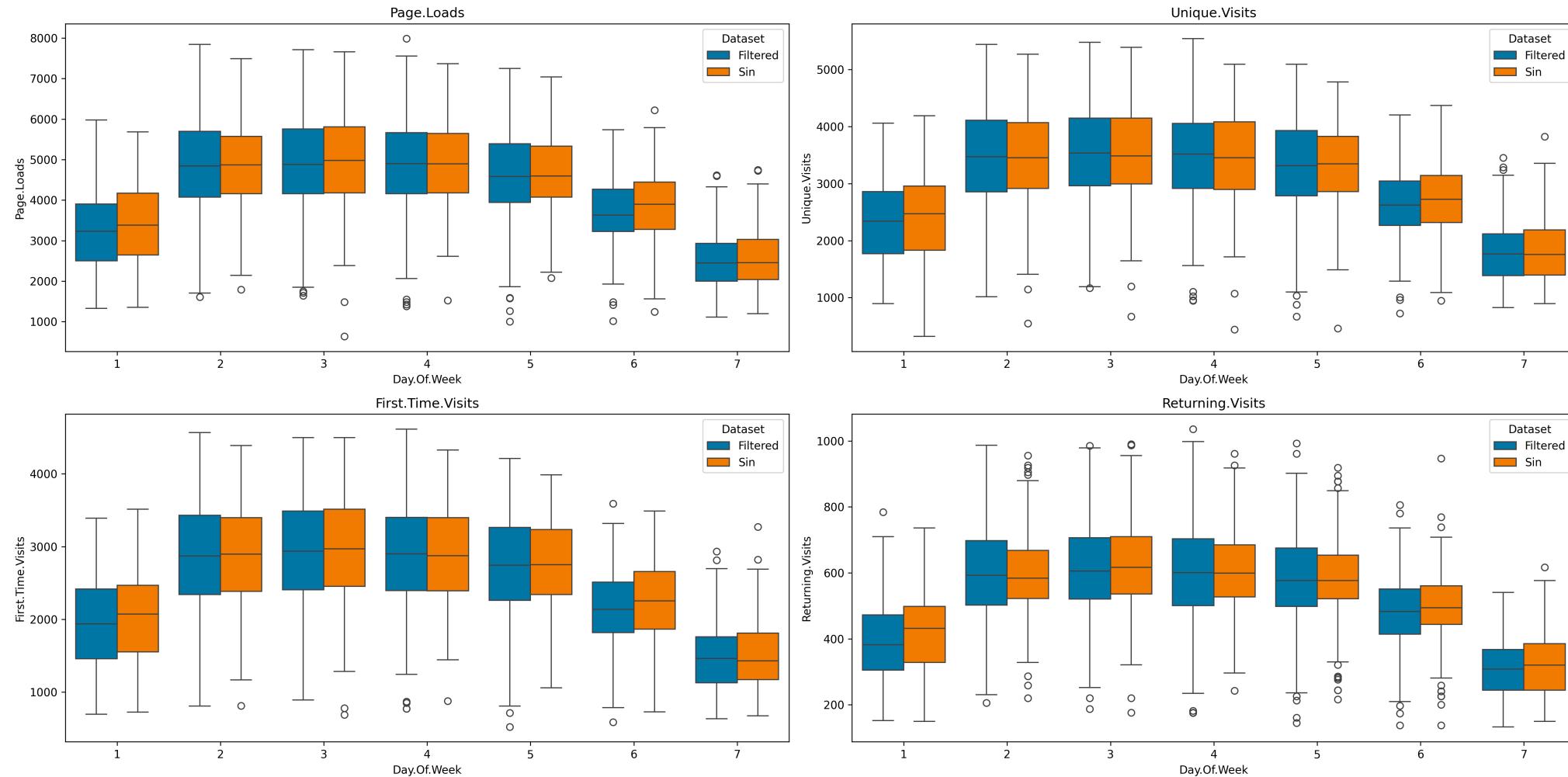
Friday Trend



# DAILY AVERAGE VALUES

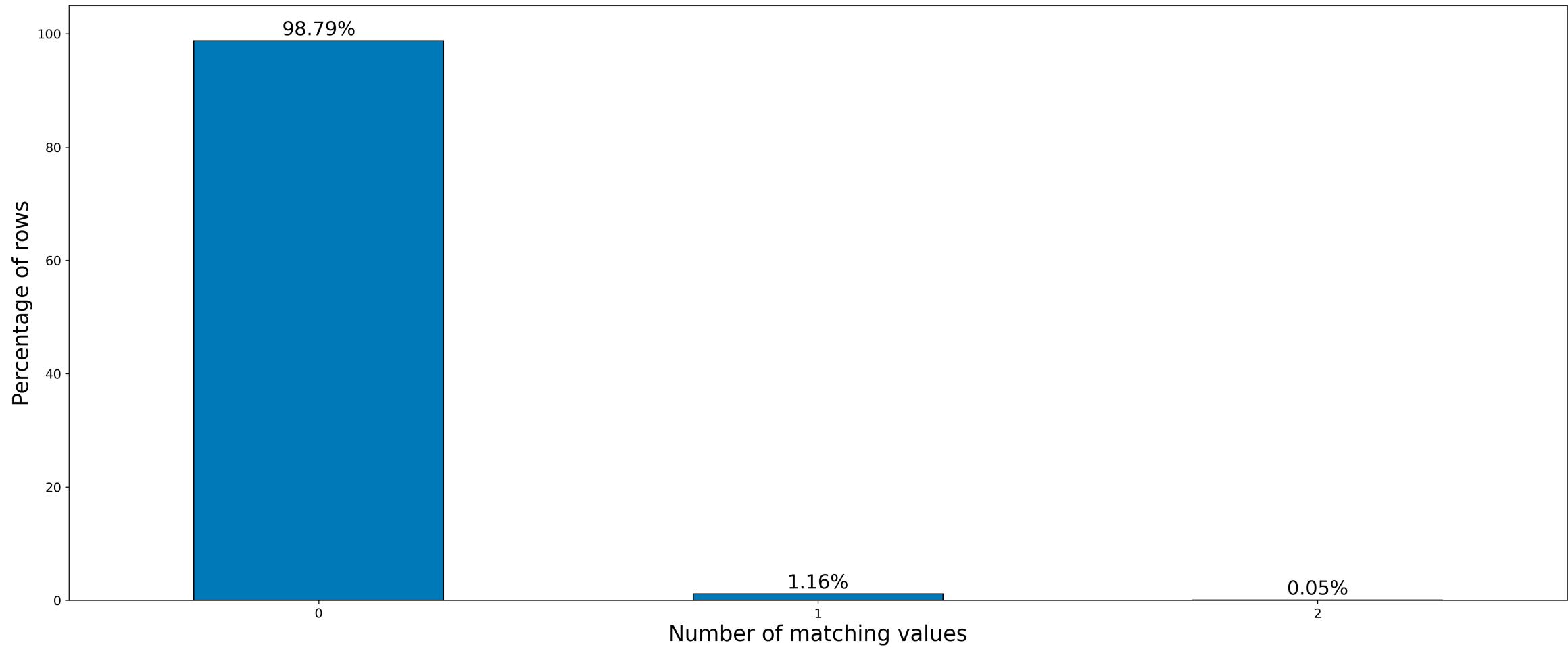


# DAILY DISTRIBUTIONS



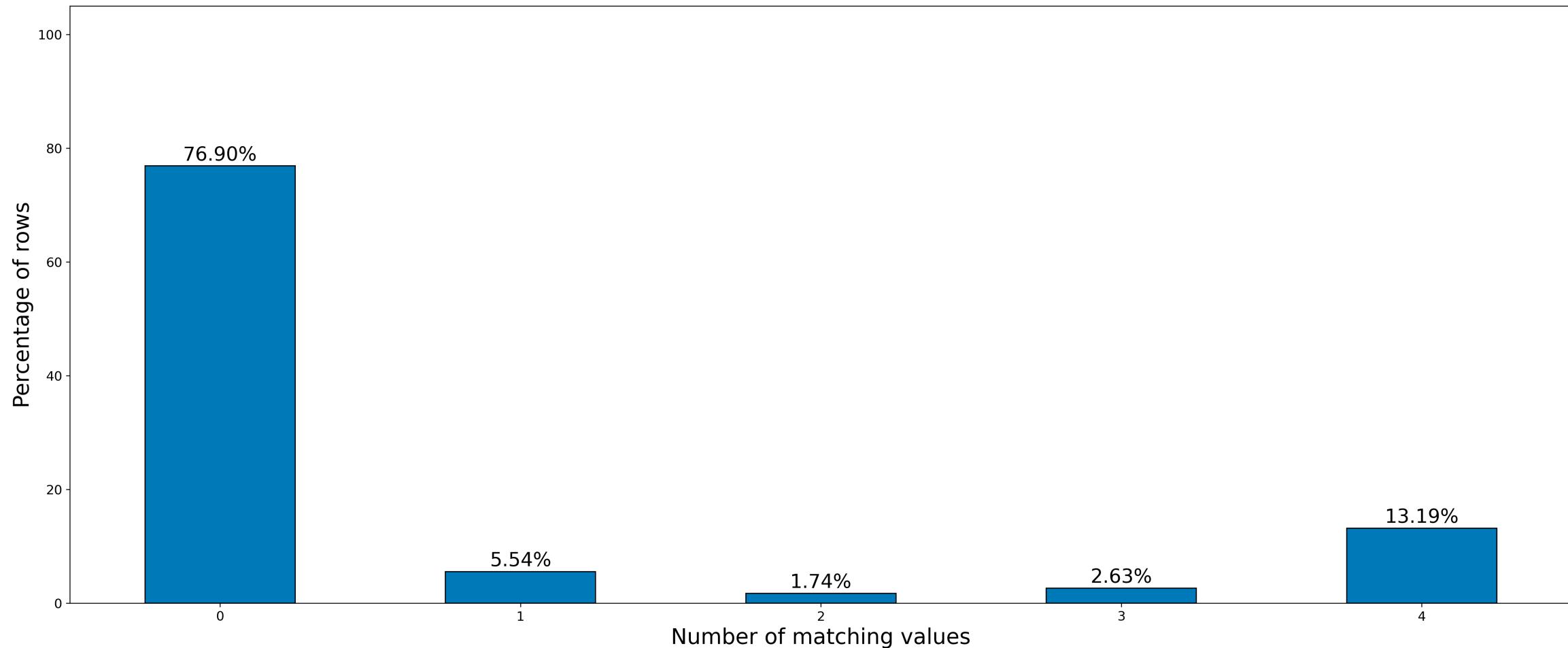
# LOOKING FOR COPIED VALUES - TIME-WISE FRAMEWORK

Percentage of matching values between corresponding rows of real and synthetic datasets



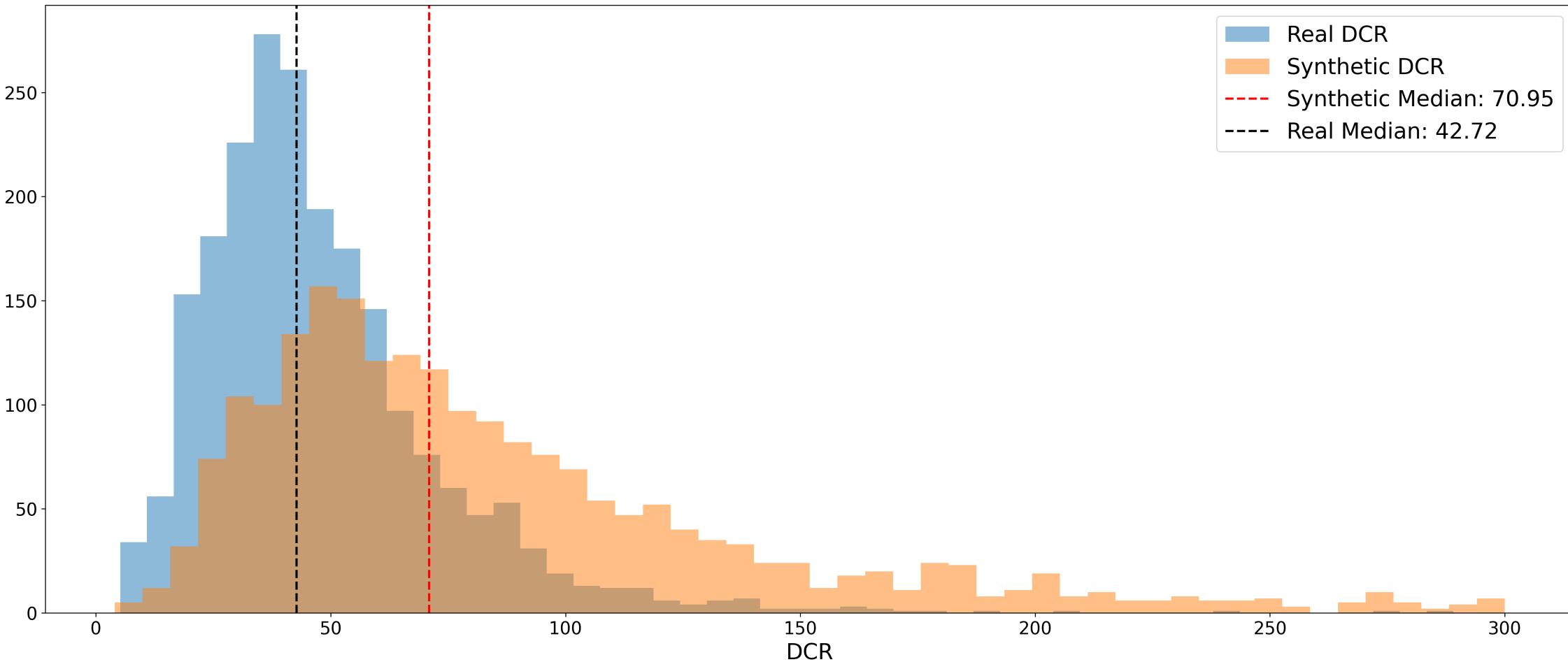
# LOOKING FOR COPIED VALUES - ORIGINAL FRAMEWORK

Percentage of matching values between corresponding rows of real and synthetic datasets



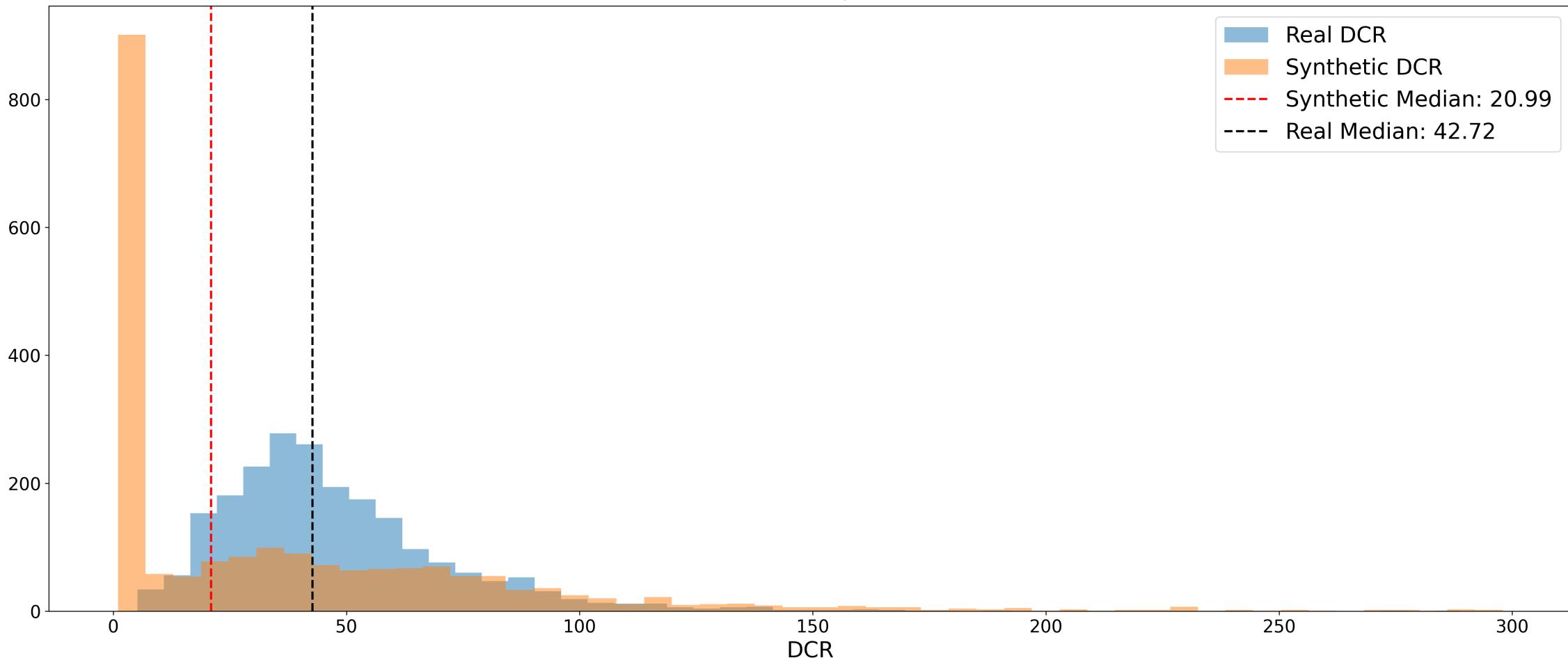
# DISTANCE TO THE CLOSEST RECORD - TIME-WISE FRAMEWORK

DCR Distribution



# DISTANCE TO THE CLOSEST RECORD - ORIGINAL FRAMEWORK

DCR Distribution



# DISCRIMINATOR AND MLE

## TIME-WISE FRAMEWORK

	Weather	Energy	Web
Discriminator	0.59	0.56	0.63
MLE S-R	0.31	0.63	0.28
MLE R-R	0.29	0.73	0.28

## ORIGINAL FRAMEWORK

	Weather	Energy	Web
Discriminator	0.42	0.34	0.37
MLE S-R	0.37	0.77	0.53
MLE R-R	0.29	0.73	0.28

# FURTHER DEVELOPMENTS: AUTOCORRELATION WITHIN LAGS

- Let the model understand the real sequentiality of data

PAGE.Loads

Lag	Real	Synthetic
0	1.00	1.00
1	0.74	0.30
2	0.35	0.33
3	0.14	0.29
4	0.13	0.29

FIRST.TIME.VISITS

Lag	Real	Synthetic
0	1.00	1.00
1	0.76	0.33
2	0.40	0.36
3	0.20	0.31
4	0.10	0.31

UNIQUE.VISITS

Lag	Real	Synthetic
0	1.00	1.00
1	0.76	0.31
2	0.37	0.32
3	0.17	0.28
4	0.16	0.28