Using Generative Adversarial Network to Generate Synthetic Population

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Outline

- Background - Census of Agriculture
- Goal of the research
- Approach: Generative Adversarial Network (GAN)
- Experiment and result
- Conclusion and future work

Census of Agriculture

Every five years, USDA's National Agricultural Statistics Service (NASS) conducts the U.S. Census of Agriculture

- The Census provides a detailed picture of U.S. farms, ranches and the people who operate them
- It is the only source of uniform, comprehensive agricultural data for every state and county in the United States
- NASS makes Census data publicly available only as summary statistics
- Record-level information should be provided and disclosure of the confidential information should be averted

Goal of the research

- Problem: To provide detailed information based on the Census data
- Constraint: To avoid the disclosure of the confidential information
- Solution: A modified or synthetic dataset that preserves the internal relationship of the original dataset
- Previous approaches (Rubin, 1993; Reiter, 2005a,b,c; Paiva et al., 2014; Drechsler and Reiter, 2009):
  - Synthetic data distributions generated from models
  - Pooled or near-neighbors, used as exchangeable observations
  - Inter-changes of data elements among units
- The trade-off for synthetic data is disclosure protection vs preservation of data complexity

Motivation of Generative Adversarial Network (GAN)

Idea:

- To preserve finer internal structures
- To duplicate statistical properties with the original dataset

Approach:

- To use deep learning networks to synthesize
- To revise until synthetic data cannot be distinguished from the original data

Solution: Pair of networks

- Generative network (G-network) creates record-level synthetic data
- Discriminative network (D-network) distinguishes real data from the synthetic

Generative Adversarial Network (GAN)

GAN (Goodfellow et al., 2014) consists of two neural networks that train simultaneously and "compete" with each other

- G-network takes in random numbers and returns record-level synthetic data
- The generated synthetic data concatenated with the real data are fed into the D-network
- A D-network learns to distinguish real data from synthetic data
- Parameters of G-network are updated to "fool" the discriminator

Iterate

- Process stops when the G-network's output (synthetic data) can't be distinguished by D-network from the real population

Two utility measures

Two utility measures are used adapted from Woo et al. (2009)

Propensity score

- Assume: Original population and synthetic population have the same size
- Original records labeled 0, synthetic records labeled 1
- Propensity score for each record is generated by a model with response either 0 or 1

$$U_p = 1 - \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - c)^2$$

U_p: Propensity utility score

N: Total number of records

$\hat{p}_i$: Estimated propensity score for unit *i*

c: *0.5*

- Completely indistinguishable when $U_p \to 1$, otherwise $\to 0.75$

Two utility measures - continued

Clustering Score Measure

- Assume: Original population and synthetic population have the same size
- All the clusters are equally important

$$U_c = 1 - \frac{1}{G}\sum_{i=1}^{G} w_i\left(\frac{n_{io}}{n_i} - c\right)^2$$

U_c: Clustering utility score

G: Total number of clusters

n_i:Number of observations in the *i-th* cluster

n_{io}: Number of original observations in the *i-th* cluster

w_i: *1*

c: 0.5

- Completely indistinguishable when $U_c \to 1$, otherwise $\to 0.75$

Evaluation of identification disclosure risk

Disclosure risk measure using neighborhood-based approach adapted from Hu and Savitsky (2019)

$$S_r = \frac{1}{N}\sum_{i=1}^{N} I_i$$

S_r*:* Risk score

N: Total number of records

I_i: *1* if the *i-th* synthetic record lies in the 10-neighbors of the *i-th* original record, otherwise *0*

- Completely distinguishable when $S_r \to 0$, otherwise $\to 1$

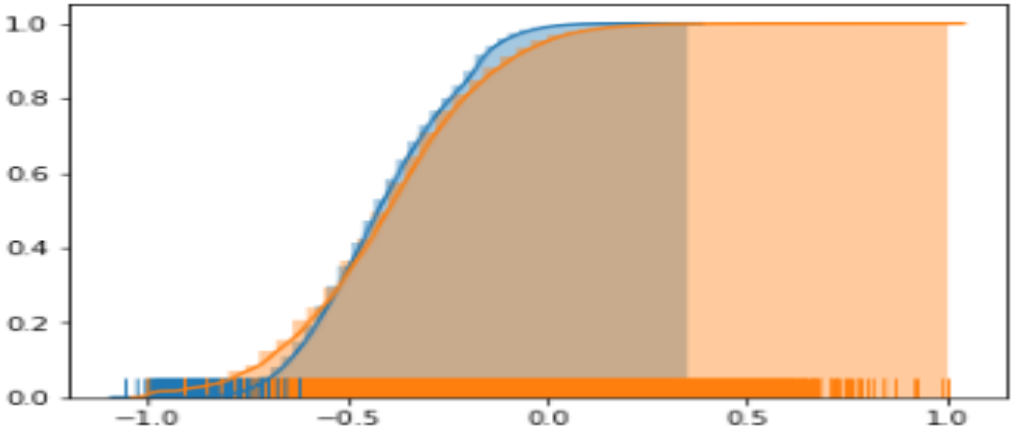
Pilot experiment

- A subset of 2012 Census of Agriculture dataset
  - One million records
  - No missing values
  - A subset of items selected
    - Total Land in Farms
    - Total Value Production
    - State (State id)
    - County (County id)
- Rescale to -1 and 1

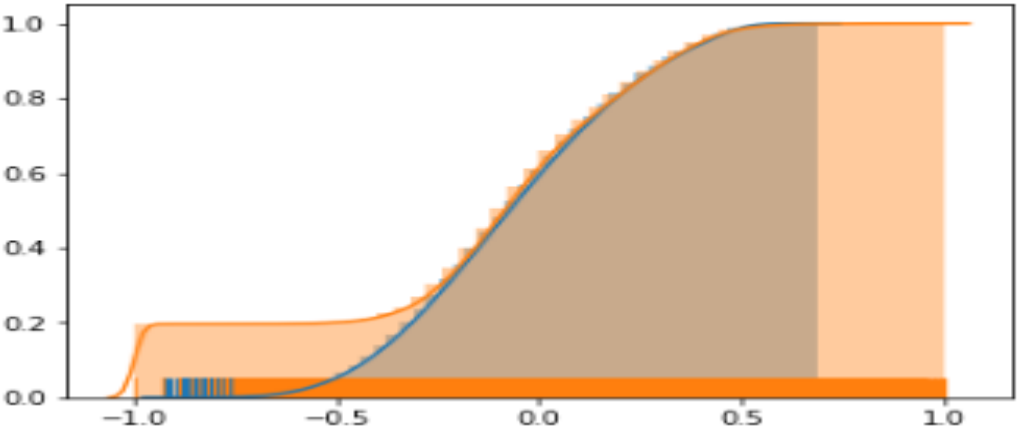
Pilot experiment - continued

- A GAN is trained on the subset of one million records dataset considering the loss function
  - In G-network
    - The cross entropy to penalize the output from G-network classified as synthetic by D-network
    - First, and second moments of the original distribution added to the loss function
  - In D-network
    - The cross entropy to penalize wrongly assigning the output from G-network to real, and real to synthetic
- Utility measures are calculated to evaluate the synthetic population
- Evaluation of identification disclosure risk measure is calculated

Result



Total Land in Farms



Total Value Production

- Original Distribution
- Synthetic Distribution

Result - continued

Propensity Score Measure: U_p = 0.97 → 1

Clustering Score Measure:

- *G* =200, U_c = 0.92 → 1

Risk Score Measure: S_r = 0.02 → 0

Conclusion

- GAN worked well for generating synthetic population for two continuous Census of Agriculture variables in terms of
  - Propensity score measure
  - Clustering score measure
- GAN failed to capture extreme values
- Identification disclosure risk of synthetic population is low

Future work

- Comprehensive experimentation
  - Multiple variables
  - Different numbers of clusters
  - Categorical, count, and skewed variables
- Further tuning of GAN's hyper-parameters
- Other measures of utility and of identification disclosure risks
- Adaptation to better fit distribution extremes

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Questions?

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